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The Persistence of Unemployment in Canada and Sectoral Labour Mobility.

by

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Thesis Abstract

This dissertation is an economic investigation into the persistency of Canadian unemployment. It examines whether this persistence is caused by sectoral shifts. Empirically, we test for persistence using the Cochrane Variance ratio and the modified rescaled range test statistics. We estimate unemployment persistence using Bayesian ARFIMA class of models. To understand employment sectoral dynamics, the thesis uses data-driven Vector Autoregression models with emphasis on Classical and Bayesian estimation techniques. At the theoretical level, two structural Real Business Cycle models are proposed to explain how aggregate unemployment persistence emerges from sectoral labour mobility. The main difference between these two models is the impetus of the shock. One model uses relative sectoral technology shocks and the other uses relative sectoral taste shocks. We show that sectoral phenomena are important in accounting for aggregate unemployment fluctuations.

Sommaire de la Thèse

Les donnés Canadiennes révèlent un chômage persistant. Est-ce-que le chômage aggrégé est le résulat des facteurs sectoriels? Je présente les faits persistants du caractère du chômage sectoriel à l'aide des statistiques de variance de Cochran, de la rescaled-range modifiée et de l'estimation Bayesian de la classe des modèles ARFIMA. À fin de mieux comprendre la dynamique du marché de l'emploi, j'ai recours aux modèles réduits de Vecteur Autoregressive en portant un intérêt spécial aux techniques d'estimation Bayesienne et Classique. Au niveau théorique, deux modèles de cycle réel économique sont suggérés pour expliquer comment un chômage persistant peut résulter de la mobilité entre-sectoriel des travailleurs(euses). Les deux modèles englobent les deux écoles dominantes de pensée économique, plus précisement la différence principale entre eux est dans la nature du choc (choc technologique et préférence des consommateurs). Les politiques gouvernementales visant à contourner et atténuer le problème du chômage, doivent porter plus d'attention aux phénomènes sectoriels.

Keywords:
Canadian unemployment, persistence, hysteresis, Cochrane variance ratio, modified rescaled range test, Bayesian ARFIMA models, sectoral phenomena, Lilien's hypothesis, Classical and Bayesian Vector Autoregression, identification, Blanchard and Quah identification, adjustment costs, labour mobility, Real Business Cycle models, sector-specific technology shocks and sector-specific taste shocks, dynamic programming, sensitivity analysis.

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0.1 Introduction

This thesis studies the effects of sector-specific shocks on aggregate cyclical fluctuations in unemployment. By integrating unemployment caused by sectoral shifts into a formal dynamic general equilibrium model, the aim is to show the importance of the relationship between sectoral shifts and the movements of output and employment observed at the aggregate level in Canadian data. The core mechanism of the models (presented here) is impulses-amplification-persistence: real random impulses are amplified by an adjustment cost to labour movements across sectors and produce persistence in aggregate unemployment.

This thesis investigates whether persistence in aggregate unemployment is a property of the impulses that impinge on the economy or a consequence of the structure of the sectoral interactions in the labour market. The objective is not to dismiss aggregate shocks and their influence, but to quantify the relevance of sectoral shocks and how they affect the labour market.

At the theoretical level, I use two real business cycle models, calibrate them to the Canadian economy, and run experiments that evaluate these models. This thesis addresses the following questions. Do shocks which induce sectoral reallocations (in terms of inter- and intra-sectoral job flows) have effects on the aggregate data mirroring the effects of the 'productivity shocks' in the real business cycle[1] literature? Do sectoral shocks account for and capture the dynamics and persistence of unem-

[1] Business cycles are measured as deviations from the trend and co-movements across time of aggregate variables.

ployment in aggregate data? Can sectoral shocks alone account for the full volatility in unemployment? Do small or large idiosyncratic shocks to key sectors influence greatly the aggregate?

At the empirical level, I test for persistence in Canadian unemployment series using the Cochrane variance ratio test and the modified rescaled range test. Once 'economic persistence' is defined, I conduct a Bayesian estimation of 16 univariate models within the class of Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. To assess the unemployment dynamics across sectors, I estimate a Bayesian sectoral vector autoregressive (BVAR) model to assess the effect of a sectoral shock on aggregate unemployment. The rationale for using both these approaches is explained in the next subsection.

0.1.1 Computational Economics

Computational analysis in economics has become an integral component of, and an important tool for, the study of business cycle models. In general, quantitative research in economics can be divided into two (non-exhaustive) approaches: the system of equations approach (SEA) and the calibration approach (CA). These approaches differ as to whether the model is designed to possess a steady state, the extent of information available to the agents, the specification of the dynamic structure of the model and the nature of the exogenous variables. For example, early SEA applications ignored the steady state design. Later, attention was paid to the long-run steady state, specifically with the development of the cointegration and the error correction modelling (ECM) tools. Nowadays, ECM is the favourite tool for estimating the steady state relationship. The CA emphasizes the construction of the steady state by its restrictive built-in assumptions in the model described by its environment and emphasizes the inter-dependence of agents' economic decisions.

Nickell (1985) considered the case in which an error correcting behaviour represented agents' optimal decisions in a dynamic setup. He provided a one-to-one mapping (in a general non-mathematical sense) between adjustment costs in dynamic modelling and an error correction mechanism. In my view, this note emphasized the equivalence of the information content in both the system of equations approach (SAE) and the calibration approach (CA). I see both approaches as complements and in this thesis I will pursue both. I compare information from a data-driven reduced form model (Vector Auto-Regressive) to two structural Real Business Cycle models.

The second difference between the approaches is in their integration of dynamics. The SEA approach does not provide a theory for dynamic lags. It lets the data decide. The lags are estimated using Classical or Bayesian statistical frameworks. At the empirical level of this thesis, I focus on the latter. The CA approach relies on intertemporal optimization jointly with the law of motion of the stock variables (with time to build) to determine the dynamics of the model.

The end-result of the CA models can be viewed as a *restricted* vector auto-regressive (VAR) model. It is a restricted VAR, because it is a VAR in the state variables and the parameters (non-estimated) are complex functions of the calibrated ones. Whereas, the SEA is an *unrestricted* VAR because all variables enter the equations and the parameters are estimated. The following table summarizes the major modelling differences between the two approaches.

	SEA	CA
Steady State	Not in older models Yes, using ECM	By design
Information	Partial Full in financial sectors	From intertemporal optimization
Exogenous	Conditioned on current value or deterministic trend	Treated as autoregressive

Source: Kim and Pagan (1995, p. 364).

I pursue a spectrum of general equilibrium models with the aim of empirically replicating both employment volatility and dynamics. Stochastic dynamic general equilibrium models have become the standard hallmark and an efficient tool of evaluating macro models. Numerical simulations of these models offer a detailed micro picture of the economy and provide a constructive platform for assessing economic policy issues. I also pursue a Bayesian VAR investigation of the same issues. Finally, I will compare the results from both approaches.

The CA approach provides an approximate solution where relevant quantitative information is not available from closed form solutions. I hereby follow the five steps outlined in Kydland and Prescott (1996). Adapting them to the thesis produce the following:

1) The question posed: can a sector-specific shock in a structural sectoral analysis account for aggregate fluctuations in employment? This question is concerned with policy evaluation. In a recession, government decision makers focus on the level of aggregate unemployment and take measures to reduce it and to provide income replacement for the unemployed. If evidence of Lilien's hypothesis,[2] tested here, is found in the Canadian labour market, then other policy solutions, such as generating

[2] The Lilien (1982) hypothesis argues that half of the variance in unemployment is due to the sectoral reallocation of workers.

easier worker mobility between sectors, ought to be considered rather than providing income replacement without addressing the source of the problem.

Also, if such evidence is found, then the '*Intensity Rule*'[3] - used to determine unemployment insurance benefits based on the level of local regional unemployment - should be discarded and replaced with one that: a) is based on the level of aggregate sectoral unemployment and b) takes into account the worker's last industry attachment. For example, if the manufacturing sector unemployment rate is higher than the unemployment rate in the service sector, then an unemployed worker in the manufacturing sector should be paid higher replacement ratio than an unemployed worker in the service sector. Such a 'sectoral intensity rule' in determining unemployment insurance benefits is deemed to be more efficient.

Another implication concerns the '*Stay Option*' policy. In Manitoba, between 1974 and 1976, the New Democratic Party (NDP) government of Ed Schreyer applied this policy. It helped workers stay in their communities, despite changes in local market conditions that influenced the availability of jobs and levels of income. Millions of dollars were poured into government-owned or government-subsidized firms that suffered huge financial losses. In describing that policy, McCallum(1991, p. 198) reported that "... *a great deal of money was wasted* " (my emphasis). Without addressing the social value of such action, the policy was not economically efficient. The government was trying to undertake measures to reduce aggregate unemployment without properly looking at sectoral unemployment. Had this money gone to

[3] The 'Intensity Rule' was recently introduced in the Canadian unemployment insurance benefit program as part of the system overhaul in 1996.

provide re-training and easier worker mobility between sectors of the economy - such as financing proper training programs for the workers - the outcome would have been different for the growth of Manitoba' economy. The merits of such a policy are yet to be assessed for the Atlantic fishery sector.

2) Which theory? We use stochastic general equilibrium dynamic models. These models imply that when modern business cycle models are confronted with a technology or tastes shock, the models' artificially generated data should display fluctuations similar to the business cycle data.

3) Constructing a model economy. The critical element of our model economy is the use of a multi-sector framework that incorporates a well defined propagation mechanism. This amendment to the stochastic general equilibrium models will generate sluggishness in employment adjustment, therefore producing persistent unemployment at the aggregate level.

4) Calibrating the model. This is done by using Canadian micro data studies to quantify and calibrate the parameters in the models.

5) Running the experiment. The computer program will determine the equilibrium process (the steady state) of the modelled economy and then uses it to generate equilibrium realizations of stochastic processes. We investigate and report the extent of the match between artificially generated data and business cycle data.

0.1.2 Economic Paradigms

This subsection underlines the schools of thought which operate in the background of this thesis. Note that the issues discussed here are explored in detail later on.

Lilien' proposal - of the sectoral reallocation of workers - highlights the important role played by sector dynamics in explaining aggregate unemployment. This view opposes the Keynesian perspective. The former view predicts a positive correlation between unemployment rates and inter-industry worker mobility, while the latter implies a negative correlation.

The framework I intend to use is Real Business Cycle (RBC) models (i.e., CA approach). The RBC models can generate Keynesian type results such as persistence (sluggish dynamics) in output and/or unemployment. This persistence culminates from real shocks. These models can also accommodate non-Walrasian assumptions.

In this thesis, using the calibration approach, two RBC models (with relative sectoral technology and taste shocks) are formulated and simulated. Each model is simulated at two frequencies, quarterly and annually. At each frequency, the model is simulated for different shock sizes and different labour adjustment costs. In total, sixty models are simulated. Their dynamic properties and their sensitivity to calibrated parameters are investigated. These models integrate the type of shock, the size of the shock, labour sectoral mobility and labour adjustment costs into an RBC framework.

The first model focuses on supply shocks (relative sectoral technology shocks) that shift relative sectoral productivity, which shifts sectoral labour demand. The second focuses on demand shocks (relative sectoral taste shocks) that shift relative sectoral goods demand, which shift relative sectoral labour demand.

Also and conforming to the SEA approach, I estimate a set of Classical and Bayesian Vector AutoRegression (VAR) models with different identification approaches and parameter specifications, using Canadian industry level data to quantify the effects of a sectoral shock on other sectors' employment. Their impulse responses and variance decomposition are reported.

0.1.3 Plan

This thesis uses stochastic dynamic general equilibrium models and Classical/Bayesian Vector Auto-Regression (VAR) to assess the importance of inter-sectoral technology shocks on the level of aggregate unemployment in Canadian data. In the process, we investigate the sectoral behaviour of the Canadian labour market. Whether one views this exercise as an investigation of the 'hysteresis' effect versus a 'temporary' effect on unemployment is open to debate. A 'hysteresis' effect occurs when certain cyclical transitory factors (such as a technology or taste shocks) have a permanent effect on the unemployment level. A 'temporary' effect occurs if the cyclical transitory factors have only a transitory effect on the unemployment level. The conclusions of this thesis report our findings on these.

0.1.4 The Map of the Thesis

Chapter One starts by tracking the development of business cycle models. It highlights the dichotomy between the impulse problem and the propagation problem. Then I explain why the labour market is central to business cycle modeling. After that, I present the labour market theories to elucidate the propagation mechanism and then discuss the types of shocks to the economy to elucidate the nature of the impulse.

Chapter Two presents the general Uhlig RBC model and the baseline King-

Plosser-Rebelo RBC model. A variety of other RBC models are also discussed. The intuition of RBC models is explained. Aspects such as de-trending, criticisms and failures are reported. The usefulness of introducing adjustment costs is highlighted. Next, we discuss the question of calibrating the Canadian economy from existing studies.

Chapter Three presents the rationale for sectoral analysis in macroeconomics. It discusses the policy implications of the different competing theories of the causes of aggregate unemployment, focusing on sectoral shifts versus aggregate disturbances. It also considers the merits of inter-industry labour mobility and the inter- versus intra- sectoral shocks. This chapter emphasizes the usefulness of sectoral analysis in explaining unemployment. It also explores the quantity dynamics of employment.

Chapter Four puts forward the stylised facts of persistence in unemployment. It discusses hysteresis and persistence. This chapter presents the theories, their implications and the evidence on hysteresis. It proposes two measures for testing persistence, specifically the Cochrane variance ratio and the modified rescaled range test. We test for persistence in Canadian unemployment and report the results within the framework of Bayesian ARFIMA class of models.

Chapter Five presents the vector auto-regressive (VAR) models. It discusses the differences between the 'Classical' and 'Bayesian' estimation approaches. We explore both approaches. The Classical approach is investigated under two identifying schemes. The Bayesian VAR is estimated using five different parameter specifications. Topics such as impulse response functions and variance decomposition methods are discussed and the usefulness of each is noted. This chapter concludes by reporting impulse response functions of Canadian employment industry-level data. It ends with results from the VAR models.

Chapter Six develops two RBC models. The models are labeled model I (relative technology shocks) and model II (relative taste shocks). We discuss the models' intuition, the size of the shock in the literature and we conduct an empirical exploration of Canadian industry-level multifactor productivity data. Such examination of the data is useful in identifying relevant empirical regularities to be used for calibration purposes. Both models are simulated using the value-grid method at the annual and the quarterly frequencies. The justification for employing two frequencies is to examine the influence of aggregation on the models' results. At each frequency, the two models are simulated, using three different values for the adjustment costs parameter and five different values for the size of the shock. In total, sixty sets of parameters for both models (thirty each) are simulated and the results are reported.

Chapter Seven presents the conclusions of the thesis. It compares the results from the system of equations approach (Chapter 4) and the calibration approach (Chapter 6). It also suggests directions for future research.

Chapter 1

The Business Cycle and the Labour Market

1.1 Yule, Slutsky, Frisch, Wicksell, Kydland and Prescott, and Lilien

"All business cycle research seeks clarification on a basic, classical question: What are the sources and propagation mechanisms for the boom/bust patterns of economic fluctuations in modern economies?"
Quah (1995, p. 1595)

This section traces the development of business cycle models, the origins of the propagation and the impulse problems, and the central place of the labour market at the heart of the business cycle models.[1]

In his 1933 seminal contribution 'Propagation problems and impulse problems in dynamic economics,' Ragnar Frisch (1933) developed a design for a macrodynamic innovative model of the business cycle. For the first time in economics, questions about the business cycle were divided into the impulse problem and the propagation problem. Frisch offered the first known cycle model that incorporated statistical analysis with mathematically formulated dynamics. The importance of this model

[1] For an excellent and valuable exposition of the historical development of econometric ideas regarding the business cycle, refer to Morgan (1995, pp. 73-100).

was in the innovative integration of random shocks into the cycle model. Frisch reported that the original idea of his model was due to Wicksell. "Knut Wicksell seems to be the first who has been definitely aware of the two types of problems in economic cycle analysis - the propagation problem and the impulse problem - ..." (p. 138).

Frisch' model was based on the Moore (1925) cobweb model consisting of two-equations: demand and lagged supply. The former model was to be of the whole economy. It consisted of a system of mixed differential and difference equations and proved useful in generating oscillations similar to the business cycle data (he focused on consumption, capital starting and carry-on-activity). Once the internal economic cycle mechanism (the propagation problem) was formulated, the paper questioned the impetus of the cycle (the impulse problem). Frisch proposed "One way which I believe is particularly fruitful and promising is to study what would become of the solution of a determinate system if it were exposed to a stream of erratic shocks that constantly upsets the continuous evolution [of the system]" (p. 197-198).

Twenty-four years after the Frisch proposal of a solution to the impulse problem, Solow (1957) provided a theoretical estimation of the technology growth based on the assumption of a constant returns to scale production function and perfect competition. Later on, the Solow residuals explained how Slutsky's random terms came to be summed in economic activity and how Yule's shocks get absorbed into the system.

Kydland and Prescott (1982) formulated a model economy that described an internal propagation mechanism captured by laws of motion. The model viewed Solow's residuals as an impetus to the economic system. A new breed of macro-modelling was born, namely the Real Business Cycle (RBC) models. In it, the irregular output movement over the business cycle was viewed as an economy perturbed by real disturbances of various types and sizes which propagated over time through the economy.

Lilien (1982) sparked interest in the effects of sectoral shocks on aggregate employment and unemployment. His study[2] found that sectoral shifts have negative effects on aggregate level unemployment. The movement of workers from unsuccessful productive units to new or growing units explained almost half of the variance in aggregate unemployment. Lilien reported that periods with aggregate downturns accompanied higher employment variability across sectors. Therefore, the direction pointed by Lilien was that, even if the economy is subjected to sectoral shocks that do not directly influence the aggregate, the propagation mechanism of workers moving across sectors will amplify the shocks and the effects will be felt on aggregate unemployment. Briefly, sectoral impulses (the impulse problem) are amplified by worker mobility across sectors (the propagation problem).

1.2 Why the labour market?

"An understanding of aggregate labour market fluctuations is a prerequisite for understanding how the business cycle propagates over time."
Kydland (1994)

Fluctuations in employment are procyclical. When focusing on economic policy issues, unemployment and inflation are at the heart of macroeconomics. The labour market is formed by a very complex interaction between incentives and disincentives on both: the demand and the supply sides of the market. The former is shaped by

[2] Lilien (1982) will be described in detail later.

basic elements such as commodity prices and labour productivity. Other elements include regulations relating to work time and taxes that increase the cost of workers. The costs are shaped by reservation wages of workers, the level and the duration of unemployment, welfare and transfer payments. These forces meet in the labour market in a very complex dynamic to determine its structure.

Many empirical investigations focus on the causes of unemployment variability. Fortin et al. (1995) provided a comprehensive study of the macroeconomic and structural causes of Canadian unemployment. The variables incorporated were: (macroeconomic variables) the real ex-ante interest rate, federal spending, the regional tax rate, the terms of trade,[3] and (structural variables) the minimum wage, the union density,[4] the demographic pressure, and the unemployment insurance generosity (the replacement rate). Using panel data of 500 observations for five Canadian regions and four demographic groups over the period 1967-1991, the study ranked the importance of the determinants in explaining the long-term increase in the Canadian unemployment rate. The ranking in descending order was as follows: the high real interest rates episode, the unemployment insurance reform of 1972, and the demographic change during the same period.

Using linear regression analysis, Nickell (1997) explored the effects on unemployment - for Europe, U.S., Canada, Australia and Japan - of many labour market measures for the period from 1983 to 1996. This study concluded that high unemployment is primarily due to certain labour market features; namely, generous

[3] The terms of trade were measured as the difference between the log of the regional net output price and the log of the regional price index. The regional net output price was defined as the ratio of nominal to real GDP at factor cost.

[4] Union density was defined as the percentage of the regional labour force who were union members.

unemployment benefits with no end restriction, high union densities characterized by coordination failure (constant friction with management), high overall taxes and poor educational standards at the lower quartile of the labour market. Also, he found no evidence that the unemployment rate is affected by generous unemployment benefits for a fixed amount of time (i.e., with end restriction), or high union density with high coordination with management.

1.3 Terminology of the labour market

This section presents a briefing of the labour market vocabulary.

1.3.1 Stocks

In general, unemployment can be divided into three parts: 1) Frictional, 2) Structural and 3) Cyclical.

Frictional unemployment is the number of people searching for a job. It is composed of people who are new entrants, re-entered or voluntarily quit their jobs. Frictional unemployment (search unemployment) exists when the worker invests time and money in finding a job. This type of unemployment may be voluntary or involuntary. The factors that influence frictional unemployment are institutional: such as unemployment insurance (UI) benefits and school-leaving age.

Structural unemployment is the number of people in the wrong location or with the wrong skills at the wrong time (mismatch unemployment). Structural unemployment is defined as the mismatch of labour supply and labour demand in certain occupations, regions, and industries. The factors that influence structural unemployment are demographic.[5] Finance Canada's definition of 'structural unemployment' is as follows, "... where workers are unable to fill available jobs because they lack the necessary skills, do not live where jobs are available or are unwilling to work at the wage rate offered in the market."[6] The same definition is adopted by Osberg and Lin (1999). Pearce (1997) considers structural unemployment as "... as a more extreme form of frictional unemployment ... ." Osberg and Lin (1999, p. 25) emphasized that in labour economics "unwilling to work at the wage rate offered in the market" is not part of the definition.

Cyclical unemployment is the number of people who are unemployed and are not in the other two categories.

1.3.2 Flow dynamics

The flows into unemployment (referred to as 'unemployment incidence') are divided into new entrants and job losers. The flows into employment are divided into job finders and job changers. The flows out of the labour force are divided into discouraged workers and people who voluntarily leave the labour force.

The rate of job loss depends on 1) technological change, 2) international competitiveness, 3) regional effects and 4) the business cycle.

The rate of job finding depends on the job search process and the reservation wage. Job search depends on 1) unemployment benefits, 2) minimum wages and 3) the degree of mismatch.

[5] For an excellent investigation of the structural factors' influence on aggregate unemployment in Canada see Hostland (1995a, 1995b).
[6] See Finance Canada's definition, source: http://www.fin.gc.ca/glosse/gloss-s_e.html#struct-unemp.

Under the assumption that the size of the labour force is constant,[7] the 'natural rate of unemployment' UE^* is a function of the rate of job losers (l) and the rate of job finders (f) (Formally $UE^* = \frac{l}{l+f}$ where l is the job loosing rate and f is the job finding rate). Labour market dynamics has been extensively exploited during the last 25 years.

This thesis is concerned with inter-industry labour mobility. Osberg (1991) reported that insufficient inter-industry labour mobility might be responsible for the rise in the 'natural rate' of unemployment. This thesis does not debate either the existence or the labeling[8] of the natural rate hypothesis. My intention is to investigate Osberg' observation.

1.3.3 Cyclical Flows

Data on cyclical flows of labour are useful in understanding sectoral reallocation. Flows out of industries, measured as net employment change or as gross job destruction, are highly correlated across industries. Note that total employment turnover is defined to be equal to the absolute value of gross job creation plus the absolute value of gross job destruction.

Extensive empirical research and estimates of the job creation and job destruction rates were reported for U.S. data by Davis and Haltiwanger (1990) and Davis et al. (1996). However, this line of empirical research resulted in theoretical models (wherein job creation results in lower unemployment) that overlook the well documented 'Todaro Paradox'. The seminal work of Todaro (1969) - well known in economic regional

[7] That is the flows of new-entrants, retirees and discouraged workers all balance out.
[8] Many suggested calling it the 'equilibrium' rate instead of the 'natural' rate.

sciences - provided a spatial analysis of urban unemployment and emphasized the role of job creation rates in increasing unemployment. This paradox argues that (Todaro (1969, p. 147)) job creation in urban areas can produce a paradoxical increase in urban unemployment in less developed countries, because the low marginal cost of travel will significantly increase the radius of the urban labour market and create new labour supply even in the absence of migration.

Similarly, such reasoning may also apply if job creation attracts discouraged workers. Specifically, an increase in the job creation rate in a specific sector of the economy might result in a significant increase in the employment of discouraged workers and consequently will not decrease the unemployment rate.

While Todaro focused on rural-urban flow migration, Nakagome (1989) emphasized the inter-play of job creation and labour supply through commuting costs. Presenting an endogenous model of the radius of labour supply - determined by the travel cost of workers - the model highlighted the role of the job creation rate in increasing wages and consequently expanding the radius of the labour supply. This study was a spatial extension of the Todaro model.

We do not investigate the cyclical flow data of the labour market for the following reasons. Job creation and destruction rates by sector are not well documented in Canada. While the inter-industry accounting system (the input-output[9] tables) traces the flow of goods and services from one productive sector to another, it does not - unfortunately - trace the flows of labour across sectors. Also, a prerequisite is to test

[9] For a review of the input-output theory and applications see Chenery and Clark (1967, chapter 2 to chapter 13).

for causality (i.e., testing the validity of the Todaro Paradox) and to examine cyclical co-movements between job creation and unemployment.

1.4 The Canadian Labour Market

This section reports the stylised facts regarding Canadian unemployment.[10] In general, the unemployment rate is high and has an upward trend. The unemployment rate rose from an average 4.2 percent in the 1950s, to 5 percent in the 1960s, 6.7 percent in the 1970s, 9.4 percent 1980s and 9.8 percent in the 1990s (1990-1998). Despite the recovery of the Canadian economy from the recession of the early 1990s, the unemployment rate stood at 8.3 percent by 1998. From 1992 to 1998, it fell only by 3.0 percentage points. Canada had never had an earlier decade with such a high rate since the 1930s.

Regionally, Ontario had the largest proportionate increase in unemployment in the 1990s. By the end of the 1990s, the Prairies and British Columbia were the only regions that experienced unemployment rates lower than the 1989 pre-recession level. The unemployment rate decreases from east to west, with the highest unemployment rate in Newfoundland.

The unemployment rate depends on the growth of employment and the labour force. The latter is determined by the working-age population and the participation rate. During the 1990s, the growth rate of the working-age population averaged 1.5 percent a year. This growth relative to the 1980s is due to the increase in immigration in to Canada. The aggregate participation rate fell during the 1990s to 65.1 percent

[10] See Sharpe (1999) for the complete references.

from 67.5 percent in 1989. It declined every year from 1990 to 1995. Three-quarters of the overall decline in the aggregate participation rate was due to young Canadians and older men.

In 1998, the industry with the highest unemployment rate was in construction at 11.6 percent and the lowest was in financial services and real estate at 2.6 percent. By sectors, unemployment was relatively higher in the goods producing sector than in the service sector, 7.6 percent and 4.8 percent, respectively. In the 1990s, a net job creation occurred in the service sector. Over the period from 1989 to 1998, goods-producing sector employment fell by 79,000, while service sector employment grew by 1,319,000. Only 10.3 percent of the unemployed in 1998 reported that they were job leavers.

1.5 Shocks to the Macroeconomy

This section explores the impulse problem and reports its treatment in the literature. Recent RBC models differ widely in their characterizations of the sources of aggregate variability. Its three predominant driving forces in the literature are:[11] asymmetric information within principal-agent problem, aggregate real shocks (including government spending and taxes) and sectoral shifts[12] (for the original classification see

[11]Pigou, A.C. in his book '*Industrial Fluctuations*' classified sources of shocks into, 1) Real causes defined as "changes that have occurred, or about to occur, in actual industrial conditions and expectations based on these are true or valid expectations". These causes include: harvest variations, inventions, industrial disputes, changes in fashion, wars and foreign demand for investment. 2) Psychological causes defined as "changes that occur in human's attitude of mind, so that, on a constant basis of fact, they do not form a constant judgment". These causes include autonomous monetary shocks to the banking and financial policies. This is the original classification due to Pigou (as reported by Shiller (1987)). One can argue that monetary shocks could be included in a seperate category.

[12]The sectoral shifts focus on the role of recessions in redistributing labour across sectors of the economy. Sectoral shifts are discussed later.

Shiller (1987)). Once a driving force is selected, the next step is to choose a theory for the framework through which a propagation mechanism story is described and finally one tries to explain aggregate variability. The following summarizes a selective literature of the suggested shocks and their propagation mechanisms.

Shock	Model	Propagation	Literature
Principal-Agent	Search	Job Availability	Howitt(1987)
Aggregate	Search	Firm Factor Demand	Kydland and Prescott (1982)
		Oil Prices	Hamilton (1983)
		Desired Consumption	Hall (1986)
		Borrow/Lend Process	Bernanke (1981)
		Union Membership	Blanchard and Summers (1986)
Sectoral	Search	Costly Labour Mobility	Lucas and Prescott (1974)
		Specific Human Capital	Topel and Weiss (1985)
		Demand for Produced Goods / Services	Lilien (1982)

Since there is no systematic way to determine what is the relative importance of different sources of macroeconomic variability, the recent literature has focused on trying to isolate the major sources of aggregate fluctuations and to suggest which shock is most significant in explaining these fluctuations.

Fair (1986) used stochastic simulation of a large-scale macroeconomic model - in the Keynesian' multi-system of equations spirit - for the decomposition of output variability into a variety of shocks. The conclusion reached was that there was no single dominant source of shocks.

The existing literature does suggest a wide multiplicity of sources that affect aggregate variability. Here, I focus on the magnitude and the effects of sectoral shocks on the Canadian economy. Burnside, Eichenbaum and Rebelo (1995) computed the sectoral Solow residuals corrected for capacity utilization. They proxied 'capital services' use by a proportion of 'electricity use' by industry. They advocated the use of such a correction for the following reasons. First, 'electricity use' is a good measure for capital services. Second, once corrected, there exists no evidence against the hypothesis of constant returns to scale. They found that using a corrected multi-factor productivity measure results in lower (but not zero) correlation between the Solow residual and the output growth rates. Such evidence puts in question the RBC baseline foundation of the technology shock as the sole impetus of the business cycle. They also reported evidence of significant heterogeneity across two digit standard industry classification (SIC) industries in terms of residuals variability and co-movement with output.

1.6 Conclusions

This chapter tracks the development of business cycle models. It highlights the existing dichotomy between the impulse problem and the propagation problem in the literature. Also, we present the importance of the labour market in explaining business cycle fluctuations as a propagation mechanism. This chapter examines the different shocks to the economy analysed in the literature. Finally, definitions of common labour market terminology are presented.

This chapter points to the domain (field) of this thesis, i.e., the labour market. Chapter 2 reveals the framework by which we will address and view the labour market, specifically Real Business Cycle Models (RBC).

Chapter 2

Real Business Cycle (RBC) Theory

2.1 Real Business Cycle model

Lucas (1977) defined 'business cycles' as the fluctuations of output about trend and its co-movements with other aggregate variables.[1] As mentioned earlier, Frisch (1933) provided an early theoretical theory of the business cycle. Keynesian oriented multiple system of equations[2] dominated the 1960's and the 1970's. These were followed in the early nineteen eighties by a new class of models based on Walrasian analysis.

The Real Business Cycle model[3] (RBC) is based on the neoclassical growth model and stochastic dynamic programming, (Kydland and Prescott (1982)). The idea of the basic RBC model is as follows. Adding a stochastic element to a standard aggregative growth model allows for changes in productivity. After calibrating the

[1] This definition was referred to as 'the business cycle phenomena' in Prescott (1986).
[2] Cooley and Prescott (1995, p. 3), referred to these models as "... fully specified artificial economies ...". Those type of models were engineered to study static output determination.
[3] Or as I prefer to use [In the language of Lucas (1980, p. 696)] "... fully articulated, artificial economic system ...".

model's microeconomic parameters, stochastic simulations of this model produce time series for output, employment, consumption and investment. The characteristics of the moments of the simulated data are then matched to their counterpart in the business cycle data. In the RBC framework, economic agents are subjected to various types of shocks and take optimal decisions in a dynamic environment.

2.2 General RBC (Uhlig)

This section follows closely the RBC model derived in Uhlig (1997). For the basic stochastic neoclassical growth model, the environment is as follows.

1) Preferences: A representative agent maximizes his expected utility

$$U = E\sum_{t=0}^{\infty}\left[\beta^t \frac{C_t^{1-\eta}-1}{1-\eta}\right] \tag{2.1}$$

where C_t is consumption, $0 < \beta < 1$ is the discount factor and $\eta > 0$ is the coefficient of relative risk aversion. β is equal to $1/(1+r)$ where r is the pure rate of time preference.

2) The technology: Firms have a Cobb-Douglas production function

$$Y_t = Z_t K_{t-1}^{\rho} N_t^{1-\rho} \tag{2.2}$$

where K_t and N_t are capital and labour, respectively. $0 < \rho < 1$ is capital's share in production and Z_t is the exogenous total factor productivity.

3) The laws of motion that describe how capital and technology evolve through time: For capital, the dynamic equation is

$$K_t = (1-\delta)K_{t-1} + I_{t-1} \tag{2.3}$$

For the technology shock, the equation is

$$\log Z_t = (1-\psi)\log \overline{Z} + \psi \log Z_{t-1} + \varepsilon_t \tag{2.4}$$

where $\varepsilon_t \sim iid \quad N(0;\sigma^2)$ and $0 < \psi < 1$.

4) Endowment: In each period, the representative household is endowed with one unit of time so that $N_t = 1$ for all t. Also, K_0 is set equal to zero.

5) The information set: The representative household chooses C_t, N_t and K_t given the above information up to time t.

Since there are neither externalities nor distortionary taxes in this economy, the social planner's solution will be the same as the competitive equilibrium.

2.2.1 The social planner problem

The problem presented for the social planner is to maximize expected utility (equation (2.1)) subject to the feasibility constraints. That is,

$$\max_{(C_t,K_t)_{t=0}^{\infty}} E\sum_{t=0}^{\infty}\left[\beta^t \frac{C_t^{1-\eta}-1}{1-\eta}\right] \tag{2.5}$$

subject to

$$C_t + K_t = Z_t K_{t-1}^{\rho} N_t^{1-\rho} + (1-\delta)K_{t-1} \tag{2.6}$$

$$\log Z_t = (1-\psi)\log \overline{Z} + \psi \log Z_{t-1} + \varepsilon_t \tag{2.7}$$

$$\varepsilon_t \sim iid \quad N\left(0;\sigma^2\right) \tag{2.8}$$

To solve this problem, one can apply the techniques of dynamic programming (section 2.2.3) or use the Lagrangian method.

2.2.2 Lagrangian method

The Lagrangian for the above problem is,

$$L = \max_{\{C_t, K_t\}_{t=0}^{\infty}} E\left[\sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\eta} - 1}{1-\eta} - \lambda_t(C_t + K_t - Z_t K_{t-1}^{\rho} N_t^{1-\rho} - (1-\delta)K_{t-1})\right)\right] \tag{2.9}$$

Its first order conditions (FOC) (called also the Euler equations) are,

$$\frac{\partial L}{\partial \lambda_t} \; : \; C_t + K_t - Z_t K_{t-1}^{\rho} N_t^{1-\rho} - (1-\delta)K_{t-1} = 0 \tag{2.10}$$

$$\frac{\partial L}{\partial C_t} \; : \; C_t^{-\eta} - \lambda_t = 0 \tag{2.11}$$

$$\frac{\partial L}{\partial K_t} \; : \; -\lambda_t + \beta E_t\left[\lambda_{t+1}(\rho Z_{t+1} K_t^{\rho-1} + (1-\delta))\right] \tag{2.12}$$

The transversality condition - to rule out explosive solutions - is,

$$\lim_{T\to\infty} E_0\left[\beta^T C_T^{-\eta} K_T\right] = 0 \tag{2.13}$$

It is obtained by summing the planner's problem for T periods rather than for ∞ (i.e., obtained from limiting the Kuhn-Tucker condition).

The steady state

To solve for the steady state, rearrange the FOC such that,

$$C_t = Z_t K_{t-1}^{\rho} N_t^{1-\rho} + (1-\delta)K_{t-1} - K_t \tag{2.14}$$

$$R_t = \rho Z_t K_{t-1}^{\rho-1} + (1-\delta) \tag{2.15}$$

$$1 = E_t\left[\beta\left(\frac{C_t}{C_{t+1}}\right)^{\eta} R_{t+1}\right] \tag{2.16}$$

$$\log Z_t = (1-\psi)\log \overline{Z} + \psi \log Z_{t-1} + \varepsilon_t \tag{2.17}$$

Equation (2.16) is the Lucas asset pricing equation. Now, drop the subscript t, and replace the variables with their steady state values. For any variable M_t which denotes the level, let $\overline{M}$ denote the steady state value, and $m_t = \log M_t - \log \overline{M}$ denote the deviation from its steady state value. If $m_t = 0.05$, then M_t is 5 percent above its steady state value. Re-writing the FOC in steady state yield,

$$\overline{C} = \overline{Z}\,\overline{K}^{\rho} - (1-\delta)\overline{K} - \overline{K} \tag{2.18a}$$

$$\overline{R} = \rho\overline{Z}\,\overline{K}^{\rho-1} + (1-\delta) \tag{2.18b}$$

$$1 = \beta\overline{R} \tag{2.18c}$$

Solving each steady state variable as a function of the parameters of the model and $\overline{Z}$,

$$\overline{R} = 1/\beta \tag{2.19}$$

$$\overline{K} = \left(\frac{\rho\overline{Z}}{\overline{R}-1+\delta}\right)^{1/(1-\rho)} \tag{2.20}$$

$$\overline{Y} = \overline{Z}\,\overline{K}^{\rho} \tag{2.21}$$

$$\overline{C} = \overline{Y} - \delta\overline{K} \tag{2.22}$$

Log-linearization

The following log-linearizes the FOC around the steady states:

1) For equation (2.14),

$$C_t = Z_t\,K_{t-1}^{\rho} + (1-\delta)\,K_{t-1} - K_t \tag{2.23}$$

replace each variable by its steady state, using $M_t = \overline{M}e^{m_t}$,

$$\overline{C}e^{c_t} = \overline{Z}\,\overline{K}^{\rho}e^{z_t+\rho k_{t-1}} + (1-\delta)\,\overline{K}e^{k_{t-1}} - \overline{K}e^{k_t} \tag{2.24}$$

and $\overline{M}e^{m_t} \approx \overline{M}(1+m_t)$,

$$\overline{C} + \overline{C}c_t \approx \overline{Z}\,\overline{K}^{\rho} + (1-\delta)\overline{K} - \overline{K} + \overline{Z}\,\overline{K}^{\rho}(z_t + \rho k_{t-1}) + (1-\delta)\overline{K}k_{t-1} - \overline{K}k_t \tag{2.25}$$

Since $\overline{Y} = \overline{Z}\,\overline{K}^{\rho}$ and $\overline{C} = \overline{Y} - \delta\overline{K}$,

$$\overline{C}c_t \approx \overline{Z}\,\overline{K}^{\rho}(z_t + \rho k_{t-1}) + (1-\delta)\overline{K}k_{t-1} - \overline{K}k_t \tag{2.26}$$

Dividing by $\overline{C}$,

$$c_t \approx \frac{\overline{Y}}{\overline{C}}z_t + \frac{\overline{K}}{\overline{C}}\overline{R}k_{t-1} - \frac{\overline{K}}{\overline{C}}k_t \tag{2.27}$$

2) For equation (2.15),

$$\begin{aligned} R_t &= \rho Z_t K_{t-1}^{\rho-1} + 1 - \delta & (2.28)\\ \overline{R}\,e^{r_t} &= \rho\overline{Z}\,\overline{K}^{\rho-1}\,e^{z_t+(\rho-1)k_{t-1}} + 1 - \delta & (2.29)\\ \overline{R} + \overline{R}r_t &\approx \rho\overline{Z}\,\overline{K}^{\rho-1} + 1 - \delta + \rho\overline{Z}\,\overline{K}^{\rho-1}(z_t + (\rho-1)k_{t-1}) & (2.30)\end{aligned}$$

using $1/\beta = \overline{R} = \rho\overline{Z}\,\overline{K}^{\rho-1} + 1 - \delta$ (Equation (2.18b)),

$$\overline{R}r_t \approx \rho\overline{Z}\,\overline{K}^{\rho-1}(z_t + (\rho-1)k_{t-1}) \tag{2.31}$$

so that

$$r_t \approx (1 - \beta(1-\delta))(z_t - (1-\rho)k_{t-1}) \tag{2.32}$$

3) For equation (2.16),

$$
\begin{aligned}
1 &= E_t\left[\beta\left(\frac{C_t}{C_{t+1}}\right)^{\eta} R_{t+1}\right] && (2.33)\\
1 &= E_t\left[\beta\left(\frac{\overline{C}e^{c_t-c_{t+1}}}{\overline{C}}\right)^{\eta} \overline{R}e^{r_{t+1}}\right] && (2.34)\\
1 &= E_t\left[\beta\overline{R}+\beta\overline{R}(\eta(c_t-c_{t+1})+r_{t+1})\right] && (2.35)
\end{aligned}
$$

using the steady state equation (2.19) $1=\beta\overline{R}$, then,

$$0 \approx E_t\left[\eta(c_t-c_{t+1})+r_{t+1}\right] \tag{2.36}$$

4) For equation (2.17),

$$
\begin{aligned}
\log Z_t &= (1-\psi)\log\overline{Z}+\psi\log Z_{t-1}+\varepsilon_t && (2.37a)\\
\log\left(\overline{Z}e^{z_t}\right) &= (1-\psi)\log\overline{Z}+\psi\log\left(\overline{Z}e^{z_{t-1}}\right)+\varepsilon_t && (2.37b)\\
z_t &= \psi z_{t-1}+\varepsilon_t && (2.37c)
\end{aligned}
$$

To summarize, let us rewrite equations (2.27), (2.32), (2.36) and (2.37c) as:

$$
\begin{aligned}
c_t &\approx \frac{\overline{Y}}{\overline{C}}z_t+\frac{\overline{K}}{\overline{C}}\overline{R}k_{t-1}-\frac{\overline{K}}{\overline{C}}k_t && (2.38a)\\
r_t &\approx (1-\beta(1-\delta))(z_t-(1-\rho)k_{t-1}) && (2.38b)\\
0 &\approx E_t\left[\eta(c_t-c_{t+1})+r_{t+1}\right] && (2.38c)\\
z_t &= \psi z_{t-1}+\varepsilon_t && (2.38d)
\end{aligned}
$$

Solving for the dynamics

Solving for the dynamics by the method of undetermined coefficients is to postulate a linear recursive law of motion between the endogenous variables c_t, k_t, r_t and the state variables k_{t-1}, z_t.

$$k_t = \nu_{kk}k_{t-1} + \nu_{kz}z_t \quad (2.39a)$$

$$r_t = \nu_{rk}k_{t-1} + \nu_{rz}z_t \quad (2.39b)$$

$$c_t = \nu_{ck}k_{t-1} + \nu_{cz}z_t \quad (2.39c)$$

The task is to solve for the coefficients ν_{ij} for $i = \{k, r, c\}$ and $j = \{k, z\}$. Note that these coefficients are the elasticities, i.e., if $\nu_{ck} = 0.5$ and $k_{t-1} = 0.1$ (K_{t-1} is 10% above its steady state value), then $c_t = 0.05$ (C_t is 5% above its steady state value). To solve for these coefficients, one has to substitute the postulated linear law of motion into the left-hand side of equations (2.38a), (2.38b), (2.38c) and (2.38d). Note that $E_t(z_{t+1}) = \psi z_t$ from applying the linear expectation operator on equation (2.38d).

1) For the equation (2.38a),

$$c_t = \frac{\overline{Y}}{\overline{C}}z_t + \frac{\overline{K}}{\overline{C}}\overline{R}k_{t-1} - \frac{\overline{K}}{\overline{C}}k_t \quad (2.40)$$

$$c_t = \frac{\overline{Y}}{\overline{C}}z_t + \frac{\overline{K}}{\beta\overline{C}}k_{t-1} - \frac{\overline{K}}{\overline{C}}k_t \quad (2.41)$$

$$\nu_{ck}k_{t-1} + \nu_{cz}z_t = \frac{\overline{Y}}{\overline{C}}z_t + \frac{\overline{K}}{\beta\overline{C}}k_{t-1} - \frac{\overline{K}}{\overline{C}}(\nu_{kk}k_{t-1} + \nu_{kz}z_t) \quad (2.42)$$

$$\nu_{ck}k_{t-1} + \nu_{cz}z_t = \left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{C}}k_{t-1} + \left(\frac{\overline{Y}}{\overline{C}} - \frac{\overline{K}}{\overline{C}}\nu_{kz}\right)z_t \quad (2.43)$$

Therefore,

$$\nu_{ck} = \left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{C}} \quad (2.44a)$$

$$\nu_{cz} = \frac{\overline{Y}}{\overline{C}} - \frac{\overline{K}}{\overline{C}}\nu_{kz} \quad (2.44b)$$

2) For equation (2.38b),

$$r_t = (1-\beta(1-\delta))(z_t - (1-\rho)k_{t-1}) \tag{2.45a}$$

$$\nu_{rk}k_{t-1} + \nu_{rz}z_t = (1-\beta(1-\delta))z_t - (1-\beta(1-\delta))(1-\rho)k_{t-1} \tag{2.45b}$$

Therefore,

$$\nu_{rk} = -(1-\beta(1-\delta))(1-\rho) \tag{2.46a}$$

$$\nu_{rz} = 1-\beta(1-\delta) \tag{2.46b}$$

3) For equation (2.38c),

$$0 = E_t\left[\eta(c_t - c_{t+1}) + r_{t+1}\right] \tag{2.47}$$

$$0 = E_t\left[\eta((\nu_{ck}k_{t-1} + \nu_{cz}z_t) - (\nu_{ck}k_t + \nu_{cz}z_{t+1})) + \nu_{rk}k_t + \nu_{rz}z_{t+1}\right] \tag{2.48}$$

$$0 = E_t\left[\eta\nu_{ck}k_{t-1} + \eta\nu_{cz}z_t - \eta\nu_{ck}k_t - \eta\nu_{cz}z_{t+1} + \nu_{rk}k_t + \nu_{rz}z_{t+1}\right] \tag{2.49}$$

$$0 = E_t\left[\eta\nu_{ck}k_{t-1} + \eta\nu_{cz}z_t + (\nu_{rk} - \eta\nu_{ck})k_t + (\nu_{rz} - \eta\nu_{cz})z_{t+1}\right] \tag{2.50}$$

$$0 = \eta\nu_{ck}k_{t-1} + (\nu_{rk} - \eta\nu_{ck})k_t + \eta\nu_{cz}z_t + (\nu_{rz} - \eta\nu_{cz})\psi z_t \tag{2.51}$$

$$0 = \eta\nu_{ck}k_{t-1} + (\nu_{rk} - \eta\nu_{ck})k_t + ((\nu_{rz} - \eta\nu_{cz})\psi + \eta\nu_{cz})z_t \tag{2.52}$$

$$0 = \eta\nu_{ck}k_{t-1} + (\nu_{rk} - \eta\nu_{ck})(\nu_{kk}k_{t-1} + \nu_{kz}z_t) + ((\nu_{rz} - \eta\nu_{cz})\psi + \eta\nu_{cz})z_t \tag{2.53}$$

$$0 = ((\nu_{rk} - \eta\nu_{ck})\nu_{kk} + \eta\nu_{ck})k_{t-1} + ((\nu_{rk} - \eta\nu_{ck})\nu_{kz} + (\nu_{rz} - \eta\nu_{cz})\psi + \eta\nu_{cz})z_t \tag{2.54}$$

therefore,

$$0 = (\nu_{rk} - \eta\nu_{ck})\nu_{kk} + \eta\nu_{ck} \tag{2.55a}$$

$$0 = (\nu_{rk} - \eta\nu_{ck})\nu_{kz} + (\nu_{rz} - \eta\nu_{cz})\psi + \eta\nu_{cz} \tag{2.55b}$$

To summarize, the equations that will solve for the 'undetermined' coefficients are, (2.44a), (2.44b), (2.46a), (2.46b), (2.55a) and (2.55b).

$$
\begin{aligned}
\nu_{ck} &= \left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{\overline{C}}} \\
\nu_{cz} &= \frac{\overline{Y}}{\overline{\overline{C}}} - \frac{\overline{K}}{\overline{\overline{C}}}\nu_{kz} \\
\nu_{rk} &= -(1-\beta(1-\delta))(1-\rho) \\
\nu_{rz} &= 1-\beta(1-\delta) \\
0 &= (\nu_{rk} - \eta\nu_{ck})\nu_{kk} + \eta\nu_{ck} \\
0 &= (\nu_{rk} - \eta\nu_{ck})\nu_{kz} + (\nu_{rz} - \eta\nu_{cz})\psi + \eta\nu_{cz}
\end{aligned}
$$

To solve for the system (6 equations and 6 unknowns), substitute equations (2.44a) and (2.46a) into (2.55a).

$$
\begin{aligned}
0 &= \left(-(1-\beta(1-\delta))(1-\rho) - \eta\left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{\overline{C}}}\right)\nu_{kk} + \eta\left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{\overline{C}}} && (2.56) \\
0 &= -(1-\beta(1-\delta))(1-\rho)\nu_{kk} - \eta\left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{\overline{C}}}\nu_{kk} + \eta\left(\frac{1}{\beta} - \nu_{kk}\right)\frac{\overline{K}}{\overline{\overline{C}}} && (2.57)
\end{aligned}
$$

Then divide the last equation $\eta\overline{K}/\overline{C}$ to get:

$$
\begin{aligned}
0 &= \frac{-(1-\beta(1-\delta))(1-\rho)\overline{C}}{\eta\overline{K}}\nu_{kk} - \frac{1}{\beta}\nu_{kk} + \nu_{kk}^2 + \frac{1}{\beta} - \nu_{kk} && (2.58) \\
0 &= \nu_{kk}^2 + \left(\frac{-(1-\beta(1-\delta))(1-\rho)\overline{C}}{\eta\overline{K}} - \frac{1}{\beta} - 1\right)\nu_{kk} + \frac{1}{\beta} && (2.59) \\
0 &= \nu_{kk}^2 - \left(\frac{(1-\beta(1-\delta))(1-\rho)\overline{C}}{\eta\overline{K}} + \frac{1}{\beta} + 1\right)\nu_{kk} + \frac{1}{\beta} && (2.60)
\end{aligned}
$$

Now rewrite the last equation as,

$$
0 = \nu_{kk}^2 - \gamma\nu_{kk} + \frac{1}{\beta} \qquad (2.61)
$$

where $\gamma \equiv \left(\frac{(1-\beta(1-\delta))(1-\rho)\overline{C}}{\eta\overline{K}} + \frac{1}{\beta} + 1\right)$. Note that from the steady state relations $\overline{Y} = \overline{Z}\,\overline{K}^{\rho}$ and $\overline{C} = \overline{Y} - \delta\overline{K}$, therefore $\overline{C}/\overline{K} = \overline{Z}\,\overline{K}^{\rho-1} - \delta$. Also from equation (2.18b),

$$\overline{Z}\,\overline{K}^{\rho-1} = \frac{1/\beta - 1 + \delta}{\rho} = \frac{1-\beta+\beta\delta}{\rho\beta} \tag{2.62a}$$

$$\frac{\overline{C}}{\overline{K}} = \overline{Z}\,\overline{K}^{\rho-1} - \delta = \frac{1-\beta+\beta\delta}{\rho\beta} - \delta = \frac{1-\beta+\beta\delta-\rho\beta\delta}{\rho\beta} \tag{2.62b}$$

$$\frac{\overline{C}}{\overline{K}} = \frac{1-\beta+(1-\rho)\beta\delta}{\rho\beta} \tag{2.62c}$$

Note that γ is defined as,

$$\gamma \equiv \left(\frac{(1-\beta(1-\delta))(1-\rho)\overline{C}}{\eta\overline{K}} + \frac{1}{\beta} + 1\right) \tag{2.63}$$

Now replace $\frac{\overline{C}}{\overline{K}}$ into γ to get:

$$\gamma = \left(\frac{(1-\beta(1-\delta))(1-\rho)(1-\beta+(1-\rho)\beta\delta)}{\eta\rho\beta} + \frac{1}{\beta} + 1\right) \tag{2.64}$$

Note that $\gamma > 0$. Solving the quadratic equation (2.61) of ν_{kk} yields,

$$\nu_{kk} = \frac{\gamma \pm \sqrt{\gamma^2 - 4/\beta}}{2} \tag{2.65}$$

$$\nu_{kk} = \frac{\gamma}{2} \pm \sqrt{\frac{\gamma^2 - 4/\beta}{4}} \tag{2.66}$$

$$\nu_{kk} = \frac{\gamma}{2} \pm \sqrt{\left(\frac{\gamma}{2}\right)^2 - \frac{1}{\beta}} \tag{2.67}$$

The product of the two roots is equal to $1/\beta$. The smaller root is the stable one, i.e. smaller than one in absolute value. Therefore,

$$\nu_{kk} = \frac{\gamma}{2} - \sqrt{\left(\frac{\gamma}{2}\right)^2 - \frac{1}{\beta}} \tag{2.68}$$

Once ν_{kk} is computed, the rest of the coefficients can be derived. Equations (2.46a) and (2.46b) compute ν_{rk} and ν_{rz} directly from the parameters. Substitute (2.68) into (2.44a) to get ν_{ck}. Plug (2.44b) into (2.55b) and solve for ν_{kz}. Finally, replace

ν_{kz} by its value in (2.44b) to get ν_{cz}. For some 'calibrated' quarterly parameters, the coefficients are:

$\beta = 0.990$	$\rho = 0.360$	$\eta = 1.000$	$\delta = 0.025$	$\overline{Z} = +1.000$	
$\nu_{kk} = 0.965$	$\nu_{kz} = 0.075$	$\nu_{ck} = 0.618$	$\nu_{cz} = 0.305$	$\nu_{rk} = -0.022$	$\nu_{rz} = 0.035$

Impulse Response Function (IRF)

The system (2.39) can be used to graph the impulse response function of the model. First to simulate the model, pick some initial values for k_{-1} and z_0, then generate ε_t. Using the system of $z_t = \psi z_{t-1} + \varepsilon_t$ (equation (2.37c)) and $k_t = \nu_{kk}k_{t-1} + \nu_{kz}z_t$, generate all the other variables c_t, r_t and y_t. The IRF is traced out by setting $\varepsilon_1 = 1$, and $\varepsilon_t = 0$ for $t > 1$. The effect of such a shock on all variables is then graphed.

2.2.3 Dynamic Programming

A dynamic programming problem is an optimization problem in which decisions are taken sequentially over a period of time. Usually, decisions taken in any period influence the environment. A 'state' variable represents the environment and moves through time in response to the actions taken by the decision maker. Also, it restricts the actions available to the decision maker at any point of time.

Taylor and Uhlig (1990) compared a set of alternative methods to provide numerical solutions for nonlinear rational-expectations models. The eight solution methods compared were: Value-Function Grid, Quadrature Value-Function Grid, Linear-Quadratic, Backsolving, Extended Path, Euler-Equation Grid, Parameterizing Expectations and Least Squares projections. They showed that different methods do lead to different results. Of the methods mentioned (more on methods later) above, we choose to use the value-function grid. However, a much easier and faster method is the parameterizing expectations method of Den Haan and Marcet (1990). This method uses the first-order conditions for the dynamic problem. A power function approximates the conditional expectation function then a nonlinear regression is estimated on one set of initial parameters. Iteration on the parameters continues until minimization of the mean square error between the power function and the conditional expectation is achieved.

2.3 Baseline RBC (King, Plosser & Rebelo)

This section underlines and follows the calibration process of the 'Baseline[4] RBC model'[5] as presented in King, Plosser and Rebelo (KPR) (1988a).

The baseline model assumes a single type of output that is consumed or invested. The output is produced by a Cobb-Douglas technology with constant returns to scale. Labour and capital are inputs. Consumers' - infinitely lived agents - preferences are ordered by the time discounted momentary utility over log of consumption and weighted log of leisure. The use of the log is adopted to match the positive trend in real wages and the zero trend in annual hours per worker.

- Preferences

$$E_t \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t) + \theta \ln(L_t)\right] \qquad 0 < \beta < 1 \tag{2.69}$$

[4] Also, referred to as the 'Benchmark RBC model' in the literature.
[5] Reproduced in the appendix with data measurements for the U.S. economy.

- Technology

$$Q_t = K_t^{1-\alpha} \left[A_t N_t \right]^{\alpha} \qquad 0 < \alpha < 1 \tag{2.70}$$

and (the impulse)

$$\ln(A_t) \equiv a_t = \gamma_a + \rho_a a_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim iid(0, \sigma_\varepsilon) \tag{2.71}$$

- Capital law of motion (the propagation)

$$K_t = I_t + (1 - \delta) K_{t-1} \qquad 0 < \delta < 1 \tag{2.72}$$

- Resource constraints

$$C_t + I_t \leq Q_t \tag{2.73}$$

and

$$N_t + L_t = 1 \tag{2.74}$$

To compute the model' predictions, maximize the utility function subject to the technology and the constraints. This equilibrium solution of the model is a function of the parameters which imply a stochastic process for the variables C_t, L_t, N_t, K_t, I_t and Q_t. In general, the solution is a non-linear function of the parameters and there is no closed-form solution. So, numerical methods are needed to calculate the stochastic process for the variables.[6] Approximating the solution by the log-linearization of the Euler equations yields a vector autoregression (VAR) for the logarithms of C_t, N_t, K_t, I_t and Q_t (usually denoted by lowercase letters c_t, n_t, k_t, i_t and q_t). All

[6] Methods of numerical solutions are exhaustively reviewed and compared in Taylor and Uhlig (1990).

the variables are nonstationary (except for n_t) and are represented by stationary deviations about a_t, which follows an integrated process by assumption (when ρ_a[7] equation (2.71), page 36 is equal to one). Therefore, they are cointegrated with a common trend, namely a_t. Note that the coefficients of the VAR are complicated functions of the parameters of the model. Once these values are replaced numerically (calibration), the equilibrium can be generated and the autocovariance generating function of $x_t = (\Delta c_t, \Delta i_t, \Delta q_t, n_t')$ follows. Finally, the properties of these artificially generated stochastic processes are compared with the real world data.

The first order conditions for this basic RBC model are

$$U_{lt} = U_{ct} MPL_t \tag{2.75}$$

i.e., the marginal rate of substitution between leisure and consumption is equal to the real wage rate (under the perfect competition condition). This implies that if the real wage rate increases and the utility function has $U_{ll}, U_{cc} < 0$, then consumption will increase and leisure will decrease. And

$$U_{ct} = E_t \beta (1 + MPK_{t+1} - \delta_k) U_{ct+1} \tag{2.76}$$

so that consumption growth is related to the net return on capital.

In this setup, the only source of fluctuation in the economy is A_t (which represents technology shocks). A change in A_t will change the quantity of labour demanded. The extent to which employment will be influenced following a shock depends crucially on the labour supply function. More technically, it depends on the intertemporal substitution of labour supply (see section 2.5 for details). If labour supply is infinitely

[7] The first order coefficient of the technology process.

elastic, then the effect of the shock on employment will be maximized and the real wage will exhibit an acyclical pattern. Note that empirical micro level studies indicate that the labour supply - especially for adult men - is inelastic (vertical) in the long-run.

The choice of parameter values[8] for quarterly variables in the U.S.A. over 1948-1986 is:

- $\alpha = 0.58$, equal to the average value of labour's share of GNP over the period.

- $\gamma_a = 1.04$, as the common trend of log per capita values of real GNP, consumption of non-durables and services, and gross fixed investment.[9]

- $\delta = 0.025$, to yield a gross investment share of GNP of approximately 30 percent.

- $\theta = 0.20$, so that the model steady-state value of N ($= 0.20$) matches the average workweek as a fraction of total hours over the period.

- $\beta = 0.988$, so that the model's steady-state annual interest rate matches the average rate of return on equity over the period. ($\beta \equiv \frac{1}{1+r}$)

- $\sigma_\varepsilon = 0.01$, as a convenient normalization.

2.4 Intuition of RBC

For the baseline model, the predictions following, say, a negative technology shock are of an immediate fall of employment. Output falls because of the direct effect of the decline in employment and the effect of the decline in productivity. Since capital is unaffected, the marginal product of capital and thus the interest rate fall. Consumption - governed by the intertemporal Euler equation - rises and investment declines by more than the decline in output. This is followed by gradual increases in

[8] King, Plosser and Rebelo (1988b, p. 314 footnote 3).
[9] King, Plosser and Rebelo (1988a, p. 226 and footnote 35 on the same page).

the interest rate and real wage back to their normal levels. As a result, consumption falls back to normal and employment rises back to normal.

After calibrating the King, Plosser and Rebelo (KPR) model, the study concluded that the model successfully reproduced the relative ranking of the variances of consumption, labour hours, investment and output in business cycle data. However, the model failed to reproduce the appropriate stylised fact on the interaction between output and labour hours.

Before presenting varieties of RBC models and their results, I will address two issues pertaining to RBC in general. The first is the importance of elasticities. The second is the issue of de-trending. These issues are important to understand RBC criticisms.

2.5 Elasticities

Since the extent of the effect of a shock on employment depends on the intertemporal substitution of labour supply, this subsection defines and emphasizes the role of elasticities in the baseline RBC model. For the general momentary utility function,

$$U(C,L) = V(C) \bullet C(L) = \frac{1}{1-\sigma} C^{1-\sigma} \bullet \frac{1}{1-\sigma_1} L^{1-\sigma_1} \tag{2.77}$$

We have,

$$\begin{aligned} &U_C = C^{-\sigma} V(L) > 0 && U_L = L^{-\sigma_1} V(C) > 0 \\ &U_{CC} = -\sigma C^{-1-\sigma} V(L) < 0 && U_{LL} = -\sigma_1 L^{-1-\sigma_1} V(C) < 0 \\ &U_{CL} = U_{LC} = C^{-\sigma} L^{-\sigma_1} > 0 && \end{aligned} \tag{2.78}$$

The elasticities of marginal utility U_C with respect to C and L are,

$$\zeta_{U_cC} = \frac{U_{CC}C}{U_C} = \frac{-\sigma C^{-1-\sigma}V(L)C}{C^{-\sigma}V(L)} = -\sigma \tag{2.79}$$

$$\zeta_{U_cL} = \frac{U_{CL}L}{U_C} = \frac{C^{-\sigma}L^{-\sigma_1}L}{C^{-\sigma}\frac{1}{1-\sigma_1}L^{1-\sigma_1}} = 1-\sigma_1 \tag{2.80}$$

The interteraporal elasticity of substitution in consumption equals σ. As σ increases (approaches 1, i.e. logarithmic), the decrease in U_C is more rapid in response to an increase in C, and the consumer is less willing to accept deviations from a uniform pattern of consumption.

The elasticities of marginal utility U_L with respect to C and L are,

$$\zeta_{U_LC} = \frac{U_{LC}C}{U_L} = \frac{C^{-\sigma}L^{-\sigma_1}C}{L^{-\sigma_1}\frac{1}{1-\sigma}C^{1-\sigma}} = 1-\sigma \tag{2.81}$$

The intertemporal elasticity of substitution in leisure equals σ_1, as shown by,

$$\zeta_{U_LL} = \frac{U_{LL}L}{U_L} = \frac{-\sigma_1 L^{-1-\sigma_1}V(C)L}{L^{-\sigma_1}V(C)} = -\sigma_1 \tag{2.82}$$

2.5.1 The Frisch Elasticity of Labour Supply

It is useful to consider the λ-constant or Frisch labour supply. Let λ be the Lagrangian multiplier associated with the worker's intertemporal budget constraint. The first-order condition associated with the labour supply is,

$$\frac{\partial U(n_1, ..., n_t, ...n_T)}{\partial n_t} = \lambda w_t \tag{2.83}$$

where w_t denotes the real wage in period t stated in period 0 prices (discounted to period 0). The Frisch inverse labour supply function is the marginal disutility of work stated in wage units:

$$\frac{1}{\lambda} \cdot \frac{\partial U(n_1, ..., n_t, ...n_T)}{\partial n_t} \tag{2.84}$$

When U is additively separable in labour, this can be solved to simplify for the labour supply as a function of the current wage. When U is not additively separable, the supply price of work in one period is a function of the level of work in that and other periods.

The elasticity of the labour supply schedule is

$$\zeta = \sigma_1 \cdot \frac{\overline{n} - n}{n} \tag{2.85}$$

It is equal to the intertemporal elasticity of substitution in leisure, σ_1, multiplied by the ratio of non-work time to work time. The elasticity ζ controls labour supply over the life cycle. If the wage rate were to double (fully anticipated by the worker at age 20) over the same period, a worker with an ζ of 1 will work twice as many weeks at age 40 as at age 20. Empirical evidence points to ζ being near the values 0.1 to 0.2. A larger Frisch elasticity generates larger responses to economic shocks in equilibrium models, since agents are more willing to substitute leisure across time.

For the utility kernel $(1-\phi)\log C_t + \phi\log(1-n_t)$, the Frisch elasticity of labour supply equals $(1-n)/n$, the steady-state ratio of leisure to labour, or $\phi/(1-\phi)$. The intertemporal elasticity of leisure is equal to 1. A 1% change in leisure results in $\frac{\phi}{1-\phi}$% change in hours of employment. This kernel is often criticized that its labour supply elasticity is much higher than that of prime age males estimated from panel data.

Christiano and Eichenbaum (1992) used a range of 3 to 5 for the Frisch elasticity. They estimated ϕ to be equal to 5/6. Prescott (1986) choose a value for ϕ closer to 2/3, but typically magnifies this elasticity by allowing past values of leisure to enter into the utility function. A value of 2/3 means[10] that 2/3 of the time is allocated to

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non-market activities. Swanson (1999b) used a value of 1.7/3.

Lloyd and Niemi (1979) investigated if the labour supply elasticity shifted over time, and for which demographic groups it did. Using quarterly U.S.A. data,[11] the study found evidence of statistically significant shifts - from the period 1956-1965 to 1966-1976 - in the labour supply elasticity. The most significant shift was due to sectoral shifts in demand, unfavourable to men and favourable to women (i.e., increased female participation rates).

2.6 De-trending

Lucas' (1977) definition of the term 'business cycle' requires detrending the business cycle data. If 'business cycle' fluctuations are defined as deviations around a trend, then a natural first step to examine the fluctuations is to de-trend the data. One way of eliminating the trend is to use the Hodrick-Prescott filter (Hodrick and Prescott 1980).

The first step of the HP curve-fitting method is to take the logarithms of the variables for two reasons: 1) to compress the units in which the variables are measured in, and 2) because of the inherent exponential trend in most aggregate economic variables. The selected trend path $\{\tau_t\}$ is one which minimizes the sum of squared deviations from a given series $\{Y_t\}$ subject to the constraint that the sum of the squared sum differences not be large. Formally,

$$\min_{\{\tau_t\}_{t=1}^{T}} \sum_{t=1}^{T}(Y_t - \tau_t)^2 \tag{2.86}$$

This is the value we adopt in this thesis.
[11]Source : *Employment and Earnings*.

subject to

$$\sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \leq \mu \tag{2.87}$$

where μ is a parameter governing the smoothness of the trend. The smaller μ is, the smoother it is. If $\mu = 0$, the least squares time trend is linear. Usually, μ is set so that the Lagrangian multiplier λ of the constraint equals 1600. When the observation period is in quarterly frequency, this produces the appropriate degree of smoothness. Therefore, the minimization problem reduces to

$$\min_{\{\tau_t\}_{t=1}^{T}} \sum_{t=1}^{T} (Y_t - \tau_t)^2 + \lambda \cdot \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{2.88}$$

$$\min_{\{\tau_t\}_{t=1}^{T}} \sum_{t=1}^{T} (Y_t - \tau_t)^2 + 1600 \cdot \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{2.89}$$

The second sum of the squared term is an approximation of the derivative of τ_t at time t. One attempts to minimize two sums of squares: the sum of squared cyclical residuals and the sum of squared $\Delta^2\tau_t$. The smoothing parameter λ gives relative weight to these two sums of squares.[12] This parameter acts as a penalty for the acceleration of growth. Finally, the deviations from trend are computed as,

$$Y_t^d = Y_t - \tau_t \qquad \text{for} \quad t = 1, ...T \tag{2.90}$$

The HP filter is a high band pass filter that eliminates all frequencies of 32 quarters (8 years) or greater. It decomposes the macroeconomic time series into a nonstationary trend component and a stationary cyclical component. Over the past twenty

[12] The rationale for setting $\lambda = 1600$ is as follows. The parameter $\lambda = \sigma_c^2/\sigma_\tau^2$, where σ_c^2 denotes the variance of the cyclical component and σ_τ^2 denotes the variance of the trend component. Hodrick and Prescott used "... the prior view that a five percent cyclical component is moderately as large as is one-eight of one percent change in the rate of growth in a quarter ...". Therefore, $\lambda^{1/2} = \frac{5/1}{1/8}$ or $\lambda = 1600$ as a value for the smoothing parameter.

years, the HP filter became the standard practice to detrend and the hallmark of real business cycle models.

Proponents of the use of the HP filter often explain that it is just a computational procedure used to fit a smooth curve through the data, i.e., that 'it is just a curve-fitting technique'. Opponents of the use of the HP filter have shown that the filter distorts the dynamic properties of the data. The filter is responsible for generating spurious business cycle periodicity when there is no cycle present in the original data (see Cogley and Nason (1995)). Also, King and Rebelo (1993) provided examples in which the use of HP filter alters substantially measures of persistence, variability and co-movements of economic time series data. They advocated the implementation of a trend component in RBC models to eliminate the use of any filtering.

There are also other detrending methods in the literature. For example, Lucas (1980b) employed an exponential smoothing filter (ES) in his investigation of the quantity theory of money. The ES filter solves a minimization problem similar to the HP filter. It is

$$\min_{\{\tau_t\}_{t=1}^{T}} \sum_{t=1}^{T}(Y_t - \tau_t)^2 + \lambda \cdot \sum_{t=2}^{T-1} [(\tau_t - \tau_{t-1})]^2 \tag{2.91}$$

Note that the parameter λ here penalizes for the changes in the growth component.

2.7 Criticisms

For a complete review of RBC controversies, see the series of discussion papers in The Economic Journal (1995). In my view, criticisms of RBC models are classified as ideological, methodological, end-result and goodness-of-fit.

Ideologically, critics attack the built-in Walrasian market clearing foundation as a way of describing markets behaviour, especially that of the labour market. Many economists object to the notion of agents' intertemporal decisions to generate a labour supply. Their argument is as follows. Explaining the Great Depression on the basis that the labour supply is the product of agents' intertemporal decisions, is likely to be unrealistic. To explain the Great Depression using such decisions, the assumption has to be that agents anticipated WWII a decade prior to its start and decided to hold off their supply for labour until the increase for demand generated by WWII. Such a voluntary-unemployment explanation during 1930s is unreasonable. In his criticism, Stiglitz (1986) questioned also capital (i.e., machines) unemployment during the same era.

Methodologically, the criticisms were about the objectivity versus the subjectivity of the calibrating exercise. The use of Solow residuals as impetus came under heavy criticism. The criticisms of the end-result of RBC point to the models' inability to reproduce certain stylised facts such as: variability of employment exceeding that of productivity, the instantaneous correlation between employment and productivity close to zero and average productivity that leads the cycle.[13] Goodness-of-fit criticisms highlighted and strongly condemned the ad-hoc method(s) of judging the merits of each model. The absence of a metric, by which one measures how good is the model as an approximation to the business cycle data, is still a topic of research. Also, the absence of formal statistical tests led many to label the RBC as 'unworthy' of acceptance.

[13] Usually referred to as 'labour productivity cycle' in the literature.

The success of RBC modeling in explaining business cycles is still a question open to debate. However, Eichenbaum (1995, p.1609) reiterated - in defense of the brittleness of RBC - that "We do not need high power econometrics to tell us that models are false. We know that. What we need are interesting diagnostic tools to help us understand the dimensions along which misspecified models do well and the dimensions along which they do poorly".

The real business cycle literature shows that if one is to reconcile the cyclical and persistent pattern of the data with a general equilibrium stochastic macroeconomic model, one must use the same pattern in the 'productivity shocks' that drive the model impulse responses.[14] Empirical measures of aggregate technology are obtained by calculating the Solow (1957) residuals. However, the standard deviation for the U.S.A. Solow residual equals 0.763, while the standard deviation of Gross National Product (GNP) is 1.8 percent. How can one use the 'productivity shocks' (measured by the Solow residual) pattern to drive the model impulse responses and get a result of 1.8 percent variability for GNP?

Cogley and Nason (1993) elaborate on this point. They showed that in a typical (baseline) RBC model,[15] output dynamics are determined by impulse dynamics. In other words, the output series generated from the artificial model is represented as a filtered transformation of the external shocks to the model. For example, if the shock is an AR(1) process, then output is an ARMA(3,2) process. In brief, external shocks completely drive the model's generated output series, pointing out how weak is

[14]This is usually referred to as 'The baseline real business cycle model' in the literature.

[15]The Cogley and Nason (1993) typical RBC model is in the appendix, as well as the parameters values used in their study.

the propagation mechanism of typical RBC models. The output dynamic properties are only a reflection of the impulse dynamic properties. There are just not enough dynamics (the propagation mechanism is very weak) in the typical RBC models since the output dynamic properties are completely dominated by impulse dynamics.

2.7.1 Goodness-of-fit

Real Business Cycle research has often relied on matching unconditional second moments from the data in the real economy with unconditional second moments from the data generated by an artificial model economy. Such an approach to assess the model's goodness-of-fit was heavily criticized and labeled - by many - as 'the eye-ball metric'. A classical alternative was suggested by Watson (1993). This study developed a goodness-of-fit measure for the class of dynamic econometric models in which all the endogenous variables are covariance stationary. In this context, the economic model is an abstraction of the real economy and is viewed as an approximation to the stochastic process generating the data. To measure the quality of this approximation, Watson proposed a measure of goodness-of-fit motivated by models of measurement errors in the Slutsky (1927) spirit. His approach was to quantify how much stochastic error must be added to the model's variables so that the model's artificial second moments do match the real economy' moments. This treats the discrepancy between the model and data as a stochastic process. Once this error is computed, one can construct a measure of fit from its size. This approach to minimizing the approximation error, in a sense, mirrors the R^2 in simple linear regression.

The criticisms of Watson' procedure are: 1) it can not account for moments other than the second ones and 2) nonlinearities and variations in conditional second moments (such as ARCH type time series) are ignored for simplicity. Another criticism is on how the procedure views the parameters. In the usual calibration exercises parameter values are viewed as a point-mass priors around the values.

A different procedure was proposed by Bayesian analysis. DeJong et al (1996) proposed a Bayesian approach to deal with the parametric uncertainty. By specifying a prior distribution over the parameter values, one can generate a distribution over the statistical properties of the simulated artificial data. In the case of the typical RBC model, this procedure concluded that modest prior specification is the road to take.

In general, the ratio of the standard deviations of aggregate hours to those of output has been emphasized in the literature as a measure of the simulated model economy's goodness of fit (see Kydland and Prescott 1982 and Hansen 1985). It is 1.47 for the U.S.A. data.

2.8 Varieties of RBC

This section presents different varieties of RBC models and their results discussed in the literature.

2.8.1 Indivisible Labour

This approach,[16] developed by Hansen (1985), assumes that all variations in employment happen at the extensive margin. It creates a highly elastic labour supply at the

[16]Such methodology have proven successful results when confronted with U.S. data but failed when European data was in question. This approach is to endogenize the labour supply.

aggregate level irrespective of the elasticity of the individual agents. Formally,

$$n_t = h_0 \phi_t \tag{2.92}$$

where ϕ_t is the proportion of individuals working and h_0 is the fixed shift length. In this setup, the agent works or does not work because of fixed costs.[17] After using a lottery to determine which individuals are working and make the preference space[18] convex, the model draws on a linear utility function in employment. This setup supports a constant marginal utility of leisure regardless of the hours worked and gives rise to a highly elastic labour supply. Individuals can either work or not work. As a result, this framework does not add persistence in unemployment, but accounts for employment volatility.

2.8.2 Labour hoarding

The focus in this model is on the intensive margin. Developed by Burnside et al (1993), this model kept the Walrasian essence and added a sequential decision-making tree. The production function used is

$$y_t = \theta_t k_{t-1}^{\alpha} \left(e_t h_0 n_t\right)^{1-\alpha} \tag{2.93}$$

where e_t, h_0 represent the effort and the work shift length respectively. The product $e_t.h_0$ represents the labour supplied by the individual. Labour hoarding increases as e_t goes to zero, and diminishes to zero when operating at full capacity ($e_t = 1$). In this model, leisure is specified by $T - \chi - e_t.h_0$ where T and χ are the time endowment and the fixed cost of hiring respectively.

[17] For example commuting time.

[18] Since the preference space is binary, to work or not to work.

The sequential decision process is as follows. The firm chooses N_t prior to the realization of the shock θ_t, then chooses e_t after the shock. The firms' decisions on hiring and firing are based on the expected productivity shock and it can adjust the amount of labour demanded only in the following period. By persuading workers to contribute more effort following a positive shock, the firm focuses on the intensive margin and effort is adjusted to clear the labour market.

Boileau and Normandin (1997) concluded that the labour hoarding model provided a better account of employment dynamics than alternative models applied to the U.S.A. data.

2.8.3 Search

In this framework, Pissarides (1990) and Merz (1995) produce persistence using a non-Walrasian analysis in the sense that the marginal productivity of labour is not set equal to the real wage. The key in these models is a matching function of unemployed workers to firms added to the law of motion of employment, which is

$$n_{t+1} = (1 - \delta_n)n_t + m_t \tag{2.94}$$

where δ_n is the proportion of the outflow from employment to unemployment and m_t is the matching function of the new hires. In these models, the Beveridge curve represents the matching function between unemployment and vacancies. The matching function is:

$$m_t = Av_t^{\eta}(1 - n_t)^{1-\eta} \tag{2.95}$$

where A is the efficiency of labour market clearing, v_t is the number of vacancies and $1 - n_t$ is the number of unemployed. The distribution of income created from the matching function depends on the firm's monopoly power and the workers' ability to bargain. The supply of vacancies determined by the firms depends positively on the level of unemployment. The higher is the unemployment, the easier it is to fill jobs at a lower cost.

2.8.4 Results of all Varieties of RBC models

In an attempt to explain unemployment persistence in the U.K., Millard,[19] Scott and Sensier (1999) simulated all of the above varieties of RBC models. The business cycle data are quarterly for the U.K. covering the period from 1976:Q2 to 1996:Q2. Their simulated results for the standard deviation of the following variables relative to output standard deviation and compared to the business cycle data are:

	Consumption	Investment	Employment	Unemployment
Business Cycle Data	0.97	2.47	1.11	8.43
Basic RBC	0.38	1.42	0.22	0.12
Indivisible Labour	0.83	3.05	0.36	0.20
Labour Hoarding	0.32	1.61	0.42	0.25
Search	0.87	1.48	0.22	0.13

Source: Millard, Scott and Sensier (1999, p. 26).

Across all models, the basic RBC performs the worst in terms of replicating employment and unemployment variability. Labour hoarding provides the best performance for both variability. However, the suggested values are much lower than the respective business cycle data. The conclusion is that all models generate low volatility in either employment or unemployment and cannot explain the observed

[19] I would like to thank Stephane Millard for providing the computer codes.

persistence of U.K. unemployment.[20]

2.8.5 Labour Adjustment Costs

Riddell (1999, p. 24) acknowledged employer adjustment costs as an explanation for the high unemployment in Europe. Amano and Macklem (1998) estimated a dynamic linear quadratic model of aggregate labour demand for Canada, the U.S.A. and Germany. They concluded that the adjustment costs of the labour demand are very similar in Canada and the U.S.A. and are an important source of employment fluctuations.

In general, adjustment costs occur when it is costly for firms to adjust employment. Employment persists for many periods and sluggishly adjusts following an economy wide technology shock. Given the inability of the above varieties of RBC in simulating unemployment persistence or adequate employment volatility, and the Riddell (1999) acknowledgment, this thesis investigates two derivatives of RBC models (impulse mechanism) that include labour adjustment costs. Note that by its nature, the adjustment costs will induce smaller employment volatility. When faced with a cost (in terms of lost leisure) to reallocate, representative agents will not to change employment across sectors so frequently as without costs. In theory, adjustment costs (i.e., propagation mechanism) are a useful means of generating unemployment persistence.

[20]Results for persistence are not replicated here. Refer to Millard, Scott and Sensier (1999, p. 27-32) for the full analysis.

2.9 RBC failures

This section focuses on RBC failures to account for observed employment variability and output persistence.

2.9.1 Observed employment volatility

Prescott (1986) reported that observed employment is twice as volatile as the one simulated from the standard RBC economy. In the U.S.A. data, the variance of hours worked relative to the variance of output equals 0.95 percent. A usual RBC baseline model generates a ratio of 0.52 percent. Most RBC models generate a substantially smaller volatility in employment than that in the data.

Campbell (1994) investigated this issue. The study found that a one percent shock, decreasing technology, lowered employment by 0.45 percent in the baseline RBC model. Therefore, to explain a decline of three percent employment in recession, one must assume a seven percent decrease in technology, a number which is obviously unrealistic. For Europe, employment did not rise during the 1970-1985 period, although total factor productivity increased more than twice as much as it did in the U.S.A. Failure of RBC models to generate matching employment variability sparked wide interest among researchers and led to a search for alternatives that could explain this observation. Examples included: indivisible labour, nominal wage contracts and labour market search.

Fraisie and Langot (1994, p. 1581) asked the same question: "Can RBC models be saved?" They considered a model with indivisible labour, labour hoarding and adjustment costs. They concluded that "... the introduction of labor adjustment costs is a necessary condition for the model to reproduce a productivity cycle ..." (p. 1582). However, they also concluded that labour hoarding is a necessary assumption to achieve a one period gap between productivity and employment (in business cycle data, employment is coincident and productivity is leading).

2.9.2 Persistence in aggregate output

Cogley and Nason (1995) concluded that actual output dynamics are more persistent than those generated from standard RBC models. Since the baseline KPR model is driven only by the single technology shock, the persistence of the output, consumption and investment depended heavily on the persistence assumption used in the technology shock.

The baseline model fails to account for the heterogeneity of the workers or jobs. It does not contain incentives for a worker to change jobs and no suggestion that a worker might be more productive in the new job than the current one. The focus here is on the movement of workers from unsuccessful productive units to growing ones.

2.10 Adjustment Costs and the autocorrelation of output

One dimension in which adjustment costs are useful is in matching of the autocorrelation function of output growth. A weakness (among many, see section 2.7) of the baseline RBC is its inability to predict (match) the positive serial autocorrelation in business cycle output growth rates. In the U.S.A. data, real output growth rates are positively serially correlated and the serial autocorrelation is significantly higher than zero for lags of one and two quarters (see Cogley and Nason 1995). This discrepancy between model generated and business cycle data is present in a wide class of RBC models.

	1st autocorrelation	2nd autocorrelation
Data	0.37	0.22
King et al model (1988b) (KPR)	0.02	0.02
Schmitt-Grohé model (1998)	0.18	0.12

Using a two-sector RBC model, and a random walk technology shock, Grohé-Schmidt (1998) focused on the matching of the autocorrelation function of output growth rates. The investment sector and the consumption goods sector were characterized by increasing returns and constant returns to scale, respectively.

Most RBC models correctly predicted this positive autocorrelation. These different models used a wide variety of assumptions: e.g., employment lags in the labour hoarding process, such as in Burnside, Eichenbaum and Rebelo (1993), adjustment costs in factor inputs [in this thesis, in employment], an AR(2) technology shock or government shock.

2.11 Aggregate Returns to Scale and RBC

Cole and Ohanian (1999) questioned the sensitivity of RBC models to the parametric form and the value of the aggregate returns to scale.[21]

If aggregate returns are constant or decreasing, then there is no mechanism by which a monetary-shock driven extension model of RBC can reproduce the procyclical labour productivity stylised fact. In the simple case where the monetary transmission mechanism holds in the model, a monetary shock will induce an increase in

[21] Aggregate returns to scale are defined as the percentage of the change in output relative to the percentage change in factor inputs.

employment (movement along the marginal productivity of labour) without shifting the demand for labour. Therefore, labour productivity will not be procyclical. Note that when the production function exhibits constant or decreasing returns to scale, a technology shock (a supply shock) generates procyclical labour productivity.

However, if aggregate returns are increasing, a monetary shock driven RBC can generate the procyclicality of labour productivity. In the case where the per capita production function of the household depends on the aggregate per capita output (as externality),[22] then a monetary shock generates procyclical labour productivity. Note that if the value of the increasing returns is large, then the model equilibria might not be unique. See for example Benhabib and Farmer (1994) where Keynesian type 'animal spirits' generate business cycle fluctuations.

Since a monetary shock is not the focus of this thesis, the models proposed do not attempt to include a monetary or a fiscal sector. I will adopt a constant returns to scale production function.

2.12 Calibration and the Canadian Economy

Calibration originated in the computable general equilibrium (CGE) modelling. Early calibration methods required setting an equilibrium point (as a benchmark) in the product space of the model variables and linearizing a non-linear system around it. In the general equilibrium (GE) setting, calibration became the quantification of unknown parameters either by using micro-level data estimates (plug-in estimates) or by just fixing the parameters (backward reasoning) such that the model produces

[22] In the model, the value for the externality parameter determines aggregate returns to scale.

a steady state within a given interval. For these quasi-scientific practices, calibration has long been a subject of debate in the economic profession.[23] In brief, calibration is the process of choosing parameter values based on microeconomics evidence.

To calibrate the models proposed in this thesis, I refer to the pioneering work of Goldstein (1998). His study examined the projections of Canadian long-term economic growth prepared by various forecasters. It provided a range of parameter estimates which are well suited to this thesis. By reporting values for the basic components that make up a potential output projection, Goldstein discussed how the assumptions made (by different forecasters' institutions) in the estimation process, impacted on the projection as a whole. Based on formal and well documented models, Goldstein (1998) reported the estimates of the following institutions: The Conference Board of Canada (CBoC), the University of Toronto's Fiscal and Economic Analysis Program (PEAP), DRI-McGraw Hill (DRMG), Informetrica (Info) and the Department of Finance (DoF).

Growth Accounting

In general, potential output is estimated using principles of growth accounting. The ratio of actual output relative to potential output is useful for fiscal and monetary policies. It gives an indication of demand pressure on the economy. Once the trend in real gross domestic product (GDP) is identified, one can project potential output. There are two approaches to identifying the historical trend in real GDP.

The time series approach to find the trend in GDP data involves a simple regression

[23]For an excellent exposition of the merits of calibration versus estimation, see Quah (1995), and for the statistical aspects of calibration in macroeconomics, see Gregory and Smith (1993).

of real GDP on a time trend (linearly or non-linearly) or using the Hodrick-Prescott filter. One criticism of such an approach is that it is not possible to identify historically the sources of the trend movements (example: the impact of the aging or the growth rate of the population over the trend growth rate) and therefore difficult to forecast. Another criticism regarding the HP filter concerns the reliability of the end points.

An alternative approach is to use a macro model. Using a formal production function, one can break the level of output into different components. The levels of these components are then de-trended and forecasted over time. The projected trend levels are then introduced into the production function to form a potential real GDP projection. The former approach is referred to - in the literature - as a 'Top-Down' approach, while the latter is referred to as a 'Bottom-Up' approach.[24]

The Cobb-Douglas function with a constant returns to scale assumption to model output is,

$$Y_t = A_t.K_t^{\alpha}.L_t^{1-\alpha} \tag{2.96}$$

where Y, K, L denote output, capital stock and labour input respectively. A is the total factor productivity (TFP) and reflects the Hicks-neutral technological change. Usually, A is estimated as the residual[25] (the amount of output not accounted for by either capital or labour). Under the assumptions of perfect competition and constant returns to scale production function, α denotes the capital share in income (nominal GDP at factor cost). α is the elasticity of output with respect to capital. Taking logs of both sides of equation (2.96) and differentiating yields the growth rates equation

[24]Goldstein (1998, p. 144).
[25]A is referred to as Solow' residuals since Solow (1957).

(lower case letters represent the log)

$$\frac{\Delta a}{a} = \frac{\Delta y}{y} - \alpha\frac{\Delta k}{k} - (1-\alpha)\frac{\Delta l}{l} \tag{2.97}$$

where $\frac{\Delta a}{a}$ denotes the growth rate of the TFP and is the estimated residual using actual real GDP and the actual values of the inputs. Note that this estimate of the residual may differ from the true one if one uses a misspecified assumption on the returns to scale of the economy. Also, equation (2.97) is useful in computing labour productivity (the growth in output per worker) as follows,

$$\frac{\Delta y}{y} - \frac{\Delta l}{l} = \frac{\Delta a}{a} + \alpha\left(\frac{\Delta k}{k} - \frac{\Delta l}{l}\right) \tag{2.98}$$

For the Canadian economy, various estimated shares in income values over 1980-1996 are:[26]

	Finance	CBoC	PEAP	DRMG	Info
Labour	0.64	0.61	0.70	0.62	0.605
Capital	0.31	0.39	0.30	0.32	0.395

Source: Goldstein (1998, p.149).

From the table, note that the weights do not sum to one in two cases: Finance and DRMG. Because both assume a third factor of production, namely natural resources for Finance and energy consumption for DRMG. Also, CBoC and PEAP use the units of workers in measuring labour input in contrast to the units of hours worked used in the Finance and DRMG studies. The above table is very useful in calibrating the income shares parameters for the Canadian aggregate production function.

The labour input is measured either in terms of hours worked or workers. It is made of: a) the labour force[27] source population (the most important changes in

[26]The Conference Board of Canada (CBoC), the University of Toronto's Fiscal and Economic Analysis Program (PEAP), DRI-McGraw Hill (DRMG), Informetrica (Info) and the Department of Finance (DoF).

[27]

which are due to the changes in fertility rates[28] and immigration rates[29]), b) the aggregate participation rate (changes due to the aging of the population), c) the assumed natural unemployment rate (Finance, CBoC and DRMG estimates are 8.9, 7.4 and 8.0 respectively.) and d) a measure of average hours worked per worker. Note that the decomposition of labour input measure depends on the unit in which it is measured.

The capital input is usually decomposed into machinery/equipment and non-residential construction used in non-government commercial activity. DRMG includes the federal and provincial/local governments' capital stock as well. The capital input is computed using a standard accumulation rule $K_t = I_t + (1-\delta)K_{t-1}$. There are different measures for the capital stock depending on the depreciation assumptions used and depending on the level of disaggregation used.[30] Two approaches are proposed to measure aggregate capital: the linear aggregator and the Cobb-Douglas aggregator. For the former, data on aggregate capital is generated by summing up machinery/equipment (me) and non-residential construction (nr) capital. This implies that these both types of capital are perfect substitutes and therefore have infinite elasticity of substitution (DRMG, CBoC and Info). However for the latter, using a Cobb-Douglas functional specification ($K_{total} = K_{m/e}^{0.4} K_{nr}^{0.6}$),[31] these types of capital

The labour force is computed by multiplying the source population by the aggregate participation rate.

[28]The fertility rate was around 1.7 so that, on average, a woman living to the age of 45 had 1.7 children.

[29]In Canada, immigration averaged a 250,000 per year during 1997.

[30]CBoC uses more disaggregated data than Finance and PEAP. Info divides capital stocks into 75 industries.

[31]The weights used to compute the share of total capital income are determined as follows. The share of machinery/equipment equals the sample average of $UC_{m/e}K_{m/e}/(UC_{m/e}K_{m/e}+UC_{nr}K_{nr})$, where $UC_{m/e}$ denotes the user cost of machinery/equipment. This user cost is a function of the price deflator, the tax credit, the depreciation rate, the expected inflation, the corporate tax credit

have elasticity of substitution equal to one.

In Canada, the depreciation rates broken by category over the period 1980-1996 are:

	Finance	CBoC	PEAP	DRMG	Info
Total	5.9	6.1	8.9	5.5	5.3
Mach/Equip	12.2	35.6	15.5	12.3	6.8
Non-Res	3.2	1.9	4.9	3.5	4.7

Source: Goldstein (1998, p.169).

2.12.1 Canadian preferences for work

This section is on calibrating the Canadian leisure weight in the utility function.

Drolet and Morissette (1997) investigated the Canadian Survey of Work Arrangements 1995 data to test if work redistribution would eliminate unemployment. Their study (Table 2 , page 19) shows preferences to work (fewer, same or more hours) of employees by industries . This is taken into account when I calibrate the intertemporal substitution of labour parameter in the RBC models. Preferences for work time in percentage as well as the average hours spent on the job by industry are reproduced in the next table.

	MEN				WOMEN			
Industry	fewer	same	more	hours	fewer	same	more	hours
Agriculture	2.8	72.0	25.3	48.5	—	—	—	—
Forestry and mining	4.9	75.9	19.2	44.6	—	—	—	—
Construction	2.4	63.3	34.3	41.8	—	—	—	—
Agriculture, et above.	—	—	—	—	9.2	77.1	13.7	35.9
Manufacturing	5.2	71.9	23.0	41.1	8.4	69.1	22.5	38.1
Distributive Services	5.9	66.9	27.2	41.7	8.1	69.6	22.3	35.7
Business Services	5.0	67.6	27.4	40.5	8.6	69.7	21.7	35.5
Consumer Services	3.7	57.7	38.7	39.0	3.4	56.2	40.4	32.0
Public Services	7.9	70.7	21.4	39.4	9.3	67.0	23.6	33.5

and the real interest rate. This function implies that if the user cost of an input falls, it will lower the marginal product of the input.

Source: Drolet and Morissette (1997).

They concluded that most Canadians would prefer to work longer rather than shorter hours. Those who would prefer shorter hours are professionals at the higher quartile of earnings. Accordingly and based on their conclusion, we calibrate the steady state of hours worked for the representative agent in Chapter 6.

2.13 General Equilibrium (GE) Framework

This section links Chapter 2 to Chapter 3.

GE models are not able to account for the persistence in aggregate level output and unemployment. My interest is at the sectoral disaggregated industries level. The plan is to use general equilibrium artificial economies associated with several labour market institutions to account for aggregate employment behaviour.

Within a multi-sector framework, Dupor (1996) considered the aggregate effects of sector-specific shocks to production. This study concluded that the law of large numbers - implying that positive shocks in some sectors are offset by negative shocks in others - applies and that such a modelling strategy is unnecessary to explain the business cycle character. More generally, if there are many independent shocks and labour were mobile between sectors, then the law of large numbers implies that their effect on the aggregate economy would average out to zero. The method used was to introduce interaction between sectors by an input-use matrix in a general equilibrium framework. Dupor's model assumed that every sector sells some intermediate inputs to some other sectors in the economy and that all sectors are *equally important*.

Several recent studies in the literature suggested different mechanisms by which the law of large numbers can be weakened. Mechanisms such as asymmetries, threshold effects, non-linear settings and monopolistic competition have proved useful (see Boldrin et al (1990) and Scheinkman (1990)) in modelling the effects of inter-sectoral shocks on the aggregate level.

For example, building on the Dupor model, Horvath (1997) simulated greater aggregate volatility from sector-specific shocks. He avoided the law of large numbers and assumed that *some sectors are more important* input-suppliers than others. This assumption relies on the relative sizes of the sectors.

From the above discussion, we will address the following: 1) a multi-sector general equilibrium framework is useful (Chapter 3, section 3.1), and 2) sector size is important (Chapter 6, section 6.6). The point is that, when looking at the sectoral level, one has to incorporate the size of the sector relative to the economy.

2.14 Plan

Explaining output dynamics is a central aim of quantitative macroeconomics. In this thesis, we intend to use employment dynamics at the sectoral level to account for output movement and to generate persistence that will match empirical regularities.

To explain the stylised fact of productivity leading output, Oi (1962) proposed treating labour as a quasi-fixed factor. In booms, firms increase their output but the labour input is a quasi-fixed factor. This can be explained by training costs, usually modelled by labour adjustment costs.

Bils and Cho (1994) focused on explaining the cyclical behaviour of employment (workweek), effort, capital utilization[32] and productivity. They integrated procyclical labour and capital utilization into a real business cycle model. The capital utilization rate increases as workers increase their effort or increase their hours per week. The model also featured costs of adjustment in capital, workers' preferences over weeks of work, hours per week of work and effort per hour at work. This model did mimic certain important stylised facts,[33] namely: a) employment peaks a full quarter after output (employment lags the cycle), and b) effort, capital utilization, and productivity all sharply lead the business cycle. Therefore, the adjustment costs of factor inputs can lead to favourable results in terms of replicating many business cycle data characteristics. However, Bils and Cho's model fell short in one aspect, namely, labour hours generated were less variable than observed ones.

By introducing a law of motion that captures the costly flow of employment between industries following a sector-specific shock (propagation mechanism as adjustment cost in labour mobility), and also by taking into account the size of the industries relative to the economy, one can explain the persistence of aggregate output and unemployment. In short, a correctly specified law of motion that captures the labour market structure will add to our understanding of aggregate dynamics and adequately characterize the employment behaviour.

In this thesis, the concern is to extend RBC models to include sectoral shocks (the impulse problem) and to generate persistent unemployment in the end-result by using

[32]Swanson (1999) focused on variable capital utilization within a sectoral framework. See section 3.1 for details of this study.
[33]Documented in Kydland and Prescott (1990).

an adjustment cost for workers to move across sectors (the propagation problem). This represents an enhacement of RBC models and enables the investigation of Lilien' hypothesis.

2.15 Appendix: U.S.A. Business Cycle Data

This appendix reports descriptive moments for the U.S.A. business cycle data and their definitions, in the literature.

2.15.1 Bils and Cho (1994)

Bils and Cho (1994) reported the following summary of U.S.A. data statistics. The data are taken from Citibase, quarterly covering the period from 1955:3 to 1984:1 All series are logged, detrended using the Hodrick-Prescott filter.

Series	StDev	Correlation with Output
Y	1.74	1.00
C	1.29	0.85
C1	0.81	0.65
I	8.45	0.91
K	0.63	0.05
Q	1.74	0.77
H	0.46	0.76
N	1.50	0.81
Y/H	1.18	0.35

Source: Bils and Cho (1994).

Where Y denotes real GNP, C denotes consumption of nondurable and services, C1 denotes the consumption series used by Christiano, which equals C plus the flow of services from durable goods. I is for gross private domestic investment and K is the nonresidential equipment and structures. Q is aggregate hours measured as hours of all persons. H is weekly hours per person at work. N is for all persons at work, i.e., total employment. Finally, Y/H denotes labour productivity measured as output divided by aggregate hours.

2.15.2 Prescott (1986)

Prescott (1986) reported the following descriptive statistics for the cyclical behaviour of the U.S.A. economy. All series are measured as deviations from trend covering the period from 1954:Q1 to1982:Q4.

Variable	StDev	Cross Correlation with GNP		
		x_{t-1}	x_t	x_{t+1}
GNP	1.8%	0.82	1.00	0.82
Personal Consumption				
Services	0.6	0.66	0.72	0.61
Nondurables goods	1.2	0.71	0.76	0.59
Fixed Investment	5.3	0.78	0.89	0.78
Nonresidential	5.2	0.54	0.79	0.86
Structures	4.6	0.42	0.62	0.70
Equipment	6.0	0.56	0.82	0.87
Capital Stocks				
Total Nonfarm Inventories	1.7	0.15	0.48	0.68
Nonresidential Structures	0.4	-0.20	-0.03	0.16
Nonresidential equipment	1.0	0.03	0.23	0.41
Labour Input				
Nonfarm Hours	1.7	0.57	0.85	0.89
Average Weekly Hours in manufacturing	1.0	0.76	0.85	0.61
Productivity (GNP/Hours)	1.0	0.51	0.34	-0.04

Source: Prescott (1986).

Chapter 3

Sectoral Analysis

3.1 From Aggregate to Sectoral

"Macroeconomics has always rested on the fiction that the behaviour of aggregates was stable and, therefore, individual market phenomena could be safely ignored."

Sheffrin (1984, p. 482)

"The sectoral shifts hypothesis has attracted attention precisely because it departs sharply from traditional notions about the driving forces behind aggregate economic fluctuations."

Davis (1987, p. 329)

Theoretically, most business cycle models treat production as taking place in one industry. To emphasize the changes in the technologies of different industries, one has to investigate sectoral level economies. A technology shock in one sector might influence the aggregate economy even without an aggregate level shock. For example, an adverse shock to one sector might reduce the wealth and the employment in the whole economy. This idea is the key to the first of Kaldor's laws.

Nicholas Kaldor claimed three propositions in the late 1960s. They are referred to as the Kaldor's laws in the literature. The first is that the manufacturing sector is the key in determining the overall rate of economic growth. The second (also known as Verdoorn's law) is that manufacturing productivity growth is positively correlated with output growth. The third is that faster growth in the manufacturing sector implies faster growth in overall productivity growth.

Empirically, contemporaneous sectoral aggregation of economic time series distorts the dynamic properties. Swanson (1999) reported that failure to consider sectoral phenomena resulted in a wide acceptance of a procyclical real wage. Swanson questioned this finding and found that accounting for sectoral variables results in real wages becoming countercyclical with respect to the state of their respective industries.

Rossana and Seater (1995) examined the effects of temporal aggregation on the estimation of the class of autoregressive integrated moving average (ARIMA) models. They reported that temporal aggregation resulted in substantial losses of information. In economics, aggregated time series data are usually the sum or average of disaggregated ones. Averaging distorts the time series properties and the dynamic behaviour. For example, Christiano, Eichenbaum and Marshall (1991) concluded that rejecting the random walk consumption theory might be an artifact of temporally aggregated data.

Rossana and Seater (1995) found that annual aggregates created from monthly data exhibits no low-frequency (i.e., business cycle) variation. This is why most annual data usually fit well a low-order linear time series model. Also, the absence of the reliability of the impulse response function and the variance ratio as persistence measures (described in the persistence chapter of this thesis) is due to the temporal aggregation. This loss of low-frequency cycles (i.e., cyclical variations) might be single-handedly responsible for rejecting many of the (most reliable) competing models of business cycle. The study also reported that annual observations have much more persistence[1] than disaggregated data. The same finding was reported by Krol[2] (1992).

I argue that it is necessary to move away from the investigation of the aggregates and resort to investigation at the sectoral[3] level. Davis (1987) reported that to understand the driving forces behind economic fluctuations, one has to consider the specialization and the reallocation of resources over time and across sectors. By 'allocative disturbances', Davis (1987, p. 326) meant "... the events that impinge on the economy by inducing a costly, time-consuming reallocation of specialized resources ...".

Economists are aware of the important potential of allocative disturbances on aggregate fluctuations since Ricardo's *Principles* in 1817. However, the idea of using 'allocative disturbances' as a channel for a propagation mechanism in business cycle models was only presented after Lilien's (1982) observation. Today, the difficult task facing business cycle theory is how to incorporate specialization and reallocation technologies into tractable general equilibrium models of economic variability. This should be such as to capture the substantial shift in inputs across sectors - following a sectoral shock - which results in aggregate variability.

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[1] They measured 'persistence' by a unit root.
[2] Krol measured 'persistence' by the Cochrane variance ratio.
[3] In Canada, data are available relative to the level of aggregation of Input-Output tables. There are, S-level: 13 industries; M-level: 35 industries; and L-level: 112 industries.

Davis (1987) argued that allocative disturbances have a large influence on aggregate unemployment fluctuations. This study reported three reasons why labour reallocation is the largest component of short-run unemployment fluctuations: 1) the co-movement pattern observed - in CPS data on unemployment duration - between the unemployment rate and the inflow/outflow rates to/from unemployment, 2) a zero contemporaneous correlation between changes in labour force participation (ΔLF) and the outflow from the unemployment pool, and 3) higher incidence of permanent separations during recessions.[4]

Note that in Canada, each industry is often concentrated in one region of the country. For example, the financial and services sector is concentrated in Toronto while textile manufacturing is in Montreal. I intend to use industry level analysis when dealing with sectoral analysis, so that, the word 'sectoral' will be used interchangeably with 'industry'.

Long and Plosser (1983) presented a multi-sector model for the co-movement of real aggregates across sectors in response to a sector specific shock. Noting that many sectors in the economy tend to move together and others tend to lag the economy-wide activity, the model motivated interest in exploring structural macroeconomic dynamics with an accent on the labour market. Dropping the assumption of a common or an aggregate shock that drives the economy's fluctuation over the business cycle, opened a new perspective to a fruitful line of research agenda, namely sectoral analysis. In my view, multi-sector analysis is crucial in explaining unemployment.

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[4] Permanent and temporary job separations can be calculated from CPS data on unemployment by reason. Empirically, both contribute about equal amounts to the rise of unemployment in recessions. Davis argues that raw numbers on temporary separations overstate its importance.

In each sector, a fraction of factor inputs are highly specialized. A sector-specific shock to technology will induce resource reallocation between and within sectors. If labour is highly specialized, then it will be costly to move between sectors and hence adjustment cost models are necessary to explain the deviation of unemployment from its long-run level.

In the search for the normative and positive aspects of the business cycles, macroeconomists are often concerned with two 'stylized facts': the correlated movements in aggregate output over time and the co-movement in output and employment across sectors. The emphasis on persistence in the former reflects the assumption that economic agents make rational correlated decisions that are reflected in aggregate output movements. To understand the co-movement in output and employment across sectors, intertemporal linkages must be specified in multi-sector models to produce the mechanism by which an aggregate shock or a sector-specific shock propagates in the economy.

Consider an extreme economy in which workers have no disutility from work and the equilibrium is at full employment. Here, a sector-specific shock will cause opposing co-movements in employment across sectors (increases in a few and decreases in others). This shock may produce a movement of resources across sectors generating a negative employment co-movement (i.e., negative employment correlation across sectors). Employment increases in a few sectors and decreases in other sectors. Here, the economy is at full equilibrium. In this extreme case of no disutility from work combined with perfect labour mobility across sectors, the substitution effect is reflected in the negative co-movement. This effect is also present to a certain degree in less extreme cases (Lilien 1982, Abraham and Katz 1986, Rogerson 1987).

However, there exist other alternative models in which a positive co-movement of employment across sectors is generated. Lucas (1972, 1975) described an economy in which aggregate monetary disturbances are the driving force, coupled with agent information asymmetry. In this economy, an economy-wide shock increases output in all sectors, thereby generating a positive employment co-movement.

Long and Plosser (1983, 1987) presented a multi-sector model in which they traced the influence of a sector-specific shock on the aggregate fluctuations. Shocks to the production function in one sector were spread over time and to other sectors creating persistent aggregate fluctuations. The propagation mechanism in the model was provided by the 'factor demand flows'. A technology shock in a single sector led to an expansion of that sector's output. The output of one sector was fed as an intermediate input into other sectors. This extra output was partly consumed and partly used as an input in the production of the other sector output in the next period. The result was that this additional output effect was spread over time and over the other sectors creating persistent aggregate fluctuations. However, because of the specific formulation of preferences, employment levels did not fluctuate in the model. Also, this type of 'intermediate input linkage' models (Long and Plosser (1983) and Horvath (1997)) address only movements in aggregate output and do not provide an explanation of the cyclicality of aggregate productivity.

Cooper and Haltiwanger (1990) presented two sector models for an imperfectly (with sellers having market power, the model was labeled as section I) and a perfectly competitive economy (labeled as section II). Their propagation mechanism was 'the normality of demand for final consumption goods'. This mechanism excluded the production of commodities by other commodities. The approach relied on the holding of inventories by the firm in one sector. Other sectors produced goods and services which cannot be held in inventories. A build-up of inventories[5] in one sector would reduce production in that sector which then led to a reduction in demand for the products of other sectors. These demand linkages created output and employment movements when the economy was in the under-employment state due to the imperfect competition. The conclusion reached was that, within a framework of a representative agent, perfectly competitive economies will tend to exhibit more substitution between labour supply decisions across sectors than imperfectly competitive economies with heterogenous agents.

How does a sectoral shock affect the aggregate economy? Phelan and Trejos (1996) pointed out that one should account for at least three phenomena or facts. These are: 1) The process of reallocating workers across sectors, (i.e., the extensive margin). 2) The increase in hours in the growing sectors is small relative to the decrease in the shrinking sector (i.e., the intensive margin). 3) The shock propagation through the unaffected sectors.

Phelan and Trejos (1996) showed that isolated sectoral shifts can have important aggregate implications, even if the size of the 'impulse' is small. The study concluded that a one-time change in the fundamentals (technologies) that determine the sectoral composition of the economy could prompt a significant downturn, which persisted and

[5] Formally presented as an endowment shock to the inventory good. This shock was the initial source of fluctuations in the economy.

propagated across sectors into a recession. They considered a one-time permanent military cut-back shock in the 1990s.

To explain Lilien's (1982) observation, sectoral shock models focus on the costly adjustment of labour between sectors. These models assume that the unemployed workers spend time searching for a match when moving between sectors (search unemployment) or incur training costs to join a different sector (structural unemployment). In this setup, the sectoral law of large numbers[6] does not hold (because of the adjustment costs) and recessions are periods of costly inter-sectoral labour adjustment.

Others have used a sectoral framework to explain aggregate returns to scale. Basu and Fernald (1997) in an attempt to explain aggregate increasing returns to scale, formulated a two-sector model economy. The model featured a durable and a non-durable manufacturing sector. The former sector was characterised by higher returns to scale and higher markup of price over marginal cost than the latter. A reallocation from the latter to the former (from the lower return, lower markup to the higher one) led to an increase in aggregate output relative to inputs and consequently to an economy that possessed increasing returns to scale. However, empirical support for increasing returns in U.S.A. sectors was weak since plant-level data failed to support evidence of significant increasing returns to scale (see Baily, Hulten and Campbell (1992) and Burnside (1996) for 2-digit manufacturing industries). Also empirical results suggested strong differences in capital utilization.[7] Swanson (1999b) attempted

[6] The sectoral law of large number states that 'given that the economy is made out of a large number of sectors, a sectoral shock to the economy will move labour between sectors and will have no effect on the aggregate level of activity'.

[7]

to explain the empirical observations using variable capital utilization across sectors but with a constant return to scale production function.

Before discussing the Swanson (1999b) findings, let us consider one more piece of evidence for constant returns to scale in sectoral-level data. Burnside, Eichenbaum and Rebelo (1995) argued the same point empirically. Using quarterly and annual data from 1972:1 to 1992:4 for aggregate and disaggregate industries (two digit level of the Standard Industrial Classification (SIC) code), they corrected the Solow residuals for capital utilization. The measure used to proxy capital services utilization was 'electric use'. Once this correction was made to the Solow technology shocks, the hypothesis of constant returns to scale was not rejected.

Swanson (1999b) demonstrated several strengths and shortcomings of the sectoral reallocation models. This study showed (proposition 1, p. 11) that unless a wedge between the marginal products of inputs in different sectors is introduced, the model will fail to explain the effects of sectoral reallocation on aggregate productivity or related variables (such as the real wage). Swanson's model featured greater cyclicality in the utilization of capital in the durable manufacturing sector. An increase in the fraction of durable manufacturing output increased output relative to the inputs, and increased aggregate productivity and real wages. This study advocated the use of variable capital utilization across sectors to explain the procyclicality of the aggregate productivity and real wages.

Shapiro (1996) reported that 40 percent of the cyclical variation in manufacturing employment originated from work in evenings and late shifts.

Swanson (1999a) reported that the myth of post-war U.S.A. procyclical real wages was unfounded. Swanson (1999a) used data covering the 458-NBER Productivity Database, and the 2-digit Jorgensen's 34-sector KLEM data set. The NBER data contain all sectoral data for all manufacturing industries at the 4-digit (SIC) level, covering the annual period from 1958 to 1994. After deflating by sectoral product prices and controlling for changes in intermediate input prices, Swanson (1999a) reported evidence of a countercyclical real wage.

This review indicates that sectoral empirical and theoretical investigations are clearly promising avenues for future research.

3.2 Sectoral Shifts versus Aggregate Disturbances

The debate over sectoral shifts versus aggregate disturbances focuses on the structural versus the deficient-demand causes of unemployment. In recessions, is large observed unemployment structural or cyclical? If observed unemployment is structural, then sectoral shifts might be the cause; otherwise, it is cyclical and the economy is in need of demand-management policies.

Brainard and Cutler's (1993, p. 222) definition of reallocation shocks and aggregate shocks was that "Reallocation shocks are defined as changes in tastes or technologies that cause changes in the sectoral pattern of returns that are sufficiently large and persistent to induce shifts in the equilibrium distribution of capital among sectors. Aggregate shocks are defined as transitory shocks that have no lasting effects on the distribution of capital profitability across sectors." Their sectoral shift hypothesis refers to those inter-sectoral shocks that are the primary cause of fluctuations in the aggregate unemployment rate.

The importance of sectoral reallocation following a sector-specific shock is a subject of ongoing debate among researchers. As in other debates, crucial empirical findings paved the way and resulted in different models reflecting different views.

The competing views to explain unemployment are: the sectoral labour adjustment versus the aggregate demand policies (sectoral shock versus aggregate shock). There exist empirical difficulties in distinguishing between sector-specific and aggregate shocks. Does an increase in unemployment reflect a contraction in aggregate demand that results in workers being laid off or does it reflect a sector specific shock that changes the pattern of demand and the composition of labour supply across sectors? The debate on the validity of aggregate demand policies to reduce unemployment took a sectoral view with the article of Lilien (1982). This debate mainly revolved around the reasons for cyclical fluctuations in aggregate unemployment. Models that explain cyclical unemployment were proposed.

First, a note on the consequences: if the sectoral view is the correct one, aggregate monetary and fiscal policies (demand policies) are not appropriate cures for high unemployment. Therefore, the economy is in need of a supply-side policy to ease the transition of ex-workers across the sectors. On the other hand, if the aggregate view is the correct one, then a demand policy can reduce the unemployment level.

Second, the intuition in the former view is that a change in sectoral labour demand implies labour reallocation across sectors from the low demand one to the higher one. The consequence of a sectoral shocks view on economic theorizing is that most unemployment fluctuations are induced by sectoral structural shifts within the economy and are better described as fluctuations of the natural rate itself (refer to section 4.4).

Building on the micro-foundation model of the equilibrium unemployment rate of Lucas and Prescott (1974) and adding the assumption of a time varying variance of the shock to the product demand in individual markets,[8] Lilien (1982) constructed an equilibrium rate of unemployment that varies as the quantity of labour reallocation varies within the economy. The study evaluated sectoral level data and concluded that sectoral shifts played a role in inducing the economic downturn. It claimed that half of the postwar unemployment variance was due to the fluctuation of the natural rate brought about by slow adjustment of labour to shifts in employment across sectors. Equivalently, a large component of unemployment fluctuations could be explained by the dispersion of employment growth across industries (also called the dispersion hypothesis, or inter-sectoral shifts in employment across industries). Also, Shaw and Arden (1968) showed that sectoral shifts represented as much as one-fourth of the output change over the period 1947-1965.

Lilien designed a dispersion index to measure the variance of employment across industries. This index was shown to have explanatory power for unemployment (using linear regression technique). Formally, the Lilien dispersion index σ_t is computed as

$$\sigma_t = \left[\sum_{i=1}^{N} l_{it}/L_t \bullet \{\log(l_{it}/l_{it-1}) - \log(L_t/L_{t-1})\}^2\right]^{1/2} \tag{3.1}$$

where l_{it} denotes employment in industry i at time t. L_t denotes total employment.

[8] The Lucas-Prescott (1974) model assumed that: 1) aggregate demand is constant, 2) product demand in individual markets is subject to stochastic fluctuations and 3) the mobility of labour across sectors takes time and is costly. The last assumption implied that positive unemployment will exist in a stationary equilibrium. The second assumption implied that a change in an individual labour market demand will create a wedge between wages in different markets (wages differentials). The model emphasized the sectoral shifts of labour supply that resulted from workers leaving the low wage market for the higher one. In this model, the variance of the shock to the product demand was constant over time and created a constant equilibrium unemployment rate.

The index is a weighted standard deviation of annual employment growth by industry. A higher value of the index means more dispersion. Shortly after Lilien' observation, a wave of empirical evidence against and for the dispersion hypothesis followed. Lilien's index was later proven to reflect both demand and sector shocks (Abraham and Katz (1986)).

Abraham (1983) and Abraham and Katz (1986) argued that both a pure shock to the level of demand or to the structure of demand (sectoral view) can produce a positive correlation between the dispersion of employment growth rates (σ_t) and the change in the unemployment rate (ΔUE). Their study contradicted Lilien's findings that the sectoral shock was solely responsible for the positive correlation. Using the information content in the job vacancy rate (proxied by the help wanted index)[9] they claimed that one can distinguish empirically between the two processes: pure sectoral shift and pure aggregate demand. If the former process applies, then the job vacancy rate should be positively related to the dispersion of the employment growth rates. However, if the latter process applies, then the relationship should be negative (known as the Beveridge Curve).[10] Changes in the structure of the economy will shift this curve. For example, an increase in the dispersion of the employment growth rates across sectors shifts this curve outward, implying an increase in unemployment and vacancies at the same time, hence a positive relation between them due to a sectoral

[9] In Canada, the help wanted index (HWI) source is CANSIM matrix 105. The Canadian' HWI is patterned after the U.S. one produced by the Conference Board. A survey of twenty metropolitan newspapers is conducted. The base year is 1981 in Canada and 1967 in the U.S.A.

[10] The Beveridge Curve claims a negative relationship between unemployment and job vacancies in response to aggregate shocks. A negative aggregate shock reduces the demand for labour across many (if not all) sectors producing a reduction in job vacancies with an increase in unemployment. However, the sectoral view proposes that reallocation shocks increase job vacancies in some sectors and reduce them in others. Therefore the aggregate effect on job vacancies may be positive with an increase in unemployment (an outward shift of the Beveridge Curve).

shock. Using annual data on the help wanted index and the dispersion of the rates, Abraham and Katz (1986) concluded that the sectoral view was rejected in favour of the aggregate demand story. However, a strong criticism against the study is the use of proxy variables which lead to an artifact result due to statistical mismeasurement (see Davis 1987 for references).

Rogerson (1987) pointed out that the analysis of Lilien (1982) and of Abraham and Katz (1986) used time series approaches to study the aggregate behaviour of unemployment following a sectoral shock. Using a dynamic general equilibrium model - a two-period, two-sector version of the Lucas-Prescott (1974) model in which the sectoral shock was permanent - Rogerson (1987) showed how mobility costs across sectors influence aggregate-level variables in the economy.

Sheffrin (1984) acknowledged the dispersion hypothesis effect and posed a different question "... does inter-sectoral dispersion activity influence aggregate variables (such as consumption and investment spending) other than unemployment?" The study designed two measures of economic dispersion based on variation of, 1) personal income growth and 2) investment spending across states. In general, Sheffrin proposed a modified σ_t dispersion index,

$$\sigma_t = \left[\sum_{i=1}^{N}\left(\left(\frac{\chi_{it}}{\chi_t}\right) \bullet (\Delta \log \chi_{it} - \Delta \log \chi_t)\right)\right]^{\frac{1}{2}} \tag{3.2}$$

where χ_t denotes the aggregate level of economic activity in year t, χ_{it} refers to the economic activity in sector i in year t and Δ is the difference operator. This dispersion index is a weighted squared deviation of the growth rate in sector i as compared to the overall growth rate for all the sectors. A value of zero means that all sectors grew (or fell) at the same rate. A high value means more dispersion. Sheffrin constructed two indices, namely σ_y and σ_I. The former index is used for the consumption study and is based on χ_{it} as the deflated disposable income for the 48 mainland U.S.A. states covering annually the period from 1951 to 1982. The latter index is used for the investment study and is based on χ_{it} as the non-farm new plant and equipment expenditures[11] over the same period with quarterly data. The study concluded by pointing to evidence for the dispersion hypothesis as having explanatory power over aggregate consumption and investment.

Davis (1987) tested the effect of sectoral shifts on aggregate unemployment. The study covered the period from 1924 to 1985. Indices of cross-sectoral (weighted) covariance measures were constructed and used in the testing process. These indices of the current direction of the labour reallocation relative to past directions are (Davis 1987, p. 330):

$$\sigma^H_{t,j} = \sum_{i=1}^{N} \left((\frac{x_{it}}{X_t})(\Delta_1 x_{it} - \Delta_1 X_t)(\Delta_j x_{i,t-1} - \Delta_j X_{t-1}) \right) \qquad j = 1, ..., J \quad (3.3)$$

where x_{it} denotes employment in sector i at time t, X_t is aggregate employment at time t. $\Delta_j x_{i,t}$ is equal to $(\ln x_{it} - \ln x_{i,t-j})$ and N is the number of labour market sectors broken down by industrial classification. $\sigma^H_{t,j}$ indexes the time t direction of labour reallocation over one period horizon relative to the $(t-1)$ direction over a j period horizon. High (Low) values of $\sigma^H_{t,1}, \sigma^H_{t,2} ... \sigma^H_{t,J}$ indicate that the time t direction of labour reallocation reinforces (reverses) past patterns of labour reallocation. Evidence of the sectoral-shifts hypothesis was found when the estimated partial correlation

[11]Both are taken from the Survey of Current Business.

between these indexes and the aggregate unemployment rates was positive.

Neelin (1987) tested the sectoral shifts hypothesis using Canadian data over the period 1954-1984. She found that Lilien's index is positively correlated to unemployment in Canada. However, when the index was decomposed into two components, one which was attributable to aggregate activity (to test causality from aggregate to sector) and one which was not, only the former component was correlated with unemployment. The results suggested that, in Canada, economy-wide shocks cause shifts in the industrial composition of employment which influence the aggregate unemployment level.

Highlighting the importance of the sector-specific shocks for national aggregate output growth, Stockman (1988) posed a different question. He asked how the fraction of the variations in output growth can be attributed to industry specific shocks versus a nationwide shock. In a comparison of national output growth across seven European nations and the U.S.A., the aim was to quantify how much variation was due to national fiscal and monetary policies specific to the country versus how much variation was due to industry-specific shocks common across nations. In a broader sense, the study assessed the validity of the supply-side driven real business cycle view versus the aggregate demand driven view in macro-economic modelling. Out of a dynamic general equilibrium model in which N nations and J industries interacted, a linear statistical model was derived and estimated using international data. Formally,

$$\Delta \ln y_t^{in} = f(i,t) + g(n.t) + u(i,n,t) \tag{3.4}$$

where y_t^{in} denotes the output growth of industry i in country n at time t. The two functions $f(i,t)$ and $g(n,t)$ referred to an industry-specific component and a nation-specific component respectively, while $u(i,n,t)$ is an idiosyncratic component. The results cast doubt on the hypothesis that most macroeconomic fluctuations are the result of technology shocks alone. Also, the study concluded that both types of shocks are empirically present and important.

Using data from the Current Population Survey (CPS) on prime-age males over the period 1968-1985, Murphy and Topel (1987) identified movers across industries by tracking the workers' move across 2-digit industries. They concluded that non-movers accounted for most of the variations in unemployment. Only two to four percent of unemployment was due to industry switchers. Also, this component lacked any cyclical variation pattern. The measured mobility of workers between sectors was procyclical. This stands as clear evidence against the Lilien hypothesis.

Loungani and Rogerson (1989) documented the correlation between permanent sectoral reallocation and business cycle data using the Michigan Panel Study of Income Dynamics (PSID). Their study differed from Murphy and Topel (1987) in some aspects. The definition of 'industry switcher' differed in two ways (a) They distinguished between permanent movers and temporary ones and (b) if the worker moves from industry 1 to unemployment, then stays unemployed for any period of time, then moves into industry 2, the worker is classified as switcher. The latter classification will include individuals who experienced any length of unemployment spells in the process of moving across industries (usually referred to as 'long-spell switchers'). Using PSID data over the period 1974-1984, the study concluded the following: a) movers from the goods-producing sectors towards the services sectors showed an increase during recessions, b) movers from the services-producing sectors towards the durables goods-producing sectors showed an increase during booms, and c) switchers accounted for over a quarter of total weeks of unemployment during booms and over 40 percent during recessions. Evidence (a) and (c) support, while (b) contradicts, the Lilien hypothesis. Evidence of (b) implies that labour mobility is procyclical. If true, then in recessions very little unemployment is due to labour mobility. A clear contradiction to Lilien's hypothesis.

Meanwhile, Layard (1991) proposed a dissimilarity index to capture employment dispersion across industries. It is calculated as,

$$0.5 \bullet \sum_{i=1}^{N} |(l_{it}/L_t) - (l_{it-1}/L_{t-1})| \tag{3.5}$$

This index is half of the sum of absolute changes in employment shares by industry. Nowadays, it is used jointly with the Lilien dispersion index in most empirical investigations of the sectoral reallocation hypothesis (see Gera and Massé (1996) for an extensive use of both indices).

Krol (1992) studied trends and persistence measures (such as unit root and variance ratio) in industrial production of U.S.A. industries. Using seasonally adjusted monthly Citibase data for 22 industries covering the period from January 1947 to March 1987, Krol investigated trends and estimated variance ratios. The study confirmed the heterogenous nature of the trend properties of industry output. For example, all durable goods industries were trend stationary but most non-durable goods were not. Krol also concluded also that individual industries did exhibit heterogenous industry-specific shocks which influenced aggregate unemployment.

Using time-series analysis, Brainard and Culter (1993) developed a new measure of reallocation shocks. The innovation to methodology[12] was the use of a series constructed from the variance of sectoral stock market excess returns[13] (labeled as cross-section volatility) instead of constructing a measure from the labour market flows. Formally,

$$R_{j,t} = \beta_{0j} + \beta_{1j} R_{m,t} + \varepsilon_{j,t} \tag{3.6}$$

$R_{j,t}$ and $R_{m,t}$ denotes the return on the portfolio at time t of industry j and the base market m (where the base market is the Standard and Poors Composite Index) respectively. The excess return from the industry-specific component of return variation is computed as

$$\eta_{j,t} = \widehat{\beta}_{0j} + \widehat{\varepsilon}_{j,t} \tag{3.7}$$

Next, one can form a measure of cross-section volatility as the weighted variance of one-quarter excess returns (CSV)

$$CSV_t = \sum_{j=1}^{N_t} w_{j,t} (\eta_{j,t} - \overline{\eta}_t)^2 \tag{3.8}$$

where N_t is the number of industries and the weight $w_{j,t} = E_{j,t}/E_t$ is the share of industry employment relative to total employment. Here, $E_{j,t}$ denotes employment in industry j at time t and E_t denotes aggregate employment.

Brainard and Cutler confirmed that - using their measure - excess returns predicted increases in employment within industries. The study concluded that, on average, the reallocation shocks accounted for a moderate variation in unemployment.

[12]First introduced by Loungani and Prakash (1989) (see also, Rush and Tave (1990)).

[13]This measure is based on the weighted variance of one-quarter excess returns where the weights are the *size* of industry employment relative to total employment.

It did account for the increase of unemployment in the mid-1970s and late 1960s, while it did not do so for the late 1950s and the early 1980s. A similar conclusion was reached in Lilien (1982). Also, Brainard and Cutler compared the cross-section volatility measure to the Lilien employment dispersion measure in terms of explaining the unemployment duration. They found that the former explains large fluctuations in longer spells of unemployment while the latter explains shorter duration spells.

Using plant-level data, Davis and Haltiwanger (1990, p. 166) confirmed that "... the frictions associated with the reallocation of jobs and workers play a major role in business cycle fluctuations ...". Also, using firm-level data, Holzer (1991) analyzed the relationship between unemployment/employment outcomes and sales growth variation within and between local labour markets. To compute various measures of product and labour demand shifts, the sales growth variable was used from the Employment Opportunity Pilot Project (EOPP) survey of firms in 1980 and 1982. The data was for 28 local labour market sites and included about 3400 firms. Given the firm-level data, three types of shifts were considered. They were 1) shifts in demand between local markets, 2) shifts in demand within local markets but between industries, and 3) shifts within local markets and within industries. The result showed that wage and employment adjustments for firms were based on the shifting of the labour demand caused by changes in the product market. Demand shifts between local labour markets did have a substantial impact on observed unemployment and employment growth rates *only* when adjustments of these shifts involved *costly migration* between markets. (Models in this thesis adopt and integrate this aspect)

Also, with micro-level data, Hyclak (1996) found an important and significant positive effect of changes in the structure of labour demand on the unemployment rate. He studied a sample of 200 metropolitan labour markets for the period 1976 to 1984 in the U.S.A. Using a measure of structural job shifts, he showed that changes in the structure of labour demand across industries had an important statistically-significant positive effect on the unemployment rate.

Using a time series analysis vector autoregressive (VAR) approach, Campbell and Kuttner (1996) reached a conclusion similar to Lilien's finding. They investigated the macroeconomic effects of reallocation shocks. Using three different identification schemes within a VAR approach, they concluded that reallocation shocks accounted for the majority of the variance in employment shares and dispersion. The three identification schemes were as follows: the naive identification where aggregate employment was a lag ahead of manufacturing's employment share in a Wold causal chain; the reallocation shocks scheme which accounted for the stochastic trend in manufacturing's employment share; and the reallocation shocks combined with the price of crude petroleum scheme where the shocks relied on the changes in the price. The first identification denied the existence of the sectoral shifts hypothesis. The second emphasized the Lilien observation. The third was to test the Loungani (1986) view. The latter view focused on the following chain of events. The changes in the price of crude petroleum affected aggregate employment to the extent that they generated employment reallocation. The results - under a variety of identifying restrictions - showed that sectoral shocks (alone) were responsible for at least 27% of the variance in aggregate employment.

Greenwood et al. (1994) used a stochastic dynamic general-equilibrium model to assess the relative importance of each shock, aggregate versus sectoral, and to analyse the cyclical behaviour of the rates of job destruction and job creation at the same time. Their model features a momentary utility function that accounts for workers searching for a job, and a production technology that encompasses aggregate and sectoral shocks as well as featuring the low productivity of new workers hired. The cost of hiring is an increasing function of the number of workers hired. The model emphasizes the intensive margin of employment decisions by including a lottery over the consumption and labour allocation decisions. The generated model moments matched the U.S.A. business cycle data over the quarterly period from 1976 to 1987, where emphasis was on the cyclical behaviour of the rates of job destruction and job creation. Regarding the Lilien hypothesis, the model concluded that each type of shock can be independently held responsible for 1 percent of aggregate unemployment.

3.3 Inter-industry labour mobility

Inter-industry labour mobility is one of the major dynamic mechanisms by which the labour market adjusts to structural changes in the fundamentals (technologies) of the economy. Understanding its determinants and its dynamics was and still is a major challenge in economic theorizing.

The empirical relationship between inter-industry labour mobility and aggregate unemployment has been investigated for Canadian data. If the relation is characterized by a positive covariance, one has to accept the 'dynamic reallocation' hypothesis proposed by Lilien (1982). In this hypothesis, the rising unemployment rate is due to the increased dispersion in the net hiring rates of firms. On the other hand, if evidence of negative covariance is found, then one is more likely to accept the Keynesian 'chilling' rationale[14] as an explanation. This rationale argues that high unemployment 'chills' the labour market. An example of it is the cobweb model in which the quantity of labour supplied depends on last period's traded quantity. Whichever way it is, the causal relationship between inter-industry labour mobility and aggregate unemployment is not clear (see Osberg 1991).

Lilien (1982) argued that employment dynamics caused by the time-to-find a job for the unemployed could explain the increase of the U.S.A. unemployment rates in the 1970's. In brief, the Lilien 'dynamic reallocation' hypothesis is a search model. The unemployed mobility is characterized by a job-unemployed-job process where finding a job takes time. For Canada, Samson (1985) found evidence that the 'dynamic reallocation' model best fit the Canadian data.

Ratti (1985) showed that unexpected inflation and the rate of growth of real GNP explain between 60 percent and 85 percent of the variability in relative sectoral employment. In a reverse causation conclusion (i.e., aggregate variables cause sectoral variability instead of the other way around). Ratti questioned the basic fundamentals of the sectoral shock view. This view is that aggregate fluctuations - mainly unemployment[15] - are due to sectoral shocks that induce employment variability across sectors. Ratti focused on the allocative consequences of unexpected inflation. Using

[14]The chilling rationale argues that the level of aggregate unemployment influences the decision-making process of the economic agents.

[15]For evidence on consumption and investment see Sheffrin (1984).

a dispersion of sectoral employment index σ_t calculated as

$$\sigma_t^2(K) = \sum_i u_t(i)(Dx_t(i) - DX_t)^2 \qquad i = 1, ..., K \tag{3.9}$$

where K denotes the number of sectors. $Dx_t(i)$ is the rate of growth of employment in the ith sector, DX_t is the rate of growth of total employment, $u_t(i)$ is the average of the proportion of total employment in the ith sector in periods t and $t-1$. $\sigma_t^2(K)$ could be computed using the number of employees N or the total number of man hours H, depending on the definition of employment. The measure of annual employment variability is taken from the nonagricultural data of *Employment and Earnings* for 28 sectors over the period 1947-1978. A proposed model - in which sectoral employment variability is a quadratic function of inflation surprises and the real rate of GNP growth - reported significant explanatory evidence. In this view, cyclical aggregate factors are found to have sectoral reallocative consequences as opposed to the sectoral shock view.

Osberg (1991) investigated the factors that influence inter-industry labour mobility and its relationships with the aggregate unemployment level in Canadian data. Using Canadian micro data on male and female workers - from 1980/81, 1982/83 and 1985/86 - the estimated logit model found evidence supporting the 'Chilling' model. The conclusion reported that individuals react to the aggregate labour market, showing how cyclically sensitive the behaviour of the market is.

Mills, Pelloni and Zervoyianni (1996) tested for the presence of the sectoral shifts hypothesis in UK data. They constructed a 'purged' sectoral employment growth to use in the Lilien index. They purged the sectoral employment growth from aggregate influences by regressing each relative sectoral employment growth rate on its lagged value, four seasonal dummies and other composite variables based on the narrow money growth rate, the logarithm of the short interest rate and the unemployment rate.[16] Using quarterly UK data covering the period from 1976 to 1991, they tested the significance of the sectoral shifts hypothesis. They found supporting evidence of the hypothesis.

Lu (1996) used both quarterly and annual data on both one-digit and two-digit U.S.A. code industries,[17] and reported no evidence of the sectoral shifts. Using data from Citibase covering the period from 1948 to 1994, the study concluded that the significance of Lilien' results diminishes at quarterly level data suggesting that Lilien results might be a special case.

Others explored sectoral data to assess their influence on unemployment. For example, Corak and Jones (1995) investigated the influence of sectoral unemployment benefits on the persistence of aggregate unemployment. They defined full persistence as a unit root and tested its presence using the Dickey-Fuller statistic. The study concluded that no evidence of a direct mechanism - through which the unemployment benefits overhaul in 1977 influenced the level and the persistence of aggregate unemployment - was found. In brief, evidence of the sectoral shifts is sensitive to the methods used and to the data employed to measure it. However, from a policy standpoint there is a growing consensus on its importance.

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[16]See p. 58 for the exact reference of the variables used.

[17]Note that Lilien, Abraham and katz have used only annual data on one-digit code industries.

3.4 Inter- versus Intra-Sectoral Shocks

Since the dispersion in the returns to human capital is not observable, one needs to use a proxy for inter- and intra-sectoral shocks. If mobility across industries is costless, then a difference in the returns to human capital will induce labour reallocation. The problem is that wage differentials across and within sectors reflect other aspects such as workers' characteristics. Therefore, the average wages do not represent a good proxy. By assuming that capital and labour are complements, Shin (1995) computed proxies for inter- and intra-sectoral shocks and studied their effects on the level of aggregate unemployment. Using accounting data from the manufacturing industries to calculate returns on capital, Shin generated proxies for both shocks.

As outlined above, Lilien (1982) used the variance of industry employment rates to measure the inter-sectoral shock. Abraham and Katz (1986) noted that if industrial trend growth rates and the cyclical sensitivities of the industries are negatively correlated, then the Lilien proxy can also be used to measure aggregate shocks. Lougani et al. (1990) used the stock market dispersion index of output price growth rates as a proxy for inter-sectoral shocks. This innovation of using stock market data was investigated further in Brainard and Cutler (1993). They used the variance of industry stock market returns as a proxy.

Most studies assumed that firms are homogenous within industries, so that an intra-sectoral shock need not exist. If one relaxes such assumptions to highlight the fact that there are some labour reallocations within industries, then intra-sectoral shocks emerge and need to be approximated. Empirical micro studies reported a positive correlation between tenure and re-employment within industries but not across. The intuition behind the innovation is that most reallocations are within industries and that it requires lower adjustment costs on the part of the workers which create an incentive to search for re-employment in the same industry.

A variance decomposition methodology was used in Shin (1995) to decompose the variability of firms' capital returns into 1) the variance of the mean returns across industries (proxy for inter-shocks) and 2) the average of the variances within industry (proxy for intra-shocks). To measure the return to capital, one can use either accounting data or stock price data. Shin used accounting data, after noting that stock price data are affected by anticipated future shocks while accounting data are immune to such expectations. The variance decomposition of the returns on capital was computed as

$$var(r_{ijt}) = var(\overline{r}_{it}) + E_t(v_{it}) \tag{3.10}$$

where r_{ijt} denotes the return of firm i in industry j at time t. Also,

$$\overline{r}_{it} = E_t(r_{ijt} \mid \text{ Industry } i) = \sum_{j \in i} w_{ijt} r_{ijt} \tag{3.11}$$

and

$$v_{it} = Var_t(r_{ijt} \mid \text{ Industry } i) = \sum_{j \in i} w_{ijt} r_{ijt}^2 - (E_t(r_{ijt} \mid \text{ Industry } i))^2 \tag{3.12}$$

where $\overline{r}_{it}$ and v_{it} are the weighted expectation and variance of the return conditional on industry i at time t. The weight w_{ijt} is the size of the capital share relative to the industry.

$$w_{ijt} = \frac{K_{ijt}}{\sum_{j \in i} K_{ijt}} \tag{3.13}$$

Shin concluded that the magnitude of the intra-sectoral shocks was greater but the inter-sectoral shocks explained to a better degree the fluctuation in aggregate unemployment.

3.5 Quantities versus Prices

In this section, I will clarify my decision to focus on unemployment rather than average industry wages, so that the focus will be on the quantities - rather than prices - in the labour market.

Gerlach (1989) outlined three approaches in the literature in which a model is able to produce output that exhibits serial correlation (persistence) in response to serially uncorrelated shocks. The first is multi-period wage contracts (price dynamics), in which the persistence of unemployment is due to shocks affecting the nominal price level until all existing wage contracts have been renegotiated. The second focuses on the law of motion of stock variables - such as inventories (Blinder and Fischer 1981) or physical capital (Kydland and Prescott 1982) - to produce the persistence effect. The temporary shock is amplified in the model by the stock variables which evolve over time.[18] The third approach explores the informational structure of the economy. This view stresses the serial correlation of the errors associated with the rational expectations hypothesis, as in Lucas (1975) and Brunner et al. (1980). Briefly, this line of investigation addresses the informational structure available to the economic agents. For example, Gerlach (1989) used the assumption that the agents never observe the underlying shocks but only their impact on the endogenous variables.

[18]Hence the label 'Time to Build'.

Coe (1990) concluded from extensive empirical analysis that industry wages are heavily affected by aggregate consumer prices as well as by industry output selling prices. Although there was some evidence of a higher unemployment influence on wages in the manufacturing sector than the service sector, the study concluded that industry unemployment plays a less significant role in the determination of industry wages.

Adjustment costs are also relevant to the determination of the optimal wage rate (the wage setting process). In Scarth (1988), the optimal rate of wage change is the one that minimizes two types of costs. First, agents incur costs whenever the wage w differs from the equilibrium $\overline{w}$, which is the wage rate that would make employment equal to its long-run desired level. Second, households and firms incur adjustment costs whenever wages have to be renegotiated. The negotiation costs are a positive function of the gap between the actual rate of change in w and the percentage change in $\overline{w}$. Whenever $w > \overline{w}$, firms will resist incurring the cost and whenever $w < \overline{w}$ workers will resist. Therefore, the determination of the optimal wage rate will be the outcome of the minimization of the sum of these two costs. One of these is due to being away from equilibrium (the difference between w and $\overline{w}$), and the other is due to different rates of change between w and $\overline{w}$. Formally, the decision rule[19] can be rewritten as

$$w_{t+1} - w_t = \overline{w}_{t+1} - \overline{w}_t + (1-\gamma)(\overline{w}_t - w_t) \qquad (3.14)$$

This sticky-wage approach has also been studied by Mussa (1981) and McCallum

[19]See Scarth (1988, pp. 15-16) for the derivations.

(1980).

Sargent (1979) demonstrated that if the firm is subject to an adjustment cost in altering employment, the desired short-run level of employment will depend on its lagged values. In other words, persistence in employment could be achieved by a costly quantity adjustment specification. His study added a neoclassical labour supply function and resulted in equilibrium output depending on its lagged values. It showed that persistent unemployment can be due to voluntary search behaviour.[20] Sargent captured 'persistence' by a lagged dependent variable.

Cuthbertson and Taylor (1987) also suggested a costly quantity adjustment model in which agents chose current 'short-run' value of y_t in order to minimize expected costs c_t with information available at $t-1$, that is,

$$\min c_t = \min E_{t-1}\left(\sum_{i=0}^{\infty}\frac{1}{2}D^i a_0(y-y^*)^2_{t+i} + a_1(y_{t+i}-y_{t+i-1})^2\right) \tag{3.15}$$

where y^* denotes the long-run equilibrium value. a_0 and a_1 are parameters. D denotes the discount factor for the quadratic adjustment cost and E is the expectation operator. In this setup, agents have quadratic costs of being away from their long-run equilibrium value. This formulation is a multi-period generalization of the first-order partial adjustment equation. y might be any real variable such as the capital stock or employment (either one is costly to adjust). The firm minimizes costs to determine employment, within the overall objective of maximizing the discounted present value of future profits. The choice of a quadratic form has the advantage of providing a linear solution in expectations (Euler equations are linear). A linear solution in

[20] In search models, the positive and finite probability that individuals will receive a wage offer below their respective reservation wage implies that unemployment will persist.

expectations is a case in which the solution does not depend on the variance of the forecasts errors.

I adopt the view that focusing on quantity dynamics rather than price dynamics will result in a framework which better captures the sectoral shifts of employment across sectors.

3.6 Conclusions

This chapter presented the rationale and usefulness of sectoral analysis in macroeconomics. Different theories of unemployment, namely sectoral shifts versus aggregate disturbances, were examined. It also explained our further use of labour quantity dynamics. This chapter serves as a basis for the presentation of sectoral general equilibrium models (Chapter 6).

Chapter 4 addresses unemployment persistence. It discusses the persistent nature of Canadian unemployment. Chapters 5 and 6 discuss the dynamics of sectoral reallocation shocks and how these sectoral phenomena can explain unemployment persistence?

Chapter 4

Unemployment Persistence

This chapter investigates the persistence of Canadian' unemployment using sectoral level data. The long-standing confusion regarding the definition of persistence is highlighted and we propose a definition for 'economic persistence'. We test for the presence of persistence using the Cochrane variance ratio and the modified rescaled range statistic. Finally, using a Bayesian ARFIMA class of models, we attempt to quantify Canadian unemployment persistence.

4.1 Introduction

Unemployment returns about one third of the way to its normal level[1] each year after a shock displaces it. This is the case for the U.S.A. and Canada. In general, modelling persistent unemployment requires a fluctuation model that is able to generate stationary but highly serially correlated movements of unemployment and to mimic the cyclical co-movements of output and employment.

Persistence in unemployment has long been documented, explored and investigated at the theoretical and applied levels. To understand unemployment persistence,

[1] Hall (1998, p. 34).

one has to investigate long-term structural policies. These policies can be divided into two groups: structural changes and reform changes. The former type of policy addresses the changes intended to reduce the business cycle fluctuations that result from any economic shock (hence the title of the thesis); the latter type concerns methods that will lower the natural rate of unemployment.[2] The focus here is on the former.

Coe (1990) investigated the hysteresis[3] hypothesis for 14 industrialized countries using annual data from 15 industries of each country. Using OECD data covering the period from 1971 to 1986 for 14 industrialized countries and using a linear regression type specification that nests two versions of insider-outsider models, the study found evidence that the institutional structure for the determination of industry wages contributes more to the persistence of unemployment in Europe than North America and Japan.

Insider-outsider[4] models assume that workers fall into three homogeneous groups, defined as follows: i) the 'insiders', whose positions are protected by significant labour turnover costs, ii) the 'entrants', who have recently acquired jobs with a future prospect of gaining insider status, but whose current positions are not associated with significant turnover costs, and iii) the 'outsiders'.

By quantifying the extent to which wages are set by insiders within the industry, one can provide an explanation for the persistent unemployment rates. Coe (1990)

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[2] The issue of the natural rate has been under much scrutiny recently. For an excellent review see Cross (1995).

[3] The concept of 'hysteresis' although different from 'persistence' will be used interchangeably for the present.

[4] Insider-outsider models usually generate real wage rigidity and turnover. The idea is that - from the firm's point of view - insiders are costly to replace by outsiders. Therefore, insiders enjoy a monopoly power that they exert to keep their wages higher than the market clearing level. Insider-outsider models were used by Benassi, Chirco and Colombo (1994, p. 100) to explain unemployment fluctuations.

pointed out one critical explanation for the cross-country difference in unemployment, namely industry wage determination. This thesis investigates the view that differences in unemployment rates across countries are due to different industry-specific structures combined with an argument regarding the ease of labour mobility across industries.

Winter-Ebmer (1991) summarized different tests, used in the literature, of persistence. Different tests that quantify the possible effects on long-term unemployment[5] in a Phillips-type wage setting equation, in a Beveridge curve equation, and on capital formation were investigated. Other tests involved the simple analysis of the autocorrelation patterns of the unemployment time series. This study focused on modeling employer and worker acceptance functions within a search framework.

Heckman and Borjas (1980) asked if current unemployment causes future unemployment and found evidence of unemployment persistence. This study presented statistical methods for testing the true state dependence hypothesis in unemployment. Heckman and Borjas drafted four ways of modeling state dependence, namely Markovian, occurrence, duration and lagged duration dependence.

Among others, for example, Carey (1997) attributed the unemployment persistence to inflation expectations relative to the actual inflation rate at the end of a recession. The intuition is that constant inflation is consistent with a rising cyclical unemployment if expected inflation is persistently higher than its current level, especially for the post-1993 data period. Therefore, persistent unemployment is caused

[5] Usually, long-term unemployed are defined in the U.S.A. as unemployed for a period in excess of six months and in excess of one year in Canada and the UK.

by persistent excess inflationary expectations.[6]

The fact that 'unemployment exhibits persistence' is well documented. Explaining persistence has been and still is a challenging task for macroeconomists. Many directions have been pursued, each of which contains some truth, but none is a completely satisfactory explanation.

4.2 The Confusion between Hysteresis and Persistence

There does not currently exist a consensus in the empirical literature on the definition of 'hysteresis' in unemployment. Different authors use different definitions for this term. As many contributions confuse 'hysteresis' with 'persistence', the first step in our investigation is to address this issue.

Section 4.3 presents the origin and history of hysteresis. Section 4.3 explains the role of hysteresis in economics. Section 4.4 presents the implications and the consequences of the hysteresis. Section 4.5 discusses the factors that cause and the proposed theories that explain hysteresis. Section 4.6 reviews a selected set of articles on economic hysteresis. Section 4.7 defines economic persistence. Sections 4.8 and 4.9 present a persistence measure (Cochrane variance ratio test) and report evidence of Canadian unemployment persistence at sectoral level. Section 4.10 examines the relationship between persistence, long-memory and fractionally integrated models. Section 4.11 investigates and tests for the presence of persistence in sectoral Canadian unemployment data using the modified rescaled range test statistic. Using a Bayesian

[6] Other studies also have investigated the relationship between unemployment and policy variables and labour market rigidities (see Nickell (1997) and Riddell (1999) for excellent expositions).

fractionally linear time series class of models - namely the class of autoregressive fractional moving average (ARFIMA) - section 4.12 estimates persistence in quarterly total Canadian unemployment and reports the results. Finally, section 4.13 concludes this chapter.

4.3 Hysteresis in economics

The basic principle of hysteresis was well recognized by economists - such as Frisch, Kaldor and Schumpter[7] - well before its revival in the seminal work of Blanchard and Summers (1986).[8]

Two vague ideas revolve around the use of this term in economics. The first is the path dependence property and the second is the permanent effect of transitory shocks. The former imply that the equilibrium state of the system depends on the transition towards it while the latter underlines the persistent effects of a shock to the system. The latter property is a major source of confusion between what is known as the 'unit root persistence in discrete time'[9] and 'hysteresis'.

In the literature, 'hysteresis' is generally defined as a particular type of response of a non-linear system when one modifies the value of the input: the system is said to exhibit the remanence property when there is a permanent effect on output after the value of the input has been modified and brought back to its initial position. Briefly, hysteresis occurs in non-linear models that exhibit multiplicity of equilibria and the remanence property. On the other hand, 'unit root persistence' lacks the

[7] See Cross and Allen (1988).
[8] Details of their study will be given later.
[9] A special case of the 'zero root dynamics' in physics.

remanence effect with asymmetric persistence mainly in linear models. Two forms of hysteresis are well documented: the weak form at the micro level and the strong form (aggregation of a large number of heterogeneous[10] agents) at the macro level.

The path dependence property, used by Blinder (1988), was described as (in the hysteresis section) "... *for these (models) bring Keynesian economics* [in which the economy can get stuck in low level production] *with a vengeance*"[11] (my emphasis). Briefly, the hysteresis notion implies the non-uniqueness and the path-dependence of the natural rate. Also, it revives the Phillips curve trade-off not in levels but in first differences.

In most textbook cases, testing persistence in a general series y_t uses,

$$\Delta \ln y_t = a + b\left[\ln y_{t-1} - (\alpha - \beta(t-1))\right] + \varepsilon_t \tag{4.1}$$

where t denotes the trend and Δ refers to the first difference linear operator. If y reverts toward its trend, then b is negative and non-zero. If it does not, then b is zero. Rewrite equation (4.1) as in Romer (1996, p. 176),

$$\Delta \ln y_t = \alpha' + \beta' t + b \ln y_{t-1} + \varepsilon_t \tag{4.2}$$

where $\alpha' \equiv a - b\alpha + b\beta$ and $\beta' \equiv -b\beta$. The usual test is $H_0 : b = 0$ (permanent shock where y does not revert to trend and has a unit root) versus $H_1 : b < 0$ (trend reversion).[12]

[10] Called 'hysteron'.

[11] Also, from the conclusion section "... and hysteresis seems to characterize some economies some of the time, not all economies all the time ...".

[12] See also Nickell (1985, p. 119).

4.4 Implications of hysteresis for policy analysis

The concept of the natural rate of unemployment - since its introduction by Friedman in an analogy to Wicksell's concept of the natural rate of interest and its formulation by Phelps - applies the doctrine of monetary neutrality to the unemployment level. Monetary policies are neutral in the long term if they only affect nominal variables and have a transient effect on the unemployment rate which converges sooner or later to its natural level. As Friedman put it " It [the natural rate] is the level that would be ground out by the Walrasian system of general equilibrium equations." In the early 1950's and through the 1960's and 1970's, the Phillips curve became the major policy trade-off.[13] However, the experience of stagflation in the 1970's cast some doubts on the usefulness of the Phillips Curve and the natural rate of unemployment hypothesis as a policy tool and a policy goal. Many voices suggested correcting the hypothesis to explain what happened and a few went even further to discard the hypothesis (see Blanchard et al. (1988) and Goodinson et al. (1994)). Hysteresis was adopted to explain the behaviour of high unemployment even when the initial shock (supply shock) to the economy was removed. Hysteresis - juxtaposed with the NAIRU - is an explanation of how the natural rate is affected by the disequilibrium path of the economy, and in a way discredits both the Phillips Curve and the natural rate of unemployment hypothesis. Given hysteresis, the NAIRU would be unstable.

Hysteresis is not a concept which can be accommodated within the natural rate hypothesis or within the classical doctrine of neutrality. The natural rate proponents

[13]For a survey of the natural rate hypothesis evolution, see Goodinson and Frohlich (1994).

tried to amend hysteresis by postulating that the natural rate will be a strong attractor for actual unemployment in the long-run. However, the debate still goes on. A survey of the seminal contributions to the natural rate[14] hypothesis is presented later.

The high unemployment rate in Europe and in Canada in the 1990s can be explained by labour market rigidities that cause high costs of adjustment for firms. To investigate such an explanation, the empirical agenda would rely on pin-pointing the factors that have caused wage and price equations to shift. The increase in unemployment could be due to the increase in unemployment insurance benefits measured by a generosity index or due to hysteresis. The debate on this is still open. If the actual unemployment rate is high because it is high relative to its natural rate, one should observe a decrease in inflation rates (a recessionary gap in aggregate demand / aggregate supply analysis); otherwise, one's intuition tends to suspect that the natural rate itself is high.

Whenever evidence of hysteresis is found, there exists room to decrease the unemployment rate without changing any structure in the organization of the labour market. How fast the unemployment rate can be decreased depends on the hysteresis mechanism. Also, disinflation policies based on the unemployment rate will prove very costly in terms of lost output. Since unemployment exhibits hysteresis, it will never go back to its original starting point. This is a vital implication of hysteresis, and applies to the Bank of Canada's disinflation policies pursued in 1981-1982 and again in 1988. When hysteresis is present, the short-run adjustment of the economy

[14]Note that the mechanics of measuring the natural rate of unemployment is not of interest here.

can take place over a very long period.

4.5 Factors and theories

This section reviews the proposed factors in the literature that cause hysteresis and the theories that explain it. The factors can be classified into the following categories: 1) aggregate variables where long periods of low growth and investment decrease the potential of the economy, 2) human capital where a long spell of unemployment leads to deterioration of skills and work ethic and 3) the price mechanism where the wage formation process, in wage bargaining context, is responsible for hysteresis.

The theories that explain hysteresis are:

1) Duration theory.

This is concerned with the negative effects of unemployment duration on the labour demand and the labour supply of the unemployed. The human capital story explains this as follows. The longer an unemployment duration is, the less likely is an unemployed worker to be offered a job because firms hold the belief that the long-term unemployed are low-quality workers. In other words, if firms are using unemployment experience as a screening device, then unemployed persons with long unemployment durations are perceived as less promising candidates. Also, the longer the unemployment duration, the more discouraged the worker will become and the more likely the agent is to drop out of the labour force.

2) Insider-outsider theory.

This is concerned with the loss of the influence on wage formation by the long-term unemployed. The so-called insiders (incumbent workers) possess market power in determining wages independently of the unemployment in the economy. The market power of the insiders is due to high labour turnover costs, which make it costly for firms to replace an insider by an outsider (an unemployed worker). This allows unions to influence wage determination. Insider-Outsider models are based not on human capital but on the differentiation between insiders and outsiders in a wage bargaining context (see Blanchard et al. 1986 for an exposition).

3) The capital stock theory.

An adverse demand shock leads to a reduction in firms' capital stock. Firms may close plants or scrap capital (firms reaching the shut down point on their respective marginal cost function where, given the price, the marginal cost is lower than the average variable cost). This will cause unemployment to persist because firms can not suddenly open their plants, once the shock is removed and product demand increases.

In this thesis, I add to the above the sectoral view as an additional mechanism for generating persistence.

4.6 Evidence of persistence in the labour market

There does not exist a consensus on the definition and evidence of hysteresis. Many papers tested whether hysteresis is present in Canada, the U.S.A. and in many European countries. A selective review of the literature follows and for each the definition used is reported.

Gordon (1989) used a simple version of a reduced-form equation. Formally, the underlying model was $\pi_t = \alpha\pi_{t-1} + \beta(U_t - U_t^*)$, where π is the inflation rate, U is the level of unemployment and U^* is the natural rate of unemployment (or the NAIRU) obtained for the steady-state $\pi_t = \pi_{t-1}$. To add hysteresis, the model was amended by the equation, $U_t^* = \eta U_{t-1} + \gamma Z_t$. Inserting the latter equation in the former one yields, $\pi_t = \alpha\pi_{t-1} + \beta(1-\eta)U_t + \beta\eta\Delta U_t - \beta\gamma Z_t$, where Δ denotes the difference operator and Z_t refers to a set of structural variables. Gordon defined full hysteresis as the case of $\eta = 1$, and persistence as $\eta < 1$. This study concluded that no evidence of full hysteresis was found in five countries (France, Germany, USA, Japan and U.K.) for the time period 1873-1986.

Fortin (1989, 1991) tested for the presence of hysteresis in Canadian data covering the period from 1957 to 1990. By adding and modeling expected inflation, Fortin was able to undertake a more accurate test for hysteresis. The Phillips curve tested was $\pi_t = \alpha_1\pi_{t-1} + \alpha_2\pi_t^e + \beta[(1-\eta)U_t + \eta\Delta U_t] - \beta\gamma Z_t$, where π_t^e denotes expected inflation. Fortin defined positive hysteresis as $\eta < 0$ and negative hysteresis as $\eta > 0$. The cases of $\eta = 0$ and $\eta = 1$ are no hysteresis and full hysteresis, respectively. Fortin (1991) reported the presence of negative hysteresis for the data from 1957 to 1972. Positive hysteresis was detected for the data covering the period from 1973 to 1990. Full hysteresis was not rejected for the latter period. Fortin pointed to the Canadian unemployment insurance benefits, productivity slowdown, and union density as possible sources for hysteresis.

Graafland (1991) reported that the labour market in the Netherlands in the 1980s was characterized by a high and persistent level of unemployment. The long-term unemployed made up more than 50 percent of total unemployment. This study investigated the relevance of the duration and insider-outsider theories in explaining hysteresis in the Netherlands. It used a small macro labour market model - consisting of four equations (Graafland (1991), p. 157) describing the dynamics of wages, employment, long-term unemployment and vacancies - and estimated it using 2SLS for 1960-1987. The endogenous variables were: number of vacancies, real wage (deflated by consumer prices), labour demand (employment plus vacancies), long-term employment (over one year), actual employment and short-term unemployment. The exogenous variables were: the ratio of value added prices of firms to consumer prices, labour productivity, the rate of income taxes and social transfers (as a fraction of wage costs), the labour force, the replacement ratios of short-term and long-term unemployed, the real value added of firms and a time trend. This study found evidence of duration effects after 1982 in the data. Lopez et al. (1996) reported that monthly unemployment in Spain was consistent with an insider-outsider model and hysteresis.[15] The data in this study was monthly, from 1977:6 to 1994:10.

Measuring shock persistence in time series can be divided into two major approaches. The first is the 'unit root' approach presented by Nelson and Plosser (1982). Such an approach was heavily criticized regarding the low power of unit root tests and the failure to test for structural breaks. Most importantly, using Bayesian analysis, DeJong and Whiteman (1991) reversed the Nelson and Plosser results. The second approach is to use the Beveridge-Nelson decomposition to assess the relative importance of the transitory and the permanent component in the time series. In empirical terms, it amounts to estimating an unrestricted low-order ARIMA.

Recently, Nott (1996) did not find evidence of hysteresis in Canadian data. Yet,

[15] Hysteresis is defined as in Blanchard and Summers (1986).

a non-linear Phillips curve was not rejected. The method followed Fortin (1991) in testing for the presence of hysteresis by estimating a linear Phillips curve equation. The data covered the period from 1954 to 1995. Nott's results contradicted Fortin's findings of hysteresis and showed how sensitive the latter's results were to the sample period used.

Jones (1995) investigated the hysteresis hypothesis in Canadian data at the microeconomic and macroeconomic level. He concluded that the overall picture is not one of hysteresis, but did not rule out the presence of persistence (dependence) in unemployment rates.

Wilkinson (1997) investigated the hysteresis hypothesis in Canadian data using the Labour Market Activity Survey (LMAS). Defining hysteresis as irreversibility in the change of the unemployment rate and by testing evidence of negative duration dependence in unemployment spells, the study concluded that there is evidence of hysteresis at the micro level of the data. Wilkinson attributed the evidence of hysteresis to the loss of skills hypothesis of human capital (the human capital view is in subsection 4.5). The intuition is that prolonged periods of unemployment erode the skill level of the unemployed which decreases the probability of exiting the unemployment spell and finding a job. Therefore, unemployment spells will exhibit negative duration dependence.[16] Using the LMAS data, single-risk[17] hazard rates were estimated, then aggregated to estimate hysteresis at the macro level. The study

[16]Negative duration dependence means that the probability that a spell will end shortly decreases as the spell increases in length (Kiefer 1988, p. 652, and Lancaster 1990, p. 9, figure 1.1.(b) p. 10 and p. 39).

[17]Single-risk hazard rates occurs when no distinction between transition to work or transition to out of the labour force is made.

concluded that hysteresis accounts for three percent to eight percent of the Canadian unemployment rate. This small upperbound points to the difficulty of estimating hysteresis in the aggregate data.

However, Heckman and Singer (1984) argued that negative duration dependence of exit rates in the data is by no means a signal of persistence. They examined econometrically the negative duration dependence view and showed that the existence of two types of jobs, good and bad (i.e., using the dual labour market theory), creates unobserved heterogeneity in aggregate unemployment data. This heterogeneity will always bias the estimated hazards towards negative duration dependence. Therefore, negative duration dependence might be a signal of unobserved heterogeneity and not of persistence in the data.

Hence, while there is no consensus on the definition of hysteresis, empirical evidence of the existence of hysteresis (each author with a distinct definition) is mounting.

4.7 Definition

For the purpose of this thesis, we define 'economic persistence' as the 'effect of the shock felt for a minimum period of two years'. We assume that following a shock, a system that exhibits persistence will return to its steady state after a period of two years.

4.8 Cochrane's Variance Ratio Test

In time series analysis, the slow decline in the sample autocorrelation function is generally viewed as an indication of an integrated process. Similarly, Cochrane (1988) proposed using the variance ratio to test for non-stationarity. If a process y_t is stationary (i.e., $I(0)$) then its $var(y_{t+1} - y_t) = 2var(y_t) + c_1$ and $var(y_{t+k+1} - y_t) = 2var(y_t) + c_k$, where c_1 and c_k are non-negative constants. Note that if y_t is a white noise, then c_1 and c_k are zero. However, if the process is $I(1)$, then $var(y_{t+k+1} - y_t) = (k+1)var(y_{t+1} - y_t)$. Therefore, one can use the following ratio to test for non-stationarity,

$$V^k = \frac{1}{k+1}\frac{var(y_{t+k+1} - y_t)}{var(y_{t+1} - y_t)} = 1 + 2\sum_{j=1}^{k}\left(1 - \frac{j}{k+1}\right)\rho_j^{(\Delta y)} \tag{4.3}$$

where $\rho_j^{(\Delta y)}$ denotes the jth autocorrelation of Δy. If the process is stationary, then V^k tends to zero as $k \to \infty$. To estimate this quantity V^k, one uses the sample autocorrelation r_j instead of the population ρ_j, so that,

$$\widehat{V^k} = 1 + 2\sum_{j=1}^{k}\left(1 - \frac{j}{k+1}\right)r_j^{(\Delta y)} \tag{4.4}$$

The standard deviation of this ratio is,

$$StDev(\widehat{V^k}) = \frac{\widehat{V^k}}{\sqrt{\frac{3}{4}\frac{T}{k+1}}} \tag{4.5}$$

Therefore, once the $\widehat{V^k}$ are computed, one graphs it along with two standard deviation bands to assess the persistence in the series.

If the value of $\widehat{V^k}$ tends to 1 as k increases, the time series exhibits integrated behaviour. It is a driftless integrated process. If the value is negligible, then permanent shocks have no lasting effects. If the time series is a random walk, the level of the variable becomes increasingly uncertain. Specifically, the variance ratio of two consecutive time periods increases as time goes on. If the value of the ratio converges to zero, then the series shows temporary changes when faced with a shock. Cochrane suggested that a value higher than 1 implies strong persistence.

4.9 Canadian industry-level unemployment

This section reports Cochrane's variance ratio test of Canadian industry-level unemployment. Table 4.1 identifies the data source and their CANSIM labels. Figures 4.6 and 4.7 graph the unemployment rates for the Canadian industries. The two recessions of 1981-1982 and 1990-1991 are well identified across the board. Unemployment rises sharply during recessions reaching a peak of 14.2 percent and 12.0 percent for both recessions, respectively.

For the tables, all series are in log-level form and detrended using the Hodrick-Prescott (HP) filter.[18] Table 4.2 reports basic descriptive statistics for Canadian unemployment. Table 4.3 presents the correlation matrix between Canadian sectoral unemployment. Services unemployment is highly correlated (0.836) with total unemployment. Also, manufacturing unemployment is highly correlated with goods sector unemployment (0.877). All unemployment series are positively correlated with each other. Table 4.5 shows the cross correlation of the unemployment series at different lags. Goods and manufacturing lead total unemployment, while services unemployment is coincident with total unemployment and lags goods and manufacturing unemployment.

[18]Section 4.11.1 examines the effect of the HP filter on persistence.

Table 4.4 reports the sample autocorrelation for all unemployment series and for a maximum lag of 6. All monthly unemployment series exhibit slow decay. Faced with a shock, all monthly unemployment series qualify for persistence. However, the higher the time aggregation level, the pattern tends to stationarity. If one analyses only the annual level data, one is bound to miss this evidence of persistence. All autocorrelations are significant at the 1 percent level. For all autocorrelations, the Q_{LB} statistic[19] rejects the null of independent error terms at less than 1 percent level. Table 4.5 reports the cyclical properties of the unemployment series.

Figures 4.8 to 4.11 show, for each unemployment level data series, the Cochrane variance ratio at two different frequencies. Again, the same proposition holds. The lower the frequency, the less significant becomes the evidence of persistence. The total unemployment variance ratio reaches a quarterly value of 3.0 after 12 quarters and then declines sharply, whereas after the same duration measured in months, the value is relatively lower but increasing. The monthly (quarterly) series tends to 2.8 (0.8) at the limit as k increases, a clear evidence of more persistence in the monthly frequency. All other unemployment series reflect the same pattern.

Figures 4.12 to 4.15 show the Cochrane variance ratio and its confidence level for all monthly unemployment series. Figures 4.16 to 4.18 show the same ratio for quarterly data. After 3 years, the persistence ranking of the Canadian unemployment series (from highest to lowest) is: total unemployment, services, goods and manu-

[19]The Ljung-Box statistic for the sample autocorrelation is computed as follows, $Q_{LB} \equiv T(T+2)\sum_{k=1}^{M}\left[\frac{r_k^2}{T-k}\right] \sim^{asy} \chi^2_{(M)}$. This test statistic is used to test H_0 : independently distributed error terms. In small sample, the Q_{LB} suffers from lack of power. This is the principal reason for not undertaking annual data persistence analysis.

facturing unemployment. For the subsequent sections in this chapter, we focus on documenting this persistence in aggregate unemployment.

4.10 Persistence, Long Memory and Fractional Integration

This section presents another approach to testing and estimating long-range dependence. The rescaled range test statistic presented here has a distinct advantage over conventional methods - such as the Cochrane variance ratio test - for determining long-range dependence. For the superiority of the rescaled range test statistic over analyzing variance ratios, see Mandelbrot (1972).

There is a growing literature on long-memory processes. Most of this literature treats long-memory processes as fractionally integrated processes (for reasons emphasized below). It focuses on the hyperbolically decaying autocorrelations and impulse response weights properties of the time series under investigation. Note that a hyperbolic decay rate is lower than the exponential rate observed with the ARMA class of models.

By derivation, the ARMA class of models considers only the exponential or geometric rate of decay on the Wold decomposition coefficients. Often in economics, time series processes exhibit a hyperbolic rate of decay that is neither consistent with an I(1) process nor an I(0) process. A fractionally differenced (i.e., long memory) process can be regarded as a midpoint [labelled as "halfway house" by Baillie (1996, p. 6)] between I(0) and I(1) processes. The attractive feature of long-memory processes is their long run predictions and effects of shocks. These predictions are very different from conventional ARMA class modeling. The next subsections present the formal definitions of long memory and fractionally integrated processes.

In our view, the main reason for regarding total unemployment as a long memory process is the following. Granger (1980) examined the time series behaviour of a contemporaneously aggregated panel data. Formally, let

$$z_t = \sum_{i=1}^{N} y_{it} \tag{4.6}$$

which is the aggregate of N component and independent processes y_{it}, such that for $i = 1, ..., N$,

$$y_{it} = \alpha_i y_{it-1} + u_{it} \tag{4.7}$$

Hence, each individual process is an AR(1) with the autoregressive coefficients α_i to be drawn from a Beta(0,1) distribution,[20]

$$dF(\alpha) = \frac{2}{B(p,q)} \alpha^{2p-1}(1-\alpha^2)^{q-1} \qquad 0 \leq \alpha \leq 1, \quad p > 0, \quad q > 0 \tag{4.8}$$

Interestingly, Granger (1980) showed that in the limit for large N, z_t is an integrated process with $I\left(1 - \frac{q}{2}\right)$. In other words, z_t is a fractional process (defined in subsection 4.10.2). In brief, Granger (1980) showed that the contemporaneous aggregation of panel data resulted in fractionally integrated processes.

Given that total unemployment is a contemporaneous sum of N sectors unemployment, we choose to proceed with long memory analysis for the Canadian total unemployment[21] level data. The plan is as follows. Given the long memory definition

[20]The standardized Beta probabilty distribution function [Zellner (1987, p. 373)] is given by, $p(z|a,b) = \frac{1}{B(a,b)} z^{a-1}(1-z)^{b-1}$, for $0 \leq z \leq 1$ and $B(a,b) \equiv \int_0^1 z^{a-1}(1-z)^{b-1} dz$.

[21]Note that - as mentioned in Chapter 3, footnote 3 - the L-level includes 112 industries.

of McLeod and Hipel (1978), we show that long memory processes are to be modeled as fractional integrated processes. Next, we test for a unit root in aggregate unemployment and report the results. Finally, we estimate unemployment persistence by a Bayesian ARFIMA class of models.

4.10.1 The Long-memory Process

Following the definition[22] of McLeod and Hipel (1978), a process is considered to be a long memory if the quantity

$$\lim_{n\to\infty}\sum_{j=-n}^{n} |\rho_j| \tag{4.9}$$

is nonfinite. ρ_j denotes the autocorrelation at lag j. Note that this is equivalent to an unbounded spectral density [frequency domain analysis] of the process at low frequencies.

4.10.2 The Fractionally Integrated Process

In this chapter, we consider only linear univariate models. The process y_t is said to be integrated of order d, or I(d), if

$$(1-L)^d(y_t-\mu)=\varepsilon_t \tag{4.10}$$

where L is the lag operator, $E(\varepsilon_t)=0$, $E(\varepsilon_t^2)=\sigma^2$, and $E(\varepsilon_t\varepsilon_s)=0$ for $s\neq t$ and where the fractional parameter d is possibly a noninteger.[23] The process is weakly stationary for $d<0.5$ and invertible for $d>-0.5$.

[22]For other definitions of long memory, see Resnick (1987).

[23]An autoregressive integrated moving average process ARIMA (p,d,q) process is defined as a process that requires d^{th} differences to produce a stationary ARMA (p,q) process. 'd' denotes an integer. 'p' denotes the number of autoregressive lags and 'q' refers to the number of moving average lags. Formally, an ARIMA (p,d,q) process is written as $(1-\phi_1 L-\ldots-\phi_p L^p)(1-L)^d Y_t = c+(1+\theta_1 L+\ldots+\theta_q L^q)\varepsilon_t$.

The infinite-order autoregressive representation of the process is given by,

$$y_t = \sum_{k=0}^{\infty} \pi_k y_{t-k} + \varepsilon_t \tag{4.11}$$

where the weights π_k are obtained from the binomial expansion,

$$(1-L)^d = \sum_{k=0}^{\infty}(-1)^k \binom{d}{k} L^k \tag{4.12}$$

$$\binom{d}{k} \equiv \frac{d(d-1)(d-2)(d-3)...(d-k+1)}{k!} \tag{4.13}$$

$$(1-L)^d = \{1 - dL + \frac{d(d-1)L^2}{2!} + \frac{d(d-1)(d-2)L^3}{3!} + ...\} \tag{4.14}$$

Therefore,[24]

$$\pi_k = \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)} = \pi_{k-1}\frac{k-1-d}{k} = \prod_{0 \leq j \leq k} \frac{j-1-d}{j} \approx^{asy} \frac{k^{-d-1}}{\Gamma(-d)} \tag{4.15}$$

where $\Gamma(.)$ is the gamma function.[25] $\approx^{asy}$denotes the (asymptotic) limit.

Similarly, the infinite moving average representation of the process can be expressed as,

$$y_t = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k} \tag{4.16}$$

where,[26]

$$\psi_k = \frac{\Gamma(k+d)}{\Gamma(d)\Gamma(k+1)} = \psi_{k-1}\frac{k-1+d}{k} = \prod_{0 \leq j \leq k} \frac{j-1+d}{j} \approx^{asy} \frac{k^{d-1}}{\Gamma(d)} \tag{4.17}$$

Note that the cumulative impulse response to a unit innovation is given by $\psi(1) = \sum_{i=0}^{\infty} \psi_j$. Equation (4.17) shows that the impulse response coefficient ψ_k decays at

[24]For the derivation, see Baillie (1996, p. 18).
[25]The gamma function is defined as, $\Gamma(q) = \int_0^{\infty} u^{q-1}e^{-u}du$ for $0 < q < \infty$ [Zellner (1987, p. 364, equation A.6)]. Here, one uses the following property of the gamma function: $\Gamma(q+1) = q\Gamma(q)$ for $q > 0$.
[26]For derivation see Baillie (1996, p. 18) and Hamilton (1994, pp. 448-452).

a slower rate than the geometric decay of ARMA class.[27] For this reason, Granger and Joyeux (1980) proposed the fractionally integrated process as an approach to modeling long memories in time series.

The autocorrelations of a fractional white noise process follow,

$$\rho_k = \frac{\Gamma(k+d)\Gamma(1-d)}{\Gamma(k-d+1)\Gamma(d)} = \prod_{0\leq j\leq k} \frac{j-1+d}{j-d} \approx^{asy} \frac{\Gamma(1-d)}{\Gamma(d)} k^{2d-1} = \mathrm{C}\; k^{2d-1} \qquad (4.18)$$

where C denotes a constant term. Given the definition of long memory by McLeod and Hipel (1978) (equation (4.9)), fractionally integrated processes are long-memory processes.

The autocorrelation coefficients have the same sign as d. When $d < 0$, the process is called 'anti-persistence' or 'short memory'. When $d > 0$, the process possesses a long-memory. Note that both cases imply long-range dependence.

If $-0.5 < d < 0.5$, then ε_t is a stationary and ergodic process with bounded and positively valued spectrum at all frequencies. For $0 < d < 0.5$, the process is a long-memory process satisfying equation (4.9), i.e., the autocorrelations are not summable. The autocorrelations are all positive and decay at a hyperbolic rate. For $-0.5 < d < 0$, the process autocorrelations sum to a constant. The process is said to be a 'short memory' process and all its autocorrelations (excluding lag zero) are negative and decay hyperbolically to zero.

There are quite a few non-Bayesian statistical techniques to estimate ARFIMA class of models. The most commonly used techniques can be classified as follows, 1) Maximum Likelihood methods (Sowell (1992a)); 2) Approximate Maximum Likeli-

[27]For example, compare ψ_k for the cases where $d = 0$ versus $d \neq 0$.

hood methods (Baillie and Chung (1992), Li and Mcleod (1986), or using the Whittle approximation as outlined by Fox and Taqqu (1986)), where the estimation of the parameter 'd' is done at the same time as the estimation of the other parameters (coefficients of the AR and the MA parts); 3) Two-Step procedures (Geweke and Porter-Hudak (1983) and Janacek (1982)). The two-step procedure unfolds as follows. The first step is to make use of spectral analysis to estimate 'd'. The second step is to use $(1 - L)^{\hat{d}} Y_t$ to estimate the ARMA parameters. Finally, 4) The non-iterative approximation based estimators as in Durbin (1959, pp. 307-308) and Galbraith and Zinde-Walsh (1994, pp. 144-147). This method relies on approximating the moving average process by an autoregressive model and uses the pattern of autoregressive coefficients to deduce estimates of the parameters of the underlying process. The Galbraith and Zinde-Walsh estimator have a lower bias than Durbin's for a given approximation order. This class of estimators are asymptotically efficient and more robust - regarding misspecification - to maximum likelihood based methods.

Applications of the non-Bayesian ARFIMA model was used in Koustas et al. (1996) to model output and unemployment at the aggregate and the disaggregated data level for Canada and the U.S.A. As mentioned earlier, the advantage of the ARFIMA class of models is that the 'd' parameter captures the long run behaviour of the series. When 'd' is smaller than 1, the time series exhibits mean reversion. In other words and following their definition, the parameter 'd' is a coherent measure of the degree of hysteresis.

Koustas et al. (1996) used time series long-memory modeling to test for the presence of hysteresis in Canada and in the U.S.A. They defined hysteresis as the lack of tendency in the rate of unemployment to revert to some mean value following a shock. In other words, they looked at it as shock persistence through time. Evidence of hysteresis was measured by shock persistence. 'Full hysteresis' was regarded as a 'unit root'. They reported that $\widehat{d}$ (the estimate of d) is higher in Canada relative to the U.S.A. In other words, unemployment persistence in Canada is higher than in the U.S.A.

We tested for unit roots using the Augmented Dickey-Fuller test.[28] Including a trend and 12 lags,[29] the null hypothesis of a unit root was not rejected at the 1, 5 and 10 percent levels for all logs of the monthly level of unemployment series covering the period 1976:1 to 1998:12.

Table 4.A

	ADF Test Statistic		**MacKinnon (1990) Critical Values**
Total Unemployment	-2.040	1 percent	-3.996
Manufacturing Unemployment	-2.148	5 percent	-3.428
Services Unemployment	-1.821	10 percent	-3.137

However,[30] any evidence of a unit root is weak, since I(1) is the null and the result could be attributable to structural breaks in the series. The recessions of 1981-1982 and 1991-1992 are well documented and apparent in the graph of the series (Figures 6 and 7). As noted by Rappoport and Reichlin (1989), among others, most unit roots tests have difficulty discriminating between an I(1) process and an I(0) process

[28]The Augmented Dickey-Fuller test the null hypothesis of unit root as follows, $\Delta y_t = \alpha_1 y_{t-1} + \alpha_2 Trend + \sum_j \beta_j \Delta y_{t-j} + e_t$ for $j = 1, 2, ...p$. where e_t is an independent, stationary process, and p is the lag length chosen for the dependent variable. The null hyppothesis of a unit root is equivalent to testing $\alpha_1 = 0$. The test statistic is then compared to MacKinnon (1990) critical values. Other unit root tests can be found in Hamilton (1994, Chapter 17, pp. 475-543).

[29]Using the AIC criterion, we experimented with other lag lengths and similar results were concluded.

[30]Within the chapter, tables are numbered alpha-numerically. In the Appendix, tables are numbered using numerals.

with a shift in its mean. They found that most unit root tests tend to favour the difference stationary (DS) model whenever the true process is a segmented trend. As a result, the DS model provides the better 'fit' in most applications. In my view, another important finding of their paper is - Rappoport and Reichlin (1989, p. 176) - "Many quantity series appear to be adequately parametrised by segmented trends, which undergo intermittent shocks, between which they behave as trend stationary processes." For our analysis, this quote suggests that the unemployment series might behave as a segmented trend type rather than a difference stationary type. In summary, structural breaks induce a bias towards non-rejection of the null hypothesis of unit root. Enders (1995, pp. 243-248) has a good exposition of unit root tests in the context of structural breaks.

Next, we shift the focus towards the midpoint between I(1) and I(0) processes, i.e., long-memory processes. To start, we investigate the shape of the sample autocorrelations to assess if further long-memory analysis is to be carried out. The following tables (Tables 4.B, 4.C and 4.D) illustrate the correlogram of monthly level data for total, manufacturing and services unemployment. The apparent pictorial evidence[31] of a hyperbolic decay rate of the sample autocorrelations will be formally tested later (see section 4.11.1). We then proceed to estimate and test this long-memory behaviour.

[31]Note that, Newbold and Agiakloglou (1993) argued that the detection of long-memory properties through the examination of the sample autocorrelations is almost impossible.

Table 4.B

Correlogram of UE_TOTAL

Sample: 1976:01 1998:12
Included observations: 276

Lag	AC	PAC	Q-Stat	Prob
1	0.986	0.986	271.36	0.000
2	0.971	-0.043	535.59	0.000
3	0.955	-0.075	791.77	0.000
4	0.936	-0.096	1038.7	0.000
5	0.915	-0.066	1275.5	0.000
6	0.892	-0.056	1501.6	0.000
7	0.870	0.012	1717.3	0.000
8	0.845	-0.067	1921.9	0.000
9	0.821	-0.023	2115.4	0.000
10	0.795	-0.034	2297.6	0.000
11	0.768	-0.047	2468.4	0.000
12	0.742	0.035	2628.4	0.000
13	0.718	0.061	2778.7	0.000
14	0.693	-0.041	2919.4	0.000
15	0.669	0.012	3050.8	0.000
16	0.645	-0.025	3173.5	0.000
17	0.621	-0.019	3287.5	0.000
18	0.596	-0.046	3393.1	0.000
19	0.572	0.030	3490.8	0.000
20	0.549	-0.008	3581.0	0.000
21	0.526	-0.011	3664.1	0.000
22	0.502	-0.034	3740.3	0.000
23	0.478	-0.053	3809.7	0.000
24	0.454	-0.016	3872.4	0.000
25	0.432	0.087	3929.6	0.000
26	0.410	-0.035	3981.2	0.000
27	0.388	-0.034	4027.5	0.000
28	0.365	-0.048	4068.6	0.000
29	0.343	0.036	4105.2	0.000
30	0.322	-0.025	4137.4	0.000

Table 4.C

Correlogram of UE_MANUFACTURING

Sample: 1976:01 1998:12
Included observations: 276

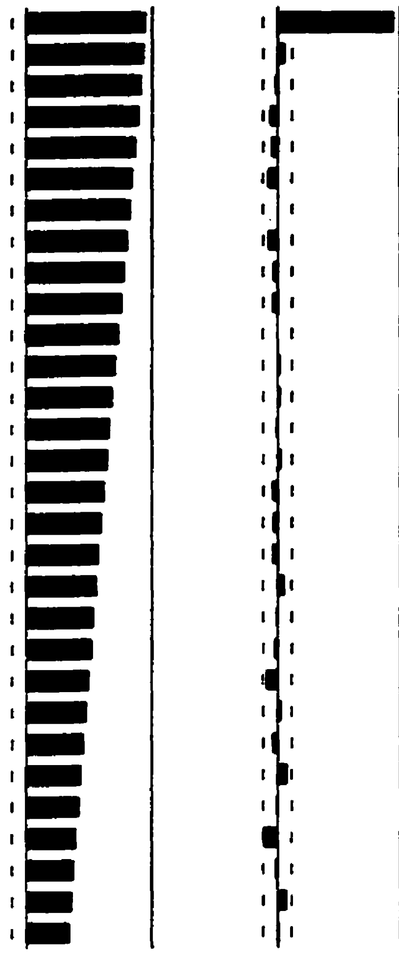
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.960	0.960	257.18	0.000
		2	0.922	0.009	495.47	0.000
		3	0.883	-0.038	714.79	0.000
		4	0.840	-0.071	914.03	0.000
		5	0.787	-0.160	1089.4	0.000
		6	0.733	-0.043	1242.3	0.000
		7	0.674	-0.105	1371.7	0.000
		8	0.618	0.019	1481.0	0.000
		9	0.559	-0.057	1570.7	0.000
		10	0.495	-0.096	1641.2	0.000
		11	0.437	0.055	1696.6	0.000
		12	0.392	0.125	1741.3	0.000
		13	0.357	0.129	1778.4	0.000
		14	0.320	-0.020	1808.4	0.000
		15	0.286	-0.033	1832.4	0.000
		16	0.263	0.070	1852.8	0.000
		17	0.245	0.021	1870.6	0.000
		18	0.228	-0.022	1886.1	0.000
		19	0.214	-0.025	1899.8	0.000
		20	0.201	-0.038	1911.9	0.000
		21	0.190	-0.055	1922.7	0.000
		22	0.182	0.014	1932.7	0.000
		23	0.165	-0.097	1940.9	0.000
		24	0.148	-0.002	1947.6	0.000
		25	0.149	0.218	1954.3	0.000
		26	0.143	-0.053	1960.6	0.000
		27	0.128	-0.097	1965.7	0.000
		28	0.110	-0.055	1969.4	0.000
		29	0.090	-0.064	1971.9	0.000
		30	0.062	-0.136	1973.1	0.000

Table 4.D

Correlogram of UE_SERVICES

Sample: 1976:01 1998:12
Included observations: 276

Autocorrelation | Partial Correlation



	AC	PAC	Q-Stat	Prob
1	0.980	0.980	268.08	0.000
2	0.963	0.057	527.79	0.000
3	0.946	-0.010	779.13	0.000
4	0.926	-0.056	1021.3	0.000
5	0.906	-0.042	1253.8	0.000
6	0.884	-0.068	1475.9	0.000
7	0.862	0.001	1688.0	0.000
8	0.838	-0.070	1889.2	0.000
9	0.814	-0.029	2079.5	0.000
10	0.788	-0.039	2258.7	0.000
11	0.763	0.001	2427.4	0.000
12	0.739	0.023	2586.3	0.000
13	0.717	0.023	2736.1	0.000
14	0.694	-0.001	2877.1	0.000
15	0.673	0.026	3010.1	0.000
16	0.650	-0.036	3135.0	0.000
17	0.628	-0.030	3251.7	0.000
18	0.605	-0.038	3360.5	0.000
19	0.584	0.050	3462.3	0.000
20	0.564	-0.002	3557.7	0.000
21	0.543	-0.021	3646.6	0.000
22	0.520	-0.087	3728.4	0.000
23	0.500	0.030	3804.1	0.000
24	0.478	-0.038	3873.6	0.000
25	0.459	0.078	3937.9	0.000
26	0.440	-0.006	3997.4	0.000
27	0.418	-0.108	4051.1	0.000
28	0.396	-0.010	4099.7	0.000
29	0.378	0.072	4144.2	0.000
30	0.361	0.015	4184.7	0.000

4.11 Testing for Persistence

We test for the presence of long-range dependence using the modified rescaled range test and we quantify persistence by estimating the fractional integration parameter using a Bayesian ARFIMA model. The question at hand is how to distinguish between short-range and long-range dependence?

The most widely used notion of short-range dependence is the concept of 'strong mixing' due to Rosenblatt (1956). It measures the decline of statistical dependence between events separated by successively longer spans of time. As the time span increases and the maximal dependence between events becomes trivially small, then the time series is a strong-mixing one, such as the class of ARMA models wherein the autocorrelations decay exponentially. Dependence between events over a long span defines long-range dependence, such as long-memory processes (or fractionally integrated processes given the definition in equation (4.9)).

4.11.1 The Rescaled Range Statistic (R/S)

Originally due to Hurst (1951), the rescaled range statistic is set to detect long-range dependence. It is defined as R_T/s_T,

$$R_T \equiv \max_{0\leq k\leq T}\left\{\sum_{j=1}^{k}(y_j-\bar{y})\right\} - \min_{0\leq k\leq T}\left\{\sum_{j=1}^{k}(y_j-\bar{y})\right\} \tag{4.19}$$

$$s_T = \left\{\frac{1}{T}\sum_{t=1}^{T}(y_t-\bar{y})^2\right\}^{0.5} \tag{4.20}$$

where R is the range, s_T is the sample standard deviation, and $\bar{y}$ denotes the sample mean. Lo (1991, pp. 1287-1288) showed that $T^{-1/2}R_T/s_T$ is asymptotically distributed as the range of a standard Brownian Bridge on the unit interval and has expectation of $(\pi/2)^{1/2} = 1.253$ and a standard deviation of $[(\pi/2)(\pi-3)/3]^{1/2} = 0.272$.

The most important shortcoming of the rescaled range is its sensitivity to short-range dependence. For example, if the process is an AR(1), i.e., purely short-range dependent, then the mean of the rescaled range limiting distribution will be biased.

To counter and to correct for the impact of short-range dependency on the test statistic, Lo (1991, p. 1289) proposed using a modified rescaled range statistic. By correcting for short-range dependency, the limiting distribution of the modified statistic is invariant to many forms of short-range dependency but sensitive to the presence of long-range dependency. The modified statistic is robust to many forms of heterogeneity and weak dependence. Also, it is able to discriminate between short- and long-range dependency.

The modified rescaled range statistic is defined as,

$$Q_T \equiv \frac{R_T}{\sigma_T(q)} \tag{4.21}$$

where,

$$\sigma_T^2(q) = c_0 + 2\sum_{j=1}^{q} w_j(q)c_j \tag{4.22}$$

c_j denotes the jth order sample autocovariance of y_t and $w_j(q)$ are the Newey and West (1987) weights using a Bartlett window defined as,

$$w_j(q) = 1 - \left[\frac{j}{q+1}\right] \qquad q < T \tag{4.23}$$

In the presence of long memory, the normalized statistic $T^{-1/2}Q_T$ weakly converges to the range of a Brownian Bridge. The distribution is given by,

$$F(x) = \sum_{j=-\infty}^{\infty} (1 - 4x^2 j^2) \exp[-2x^2 j^2] \tag{4.24}$$

This distribution is positively skewed and its fractiles are tabulated in Lo (1991, p. 1288). The modified rescaled range statistic is robust to short-range dependence and consistent with a general class of long-range dependent stationary Gaussian alternatives (see Baillie (1996, p. 28)).

The choice of q is a subject open to debate. For our analysis, since we are using quarterly data, we computed the modified statistic at $q = 1, 2, 3, 4, 5, 6, 7, 8$ and $q = [k_T]$, where $[k_T]$ denotes the greatest integer less than or equal to k_T. As defined and proposed by Lo (1991, p. 1302), $[k_T]$ is a data-dependent approach for the choice of q,

$$k_T \equiv \left(\frac{3T}{2}\right)^{1/3} \left(\frac{2\widehat{\rho}}{1-\widehat{\rho}^2}\right)^{2/3} \tag{4.25}$$

where $\widehat{\rho}$ is the estimated first-order autocorrelation coefficient of the data.

The following table (Table 4.E) reports the results of the modified rescaled range (Q_T) statistic for the first difference of the log form level of total unemployment, manufacturing and services unemployment. For each q, the first column reports the $\sum_{j=1}^{q} w_j(q)c_j$, i.e., the sum of the weighted autocovariances. Subsequent columns report the logarithm of Q_T and the normalized test statistic value $\frac{Q_T}{\sqrt{T}}$.

Given the reported critical values in Lo (1991, p. 1288), we test the null hypothesis of a simple i.i.d. process. All series are in log form and y_t denotes the log of the time series. Table 4.E computes the normalized test statistic values for Δy_t and Table 4.F computes the same statistic for the Hodrick-Prescott filtered y_t. Note that the normalizing factor $\sqrt{T}$ is different in both tables. For Tables 4.E and 4.F, the sample size is 91 and 92 observations, respectively. The reason for computing both tables is to investigate the sensitivity of the modified test statistic results to the method of detrending. Also, to check the sensitivity of the statistic to the lag length, the normalized test statistic is computed for several different values of q. Given that the normalized test statistic follows a Brownian Bridge process, the null hypothesis is examined at the 95 percent confidence level by not rejecting or rejecting according to whether the normalized test value is or is not contained in the interval [0.809 , 1.862].

Table 4.E significantly rejects the simple null hypothesis of i.i.d. process at most values of q. Long-range dependence is evident in Canadian total, manufacturing and services unemployment. Table 4.F gives similar results. However, persistence of total unemployment is less evident at the data-dependent value of q. Shorter values of q are picking up the short-range dependence. Using the Hodrick-Prescott filter increases the q lag where the first evidence of persistence is reported. For example, evidence of persistence for total unemployment is first reported at $q = 4$ when using Δy_t and at $q = 5$ when using HP filtered y_t. This one lag delay holds for total and manufacturing unemployment. For services unemployment, the lag delay is longer.

Given the strong evidence of long-range dependence in the series Δy_t, we decided to continue our analysis of long-range dependence. The next section proposes a Bayesian approach to estimate several ARFIMA models in order to quantify the fractional integration parameter.

Table 4.E

Modified Range over Standard Deviation (R/S) Test Statistic (Lo (1991))
The change of the log of Quarterly Canadian Unemployment Time Series

Total Unemployment

	Sum of Weights	Log(R/S)	Normalized Test Statistic
q=1	0.00083	0.99843	1.04450
q=2	0.00132	0.94306	0.91947
q=3	0.00170	0.90835	0.84884
q=4‡	0.00197	0.88583	0.80594*
q=5	0.00215	0.87287	0.78226*
q=6	0.00227	0.86382	0.76612*
q=7	0.00236	0.85764	0.75530*
q=8	0.00244	0.85233	0.74613*

Manufacturing Unemployment

	Sum of Weights	Log(R/S)	Normalized Test Statistic
q=1	0.00095	1.00146	1.05182
q=2	0.00257	0.86828	0.77404*
q=3	0.00468	0.76656	0.61241*
q=4	0.00717	0.68730	0.51025*
q=5	0.00991	0.62423	0.44127*
q=6	0.01282	0.57275	0.39195*
q=7‡	0.01585	0.52954	0.35483*
q=8	0.01899	0.49237	0.32572*

Services Unemployment

	Sum of Weights	Log(R/S)	Normalized Test Statistic
q=1	0.00306	0.89904	0.83085
q=2	0.00462	0.84992	0.74198*
q=3‡	0.00560	0.82397	0.69896*
q=4	0.00616	0.81050	0.67761*
q=5	0.00619	0.80973	0.67641*
q=6	0.00600	0.81438	0.68369*
q=7	0.00578	0.81970	0.69211*
q=8	0.00565	0.82271	0.69692*

‡ : Denotes the value for $[k_T]$
* : Indicates significance at the 5 percent level.

Table 4.F

Modified Range over Standard Deviation Test Statistic (Lo (1991))
HP Filtered Log of Quarterly Canadian Unemployment Time Series

	Sum of Weights	Log(R/S)	Normalized Test Statistic
Total Unemployment			
q=1	0.00432	1.08805	1.27690
q=2	0.00837	1.00475	1.05403
q=3	0.01201	0.95025	0.92972
q=4	0.01513	0.91232	0.85197
q=5	0.01771	0.88538	0.80073*
q=6	0.01975	0.86611	0.76598*
q=7	0.02132	0.85241	0.74219*
q=8	0.02247	0.84294	0.72618*
q=25‡	0.01193	0.95127	0.93192
Manufacturing Unemployment			
	Sum of Weights	Log(R/S)	Normalized Test Statistic
q=1	0.00755	0.98624	1.01006
q=2	0.01415	0.90783	0.84321
q=3	0.01951	0.86003	0.75534*
q=4	0.02348	0.83040	0.70551*
q=5	0.02608	0.81297	0.67775*
q=6	0.02764	0.80315	0.66260*
q=7	0.02854	0.79771	0.65435*
q=8	0.02906	0.79460	0.64969*
q=14‡	0.02810	0.80035	0.65834*
Services Unemployment			
	Sum of Weights	Log(R/S)	Normalized Test Statistic
q=1	0.00310	1.06064	1.19881
q=2	0.00598	0.97848	0.99216
q=3	0.00853	0.92493	0.87708
q=4	0.01069	0.88799	0.80555*
q=5	0.01244	0.86213	0.75898*
q=6	0.01380	0.84391	0.72781*
q=7	0.01481	0.83134	0.70704*
q=8	0.01551	0.82308	0.69373*
q=21‡	0.00974	0.90338	0.83462*

‡ : Denotes the value for $[k_T]$

* : Indicates significance at the 5 percent level.

4.12 Bayesian ARFIMA

To model and to measure the persistence effect of shocks, we investigate the class of Bayesian Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. On the ARIMA class of models, Sowell (1992b) argued that ARIMA models tend to fit the short-run properties of the data and they are too restrictive in terms of the behaviour of the time series under investigation. Long-run inferences based on ARIMA models could - and in most cases do - lead to biased predictions. ARFIMA models allow the fractional integration parameter to adequately capture the long-run properties of the series while preserving the short-run properties to be picked up by the ARIMA part in it. The theoretical properties and characteristics of ARFIMA class of models are outlined in Beran (1994), Brockwell and Davis (1991) and Odaki (1993).

As mentioned earlier, the main reasons for undertaking the long-memory analysis of the quarterly aggregate Canadian unemployment are: 1) the evidence of persistence reported by the Cochrane variance ratio test and the modified rescaled range test statistic; 2) the non-rejection of the null hypothesis of a unit root (that might be due to structural breaks); and 3) long memory may still appear at the macro level due to contemporaneous aggregation. Finally, in support of our argument, we quote Koop, Ley, Osiewalski and Steel (1997, p. 150) "when analyzing aggregated data, we should keep the possibility of long memory open."

Adopting a Bayesian approach to estimate ARFIMA has some advantages over the classical techniques. First, it provides exact finite sample distributions for the impulse response and the fractional differencing parameter. Second, for predictive purposes, the Bayesian approach allows one to average across models instead of just picking one model. Third, one can perform small sample tests of memory properties to discriminate between ARIMA and ARFIMA models simply by attaching a positive prior to the point where the fractional integration parameter[32] equals one. The notation and derivations in this section closely follow Koop, Ley, Osiewalski and Steel (1997).

Since the modified rescaled range test statistic pointed to strong evidence of persistence in Δy_t, and to avoid any artificial distortion of the statistical properties of the data induced by the Hodrick-Prescott filter,[33] we focus our analysis on the first difference of the quarterly log of total Canadian unemployment-level. Rewrite the ARFIMA process as,

$$z_t \equiv \Delta y_t - \mu \tag{4.26}$$

The ARFIMA(p, δ, q) representation of this process is,

$$\phi(L)(1-L)^{\delta} z_t = v(L)\varepsilon_t \tag{4.27}$$

where $v(L) = (1 + \theta_1 L + \theta_2 L^2 + ... + \theta_q L^q)$ and $\phi(L) = (1 + \phi_1 L + \phi_2 L^2 + ... + \phi_p L^p)$ are polynomials in the lag operator and the roots lie outside the unit circle. Let $\theta \in C^q$ and $\phi \in C^p$. The errors ε_t are i.i.d. $N(0, \sigma^2)$, $\delta \equiv d - 1$ and $\delta \in (-1, 0.5)$. In other words, we are restricting the space of the fractional differencing parameter to

[32]Defined later.

[33]The HP filter "removes important time series components that have traditionally been regarded as representing business cycle phenomena" King and Rebelo (1993, p. 208). For a complete discussion of the negative effects of the Hodrick-Prescott, see Stadler (1994, pp. 1768-1769). For spurious cyclical behaviour induced by the filter, see Harvey and Jaeger (1993, pp. 233-235).

$d \in (0.0, 1.5)$. In the case where $\delta = 0$, d equals 1 and the process y_t is modeled as an ARIMA$(p,1,q)$, i.e., z_t is an ARMA(p,q). The restriction on the space of δ merits some explanation. The lower bound of δ (-1) ensures that Δy_t is invertible (see Odaki (1993)). Also, from Table 4.B (page 124), the autocorrelations are positive and decay hyperbolically. Therefore, restricting the lower bound of d to zero is coherent. A reasonable implication of the unit root test (Table 4.A, page 122) is to restrict the upper bound to 0.5 which ensures that Δy_t is stationary. Whenever $d \in (0.0, 0.5)$, y_t is said to be trend-stationary with long memory. Whenever $d \in (0.5, 1.5)$, Δy_t is stationary with intermediate memory for $d < 1$ and with long memory for $d > 1$.

Let $I(n)$ denote the impulse response function of this y_t process. The impulse response function measures the impact of a shock of size equal to 1 at time t on y_{t+n}. For a stationary process z_t, $I(n)$ equals the coefficients of the infinite-MA representation of the process. Formally, the coefficients of the infinite-MA are $A(L) = (1-L)^{-\delta}\phi^{-1}(L)v(L)$. The n^{th} order partial sum of these coefficients is the cumulative response for z_t. They also represent the impulse responses $I(n)$ for the level of y_t. Formally, $I(n)$ could be represented by the n^{th} coefficient of $A^*(L) \equiv (1-L)^{-1}A(L) = (1-L)^{-d}\phi^{-1}(L)v(L)$.

The coefficients of $\phi^{-1}(L)v(L)$ are defined as,

$$J(i) = 0 \qquad i+1-j \leq 0 \tag{4.28}$$

$$J(i) = \sum_{j=0}^{q} \theta_j f_{i+1-j} \tag{4.29}$$

$$f_1 \equiv 1 \text{ and } f_h \equiv -(\phi_1 f_{h-1} + \ldots + \phi_p f_{h-p}) \text{ for } h \geq 2. \tag{4.30}$$

Therefore, the coefficients of $A^*(L) \equiv (1-L)^{-d}\phi^{-1}(L)v(L)$ are computed as follows,

$$I(n) = \sum_{i=0}^{n} c_i(-d)J(n-i) \qquad (4.31)$$

where $c_0(.) \equiv 1$ and $c_j(a) \equiv \prod_{k=1}^{j}(\frac{k-1-a}{k})$. When $\delta = 0$, $d = 1$ and $c_i = 1$ for $i \geq 0$. In the limiting case, where $\delta = -1$, $d = 0$, so that $c_o(0) = 1$ and $c_i(0) = \Pi_{k=1}^{i}(1-\frac{1}{k}) = 0.0$, since $c_1(0) = 0.0$. In the latter case, the impulse responses coefficients $I(n)$ equal $J(n)$, i.e., they collapse to the same coefficients as an ARMA(p,q) process. We now examine the behaviour of the impulse responses under different fractional parameter specifications. In the limit,

$$\begin{aligned}
\lim_{n\to\infty} I(n) &= 0 && \text{if } \delta < 0, \text{ i.e., } d < 1 && (4.32)\\
&= A(1) = \frac{v(1)}{\phi(1)} && \text{if } \delta = 0, \text{ i.e., } d = 1 && (4.33)\\
&= \infty && \text{if } \delta > 0, \text{ i.e., } d > 1 && (4.34)
\end{aligned}$$

The problem at hand is the following. Whenever δ deviates from 0, $I(\infty)$ equals 0 or ∞. Since finding an estimate for δ that is different from zero is highly likely, an impulse response that is infinite or zero will also be highly likely. This theoretical weakness of ARFIMA is documented in Hauser, Pötscher and Reschenhofer (1992, p. 8). They argued that ARFIMA modelling is inappropriate for the purpose of estimating persistence (defined as $I(\infty)$).

Here, we adopt the answer to this criticism given by Koop, Ley, Osiewalski and Steel (1997, p. 154). Since $I(\infty)$ is of little relevance to the economic forecaster, they defined the following. If the frequency of the data at hand is quarterly, and we refer to $I(4)$, $I(12)$ and $I(40)$ as the short-run, medium run and long-run impact of a shock respectively, then an economist is only interested in these quantities: $I(4)$, $I(12)$ and $I(40)$. Note that our definition of 'economic persistence' is consistent (section 4.7 of this chapter) with their definition. If one accepts our definition of economic persistence, computing the suggested impulse responses will quantify persistence. Also, our definition makes no distinction between the intermediate and the long run impact, as classified by Koop, Ley, Osiewalski and Steel (1997, p. 154).

By giving a positive prior mass to the point where $\delta = 0$, one reaches a non-degenerate distribution for $I(\infty)$. The point masses for $I(\infty)$ at 0 and ∞ are to be measured by the posterior probability of $P(\delta < 0)$ and $P(\delta > 0)$, respectively. The posterior probability distribution for $I(\infty)$ will be continuous and non-zero between 0 and ∞.

Here we consider only the class of ARFIMA models. Given the above notation, the problem we are facing is a standard Bayesian one. The parameter space is partitioned into μ, σ^2 and $\omega^T \equiv (\delta, \Theta^T, \Phi^T)$, where $\Theta \equiv (\theta_1, ..., \theta_q)^T \in C^q$ and $\Phi \equiv (\phi_1, ..., \phi_p)^T \in C^p$. Let w denote the observed vector of data, with $w^T \equiv (\Delta y_1, ..., \Delta y_N)^T$, and let w^{*T} denote the predictions of the observed data, with $w^{*T} \equiv (\Delta y_{N+1}, ..., \Delta y_{N+n})^T$. The model is defined as,

$$\begin{pmatrix} w \\ w^* \end{pmatrix} = \mu \begin{pmatrix} \iota_N \\ \iota_n \end{pmatrix} + \begin{pmatrix} \xi \\ \xi^* \end{pmatrix} \tag{4.35}$$

where

$$\begin{pmatrix} \xi \\ \xi^* \end{pmatrix} \sim N(0_{N+n}, \sigma^2 \begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix}) \tag{4.36}$$

$$\begin{pmatrix} \xi \\ \xi^* \end{pmatrix} \sim N(0, \sigma^2 V) \tag{4.37}$$

ι_N refers to an $N \times 1$ vector of ones. The elements of V are given by $v_{ij} = \sigma^{-2}\gamma(i-j)$ for $i, j = 1, ..., N+n$. $\gamma(s)$ denotes the autocovariance function given in Sowell (1992a, p. 173, equation (8)). The sampling density distribution of w is given by,

$$p(w|\omega, \mu, \sigma^2) = f^N_{Normal}(w|\mu\iota_T, \sigma^2 V_{11}) \tag{4.38}$$

where f^N_{Normal} is the N-variate Normal density function. Formally,[34]

$$p(w|\omega, \mu, \sigma^2) = \frac{|\sigma^2 V_{11}|^{-\frac{1}{2}}}{(2\pi)^{\frac{N}{2}}} \exp\left\{-\frac{1}{2}(w - \mu\iota_N)^T(\sigma^2 V_{11})^{-1}(w - \mu\iota_N)\right\} \tag{4.39}$$

The prior over the parameters is assumed to be as follows,

$$p(\omega, \mu, \sigma^2) = p(\omega)p(\mu)p(\sigma^{-2}) \propto \sigma^2 p(\omega) \tag{4.40}$$

where $\omega \in \Omega \equiv (-1, 0.5) \times C_q \times C_p$. $\mu \in R$ and $\sigma^{-2} \in R_+$. The improper prior on σ^{-2} leads to perfect robustness with respect to all $(N+n)$-variate elliptical densities with the same location and scale.[35] Given the sampling distribution and the prior, we integrate out μ and σ^{-2}, which yields the posterior density for ω.

$$p(\omega|Data) = K^{-1}|V_{11}|^{-\frac{1}{2}}(\iota_N^T V_{11}^{-1}\iota_N)^{-\frac{1}{2}} SSE^{-\frac{N-1}{2}} p(\omega) \tag{4.41}$$

[34]See Zellner (1987, p. 379, equation (B.1)).
[35]See Osiewalski and Steel (1993) for the proof.

where ι_N^T refers to the transpose of $N \times 1$ vector of ones,

$$K \equiv \int_\Omega |V_{11}|^{-\frac{1}{2}}(\iota_N^T V_{11}^{-1}\iota_T)^{-\frac{1}{2}} SSE^{-\frac{T-1}{2}} p(\omega)d\omega \tag{4.42}$$

$$SSE = (w - \widehat{\mu}\iota_N)^T V_{11}^{-1}(w - \widehat{\mu}\iota_N) \tag{4.43}$$

$$\widehat{\mu} = (\iota_N^T V_{11}^{-1}\iota_N)^{-1}\iota_N^T V_{11}^{-1} w \tag{4.44}$$

The posterior density is computed using Monte-Carlo simulations. The procedure is as follows. We draw a value for δ from a uniform distribution over the interval [-1.0 , 0.5], then we compute its antithetic replication by projecting the value through the mean.[36] We also draw the values for p and q from a uniform distribution that is bounded to ensure the stationarity and invertibility of the process. This procedure efficiently enforces the ARMA stationarity part as outlined in Monahan (1984, p. 403, equation (1)). Then, we compute the likelihood and the variance-covariance matrix. Next we evaluate the log of the posterior for the parameters using the Sowell code. We repeat this exercise 25,000 times. Simulation is carried on i686 machine running LINUX 2.2.14-5.0. The FORTRAN 77 code is from Koop, Ley, Osiewalski and Steel (1997) with modifications to fit our problem.[37]

The algorithm used is importance sampling combined with antithetic replications. Whenever the posterior density is nonstandard - from which it is difficult or impossible to generate random draws - importance sampling allows the random draws ω to be generated from a substitute density $f(\omega)$. The empirical density is then adjusted to

[36]The anthitetic replication is computed by projecting the draw through the mean of the uniform distribution [-1.0,0.5], i.e., -0.25. Therefore, the anthitetic value equals $-0.25 - [draw - (-0.25)]$. Formally, the anthitetic value $\delta^{-i} = E(\delta) - [\delta^i - E(\delta)] = 2E(\delta) - \delta^i$. See Dorfman (1997, p. 21) for more details.

[37]Conditional on the number of parameters in each model, the average time for simulating one model is 23 minutes.

account for the differences between the substitute density and the actual posterior distribution $p(\omega|y, X)$ of ω. To increase the efficiency of the numerical approximation, the algorithm relies on antithetic replications. Generating random draws from the substitute density results in an empirical density that is not a random sample from the posterior distribution. Therefore, the simple averages cannot be used to estimate the posterior mean. Instead, one corrects the simple averages by computing weighted averages as follows,

$$\hat{g}^{IS}(\omega) = \frac{\sum_{i=1}^{50000} g(\omega^i)p(\omega^i|y, X)/f(\omega^i)}{\sum_{i=1}^{50000} p(\omega^i|y, X)/f(\omega^i)} = \frac{\sum_{i=1}^{50000} g(\omega^i)s(\omega^i)}{\sum_{i=1}^{50000} s(\omega^i)} \tag{4.45}$$

where $s(\omega^i)$ refers to the importance weight for the ith observation in the empirical distribution, $g(\omega^i)$ denotes any quantity function of interest (e.g., the sample average) and the superscript IS denotes that the estimator is based on the importance sampling density.[38] Note that the combination of importance sampling with antithetic replications increases the numerical efficiency for any symmetrical or near-symmetrical posterior distribution (Dorfman (1997, p. 25)). We did not focus on other methods of simulation, such as the Gibbs sampling algorithm. The Gibbs sampling algorithm has been used for the analysis of univariate time series by Barnett, Kohn and Sheather (1996), Chib and Greenberg (1994), McCulloch and Tsay (1994), and for ARFIMA processes by Pai and Ravishanker (1996).

The predictive distributions are based on $p(w^*|Data)$. Note that $y_{N+n} = y_N +$

[38]For regularity conditions ensuring the convergence of $g(\omega)$, see Dorfman (1997, p. 24). The general criteria for choosing an importance function are discussed in Bauwens, Lubrano and Richard (1999, pp. 77-82).

$\iota_n^T w^* = y_N + n\mu + \iota_n^T \xi^*$. The posterior predictive density is given by,

$$\begin{aligned} p(y_{N+n}|\omega, Data) &= \int_\Omega f(y_{N+n}|\omega) p(\omega|Data) d\omega & (4.46) \\ &= f_s^1(y_{N+n}|N-1, y_N + n\mu + \iota_n^T V_{21} V_{11}^{-1}(w - \widehat{\mu}\iota_N), & (4.47) \\ & \quad \frac{N-1}{SSE}\left[\iota_n^T V_{22.1}\iota_n + \frac{(n - \iota_n^T V_{21} V_{11}^{-1}\iota_T)^2}{\iota_N^T V_{11}^{-1}\iota_N}\right]^{-1}) & (4.48) \end{aligned}$$

where $V_{22.1} = V_{22} - V_{21}V_{11}^{-1}V_{12}$, and $f_s^k(.|r, b, A)$ is the k-variate Student t density with r degrees of freedom, location vector b and precision matrix A. Formally,[39]

$$\begin{aligned} p(y_{N+n}|\omega, Data) = & \frac{(N-1)^{\frac{T-1}{2}}\Gamma(\frac{N+n-1}{2})}{\pi^{\frac{n}{2}}\Gamma(\frac{N-1}{2})} \\ & \left|\frac{N-1}{SSE}\left[\iota_n^T V_{22.1}\iota_n + \frac{(n - \iota_n^T V_{21}V_{11}^{-1}\iota_N)^2}{\iota_N^T V_{11}^{-1}\iota_N}\right]^{-1}\right|^{\frac{1}{2}} \\ & \left[N - 1 + \begin{array}{c} \left(y_{N+n} - y_N - n\mu - \iota_n^T V_{21}V_{11}^{-1}(w - \widehat{\mu}\iota_N)\right)^T \\ \left[\frac{N-1}{SSE}\left[\iota_n^T V_{22.1}\iota_n + \frac{(n-\iota_n^T V_{21}V_{11}^{-1}\iota_N)^2}{\iota_N^T V_{11}^{-1}\iota_N}\right]^{-1}\right] \\ \left(y_{N+n} - y_N - n\mu - \iota_n^T V_{21}V_{11}^{-1}(w - \widehat{\mu}\iota_N)\right) \end{array}\right] \end{aligned} \quad (4.49)$$

The posterior density of the parameter μ is given by,

$$p(\mu|\omega, Data) = f_s^1(\mu|N-1, \widehat{\mu}, \frac{T-1}{SSE}\iota_N^T V_{11}^{-1}\iota_N) \quad (4.50)$$

Note that the last two densities are conditional on ω, therefore one integrates it out through a numerical procedure. Our objective is to assess the relative importance of persistence in aggregate Canadian unemployment. Therefore, we focus on reporting and analysing the results for the parameter δ and the impulse responses.

As presented here, a caveat of Bayesian inference regarding the fractional differencing parameter is that the order of the ARFIMA is assumed to be fixed, i.e.,

[39] See Zellner (1987, p. 383, equation (B.20)).

known. Therefore, we consider a range of values for the orders p and q to cover model uncertainty.

4.12.1 Model Comparison, Sensitivity and Robustness

The posterior distribution provides a basis for "estimation of parameters conditional on the adequacy of the entertained model" and the predictive distribution enables "criticism of the entertained model in light of current data" (Box (1980, p. 383)). The scope of Bayesian model comparison and model assessment is quite broad. In the literature on Bayesian model comparison, there are 1) the marginal likelihood approach, 2) the 'super-model' or 'sub-model' approach and 3) the criterion-based methods such as the L measure and the calibration distribution (see Chen, Shao and Ibrahim (2000) for an excellent exposition of all methods and the references therein). The second approach is efficient whenever the posterior means or modes are not far from zero. The last approach does not require proper prior distributions over the models. Here, we adopt the marginal likelihood approach. This approach (outlined later) is essentially the same as the Bayes factor approach.

Let the joint density for potential data y and parameters ω be

$$p(y, \omega|M) = p(y|\omega, M)p(\omega|M) \tag{4.51}$$

where M indicates conditionality on the model specification. This model can also be factored as

$$p(y, \omega|M) = p(\omega|y, M)p(y|M) \tag{4.52}$$

where $p(y|M) = \int p(y|\omega, M)p(\omega|M)d\omega$ denotes the predictive distribution. With an actual data vector y_d,

$$p(y_d, \omega|M) = p(\omega|y_d, M)p(y_d|M) \tag{4.53}$$

where the first term on the right hand side of equation (4.53) refers to the posterior distribution of ω, given y_d,as

$$p(\omega|y_d, M) \propto p(y_d|\omega, M)p(\omega|M) \tag{4.54}$$

The second term on the right hand side of equation (4.53) refers to the predictive density associated with the particular data type y_d actually obtained. Figure 1 illustrates this for a single parameter ω and a sample space y_d of $n = 2$ observations.

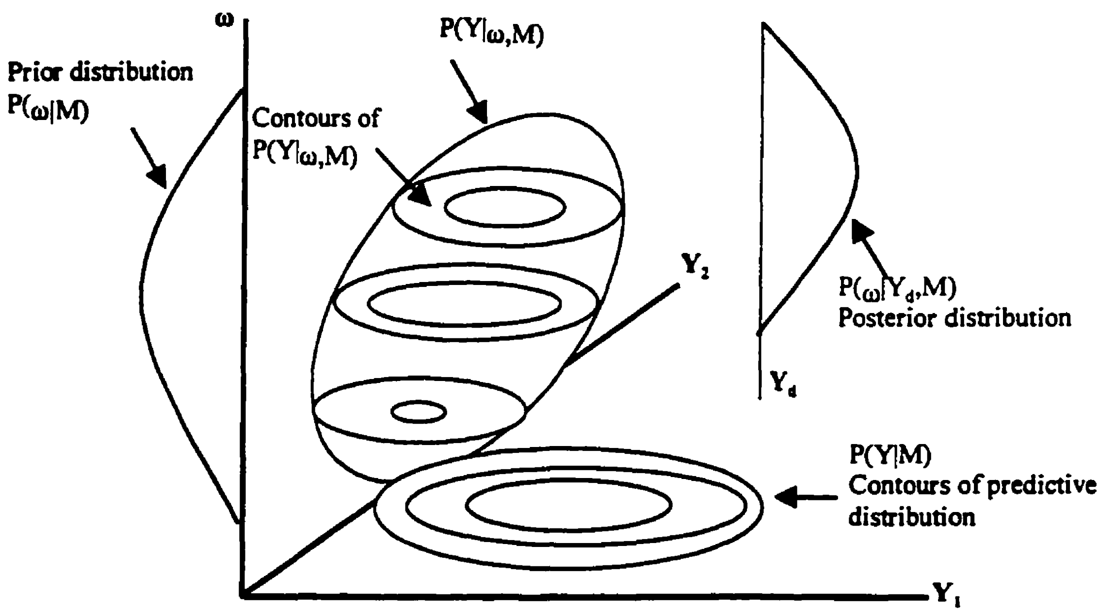


Figure 4.1: Prior distribution, posterior distribution and predictive distribution for a single parameter ω and a sample of two observations (Box (1980, p. 386)).

The posterior distribution $p(\omega|y_d, M)$ allows all estimation inferences of interest to be made regarding ω. However, if y_d was not generated by the model M, it could be assessed by reference to the density $p(y_d|M)$ to the predictive reference distribution $p(y|M)$. The success of the Bayesian predictive distribution as a model checking device is discussed at length by Geisser (1993) and Geisser and Eddy (1979). To reach successful prediction, a model must incorporate or consider structural aspects. Here, we do not address the prediction aspect of the proposed model. Our focus is on the persistence issue.

Other methods for examining robustness are sensitivity analysis approaches via: 1) asymptotic approximation; 2) scale mixtures of normals; and 3) prior partitioning. The last method relies on working the problem 'backward'. Rather then choosing (fixing) the priors, one chooses a set of posteriors that produce a given conclusion, and determines which prior inputs are consistent with the desired results, given the observed data.

Provided that the set of models under consideration is exhaustive, mixing over the models is optimal for forecasting purposes.[40] Here, we investigate the set of ARFIMA models up to and including the orders of ARFIMA$(3, \delta, 3)$. This set is not exhaustive, but since most of economic time series can be well approximated by low order ARMA models, we stop at the orders $p = q = 3$. The ARMA part of the ARFIMA should be able to capture short-range dependency and then we can investigate the long-memory properties of the process based on the estimate of δ. Since we do not consider all conceivable models for the problem at hand, model comparisons based on the posterior odds do not change if a new unspecified third

[40]Using a squared error loss, mixing over the models is optimal for forecasting (see Min and Zellner (1993) for the proof).

model is introduced. Given the intuitive economic argument, we suggest that the Independence of Irrelevant Alternatives (IIA) property holds (see Poirier (1997, p. 150) for the definition and for an excellent exposition).

There are 16 models under consideration $M_1, M_2..., M_{16}$. For model M_i $(i = 1, ..., 16)$, the posterior distribution takes the form,

$$\pi(\omega_i|Data, M_i) \propto L(\omega_i|Data, M_i)\pi(\omega_i|M_i) \tag{4.55}$$

where $L(\omega_i|Data, M_i)$ is the likelihood function and $\pi(\omega_i|M_i)$ denotes the prior distribution. The marginal likelihood is given by,

$$\pi(Data|M_i) = \int L(\omega_i|Data, M_i)\pi(\omega_i|M_i)d\omega_i \tag{4.56}$$

To compare the models, one computes the marginal likelihoods and chooses the model that yields the largest marginal likelihood. Basically, the marginal likelihood approach is the same as the Bayes factor approach. Note that $\pi(Data|M_i)$ is the normalizing constant of the posterior distribution $\pi(\omega_i|Data, M_i)$. The posterior probability of model i, M_i, is given by,[41]

$$\pi(M_i|data) = \frac{\pi(M_i)K_i}{\sum_{j=1}^{m}\pi(M_j)K_j} \tag{4.57}$$

where $\pi(M_j)$ is the prior model probability of M_j and K_i is as defined in equation (4.42).

We consider the same models investigated by Koop, Ley, Osiewalski and Steel (1997), corresponding to all possible ARFIMA(p, δ, q) for $p, q \leq 3$.

[41]See Box (1980, p. 408, equation (*)), Carlin and Louis (1996, p. 47, equation (2.17)) and Chen, Shao and Ibrahim (2000, p. 237, equation (8.1.3)).

The plan proceeds as outlined by "Given the appropriate tools, the most straightforward way of demonstrating a lack of dependence on the prior is to compute the summary measures of interest for a range of plausible prior densities" (Skene, Shaw and Lee (1986, p. 282)). The prior probabilities for each model M_i are all taken as equal (i.e., $\pi(M_i) = 1/16$ for $i = 1, ..., 16$) to reflect ignorance, i.e., 'non-informative' prior.[42] We also adopt a second 'informative' prior. The reason for assuming an 'informative' prior is the following. For the models where the AR term is zero - i.e., ARFIMA$(0, \delta, q)$ - one should expect the parameter δ to capture any short-range dependency present in the data since there is no AR term to adequately reflect it. Therefore, inference based on δ would be misleading. This 'informative' prior down-weights the prior weight of ARFIMA$(0, \delta, q)$ by assigning three times less prior mass to ARFIMA$(0, \delta, q)$. For example, the prior for ARFIMA$(0, \delta, 1)$ equals to 0.5/16 and the prior for ARFIMA$(1, \delta, 0)$ equals to 1.5/16.

Figure 2 illustrates the posterior of a simple mix of δ over the 16 ARFIMA models. The posterior distribution is highly non-linear and reflects important mass on the positive real line for δ. However, this bias towards mass over the positive real line is due to the presence of pure moving average models. In these models, the parameter δ reflects and captures both the short- and the long-range dependence of the series.

As expected and illustrated in Figures 3 and 4, ARFIMA models without autoregressive terms - such as ARFIMA$(0, \delta, 1)$ and ARFIMA$(0, \delta, 2)$ - pull the posterior distribution towards the positive side of the real line. In these cases, δ captures both

[42] On the quantification of ignorance, see the excellent exposition in Bauwens, Lubrano and Richard (1999, pp. 107-109). Briefly, the approach adopted here maximizes the entropy of the model density over the parameter space.

the short-range and the long-range dependency of Canadian unemployment. Autoregressive components models tend to put higher mass on the negative real line. In other words, when the autoregressive component is present, $\widehat{d}$ is smaller than 1. Canadian aggregate unemployment is a long-memory process that exhibits the mean reversion property. Figure 4 shows that as the number of autoregressive parameters increases (i.e., from ARFIMA$(1, \delta, 0)$ to ARFIMA$(2, \delta, 0)$), more probability is given to the negative real line and specifically to the range $\delta \in (-1.0, -0.5)$.

The question at hand is the following. Conditional on the entertained class of models and the assumptions made regarding the priors and the sample data, is aggregate Canadian unemployment trend stationary with long memory or is its first difference stationary with intermediate memory? The answer lies in Tables 4.G and 4.H. Table 4.G reports the posterior model probabilities under the assumptions of both priors: a flat and an informative. Conditional on the model, Table 4.H reports the posterior mean, standard deviation and the mode of δ. The reason for reporting all these descriptive statistics is that the posterior is highly non-linear and non-symmetrical. Therefore, conditional on the loss function[43] used, one is faced with a different optimal Bayesian point estimate. Choosing the zero-one loss function produces the 'most likely' estimate point but a small estimation error is treated the same as a large one. Choosing the quadratic loss function protects against outliers and skewed tails. The advantage of using the quadratic loss function is that it uses all the information present in the posterior distribution to derive the mean. We report the descriptive

[43]Common choices of loss functions are: 1) the quadratic loss $L(\widehat{\delta}, \delta) = (\widehat{\delta} - \delta)^2$, 2) the absolute loss $L(\widehat{\delta}, \delta) = |\widehat{\delta} - \delta|$ and 3) the zero-one loss $L(\widehat{\delta}, \delta) = c$ if $\widehat{\delta} \neq \delta$ and $L(\widehat{\delta}, \delta) = 0$ if $\widehat{\delta} = \delta$. See Dorfman (1997, p. 10) for the derivations. Choosing the quadratic (absolute, zero-one) loss results in the mean (median, mode) as the Bayesian optimal point estimate.

statistics, and to conform with the ethos of Bayesian point estimation, we adopt the quadratic loss function as our approach.

Regardless of the prior used (ignorance or informative), Table 4.H points to ARFIMA$(1,\delta,0)$ as the model with the highest posterior probability. Conditional on the prior and the sample data, this model is the most likely to adequately fit the data. Based on the posterior model probabilities, the overall ranking is as follow: ARFIMA$(1,\delta,0)$, ARFIMA$(3,\delta,3)$ and finally, ARFIMA$(1,\delta,1)$. Note that the posterior model probability is scattered across all models, which caution against choosing just one model. More specifically, the standard deviation increases with the number of parameters leading to higher uncertainty in choosing only one model (with the exception of the boundary model ARFIMA$(3,\delta,3)$).

The posterior odds[44] in favour of $(-0.5 < \delta < 0.0)$ against $(0.0 < \delta < 0.5)$ are 0.5192 to 0.4808. This evidence supports the belief that Δy_t is stationary with intermediate memory. Quantitatively, the ARFIMA$(1,\delta,0)$ model estimates a small negative value for δ, whereas the overall model estimates a small positive value for the same parameter.

[44]Here, we adopt the symmetric '0-K_i' loss function, as defined in Bauwens, Lubrano and Richard (1999, p. 29). The probability of errors of type I and II are equal. See also Zellner (1971, p. 292) where "under a symmetric loss structure, a comparison of the posterior probabilities will provide a basis for choosing between H_0 and H_1."

Table 4.G

Posterior Model Probabilities for ARFIMA(p, δ, q)		
Model	**Flat Prior**	**Informative Prior**
$(0,\delta,0)$	0.0733	0.0646
$(0,\delta,1)$	0.0681	0.0300
$(0,\delta,2)$	0.0108	0.0047
$(0,\delta,3)$	0.0359	0.0158
$(1,\delta,0)$	0.3139	0.4155
$(1,\delta,1)$	0.1128	0.0995
$(1,\delta,2)$	0.0219	0.0193
$(1,\delta,3)$	0.0235	0.0207
$(2,\delta,0)$	0.0584	0.0773
$(2,\delta,1)$	0.0541	0.0478
$(2,\delta,2)$	0.0173	0.0152
$(2,\delta,3)$	0.0218	0.0192
$(3,\delta,0)$	0.0090	0.0119
$(3,\delta,1)$	0.0280	0.0247
$(3,\delta,2)$	0.0323	0.0285
$(3,\delta,3)$	0.1181	0.1042

Table 4.H

Posterior Characteristics of δ			
Model	**Mean**	**St-Dev**	**Mode**
$(0,\delta,0)$	0.429	0.055	0.500
$(0,\delta,1)$	0.313	0.113	0.325
$(0,\delta,2)$	0.281	0.133	0.275
$(0,\delta,3)$	0.019	0.173	-0.075
$(1,\delta,0)$	-0.034	0.263	-0.200
$(1,\delta,1)$	0.053	0.326	0.400
$(1,\delta,2)$	0.052	0.313	0.250
$(1,\delta,3)$	-0.173	0.360	0.000
$(2,\delta,0)$	-0.189	0.352	0.025
$(2,\delta,1)$	-0.132	0.329	-0.175
$(2,\delta,2)$	0.019	0.335	0.150
$(2,\delta,3)$	0.042	0.400	0.475
$(3,\delta,0)$	-0.085	0.333	-0.100
$(3,\delta,1)$	-0.321	0.329	-0.575
$(3,\delta,2)$	-0.222	0.362	-0.425
$(3,\delta,3)$	0.318	0.208	0.425
Overall Model[45]	0.036	0.359	0.425

[45]Bayesian Model Averaging (BMA) as outlined by Hoeting, Madigan, Raftrey and Volinsky (1999) uses the model posterior probabilities as weights. Here, the 'overall model' is computed as the average of all 16 posterior probabilities at each bin.

In brief, conditional on the entertained class of models, the prior assumptions and the sample data, the first difference of the log of Canadian unemployment is stationary with intermediate memory. Among the class of low order ARFIMA models, an ARFIMA$(1,\delta,0)$ model is the most likely one to be observed, with $\widehat{\delta} = -0.034$, i.e., $\widehat{d} = 0.966$.

A natural question arises. What are the effects of a one time shock to the series? Further, for how long will the effects last? Table 4.I and Figure 5 answer these questions. For the chosen model, Figure 5 illustrates the impulse responses for $n = 4, 12$ and 40. As expected from previous results, the posterior standard deviation increases for longer horizons. It is highly skewed and exhibits fat tails.

Table 4.I

	ARFIMA$(1,\delta,0)$	**Overall Model**
$n=4$	2.235	2.253
	(0.372)	(0.153)
$n=12$	2.618	1.144
	(0.861)	(2.301)
$n=40$	2.874	1.684
	(1.750)	(4.997)

(.) denotes the posterior standard deviations.

Note that the impulse response function $I(n)$ measures the impact of a shock of size equal to 1 at time t on y_{t+n}. Table 4.I and Figure 5 show that economic persistence is present. The effect of the shock persists for at least 12 quarters. For the ARFIMA$(1,\delta,0)$ model, the variance - and the uncertainty of drawing conclusions - grows to $n = 40$. With more confidence in the results, one can report evidence of short- and intermediate-run persistence in total unemployment. The influence of model averaging is apparent in the impulse responses of the overall model. Higher variance and lower persistence occur relative to the ARFIMA$(1, \delta, 0)$. For the longer horizon $n = 40$, the shock is responsible for a large variance. Table 4.I and Figure 5 quantify and illustrate the increase in the variance of the effect of the shock at longer horizons.

In brief, economic persistence holds in the short- and intermediate-run. However, economic persistence over longer horizons is uncertain due to the large variance associated with $n = 40$.

4.13 Conclusions

This chapter tested for economic persistence in sectoral unemployment using the Cochrane variance ratio and the modified rescaled range statistic tests. Both tests showed significant evidence of persistence. The Cochrane variance ratio shows evidence of high instability, persistent changes or regime shifts. The modified rescaled range test statistic also provides evidence of persistence. We conclude that fluctuations in the sectoral Canadian unemployment series are characterised by persistence.

Conditional on the entertained class of models, the prior assumptions and the sample data, the first difference of the log of Canadian unemployment is stationary with intermediate memory. Economic persistence holds in the short- and intermediate-run. However, this is uncertain over longer horizons.

In summary, shocks to sectoral and aggregate unemployment have lasting effects. This chapter was within the univariate framework. The questions still to be addressed are: what types of dynamic relationships exist between aggregate, manufacturing and services unemployment? If a shock impinges on one sector, what are its effects on the other sector, and the aggregate? These questions are addressed in Chapter 5, which uses a reduced form data-driven approach (i.e., VAR modelling). Chapter 6 presents two RBC models to explain the sources of shocks and to investigate possible propagation mechanisms in order to explain how persistence could occur.

4.14 Appendix: Tables and Figures

Table 4.1

CANSIM SOURCE	
MONTHLY DATA FROM 1976:1 To 1998:12	
TOTAL UNEMPLOYMENT	D980712
UNEMPLOYMENT - GOODS	D968135
UNEMPLOYMENT - MANUFACTURING	D968140
UNEMPLOYMENT - SERVICES	D968141

Label	: D980712 (UPDATED to 2000)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / UNEMPLOYMENT AGE 15+ SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1976 - March 2000
Frequency	: monthly

Label	: D968135 (UPDATED to 2000)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / UNEMPLOYMENT GOODS-PRODUCING SECTOR SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1987 - March 2000
Frequency	: monthly

Label	: D968140 (UPDATED to 2000)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / UNEMPLOYMENT MANUFACTURING SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1987 - March 2000
Frequency	: monthly

Label	: D968141 (UPDATED to 2000)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / UNEMPLOYMENT SERVICES-PRODUCING SECTOR SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1987 - March 2000
Frequency	: monthly

Monthly Unemployment Rate Data used in Figures 4.1 and 4.2.

Total Unemployment Rate	D980745
Goods Sector Unemployment Rate	D980766
Primary Unemployment Rate	D980767
Agriculture Unemployment Rate	D980768
Manufacturing Sector Unemployment Rate	D980770
Services Sector Unemployment Rate	D980772

(M) denotes MONTHLY
(Q) denotes QUARTERLY
(A) denotes ANNUAL

Table 4.2

DESCRIPTIVE STATISTICS FOR CANADIAN UNEMPLOYMENT by INDUSTRY - HP-FILTERED

Series	Obs	MEAN	St-Dev	MIN	MAX
	ANNUAL				
Total UE (A)	23	0.0000	0.1487	-0.2050	0.2927
UE GOODS (A)	23	0.0000	0.1609	-0.1984	0.3719
UE MANUF. (A)	23	0.0000	0.1680	-0.2097	0.4673
UE SERVICE (A)	23	0.0000	0.1317	-0.2170	0.1985
	QUARTERLY				
Total UE (Q)	92	0.0000	0.0934	-0.2085	0.2399
UE GOODS (Q)	92	0.0000	0.1110	-0.2113	0.3813
UE MANUF. (Q)	92	0.0000	0.1235	-0.2341	0.4230
UE SERVICE (Q)	92	0.0000	0.0792	-0.1869	0.1992
	MONTHLY				
Total UE (M)	276	0.0000	0.0364	-0.1624	0.1243
UE GOODS (M)	276	0.0000	0.0585	-0.2377	0.2320
UE MANUF. (M)	276	0.0000	0.0751	-0.2306	0.2299
UE SERVICE (M)	276	0.0000	0.0353	-0.1297	0.1042

Table 4.3

CORRELATION MATRIX - HP FILTERED DATA				
	Total UE (M)	UE GOODS (M)	UE MANUF. (M)	UE SERVICE (M)
Total UE (M)	1.000000			
UE GOODS (M)	0.836181	1.000000		
UE MANUF. (M)	0.717364	0.877487	1.000000	
UE SERVICE (M)	0.853827	0.619120	0.540794	1.000000

Table 4.4

AUTOCORRELATION of CANADIAN UNEMPLOYMENT
HP - FILTERED DATA

	K=1	K=2	K=3	K=4	K=5	K=6
Total UE (M)	0.7552	0.5894	0.4882	0.3193	0.1773	0.0696
UE GOODS (M)	0.7817	0.6020	0.4555	0.3154	0.1683	0.0327
UE MANUF. (M)	0.7319	0.5725	0.4449	0.3255	0.1811	0.0835
UE SERVICE (M)	0.6274	0.4275	0.3239	0.2245	0.1527	0.0813
Total UE (Q)	0.9105	0.7436	0.5469	0.3421	0.1691	0.0323
UE GOODS (Q)	0.8574	0.6195	0.3595	0.1324	0.0077	-0.0579
UE MANUF. (Q)	0.8118	0.5464	0.2490	-0.0181	-0.1383	-0.1455
UE SERVICE (Q)	0.8874	0.7170	0.5105	0.2961	0.1285	-0.0161
Total UE (A)	0.6342	0.1411	-0.2573	-0.4802	-0.5080	-0.4618
UE GOODS (A)	0.5600	0.1308	-0.2492	-0.4255	-0.4267	-0.4039
UE MANUF. (A)	0.4857	0.1471	-0.2090	-0.4413	-0.3700	-0.3801
UE SERVICE (A)	0.6225	0.1668	-0.1508	-0.3129	-0.3636	-0.3483

Table 4.5

CROSS CORRELATION between CANADIAN UNEMP by INDUSTRY
AT DIFFERENT LAGS - HP FILTERED

	TOTAL UNEMPLOYMET						
	T+3	T+2	T+1	T	T-1	T-2	T-3
UE GOODS	0.3327	0.4657	0.6424	0.8362	0.7123	0.6067	0.5512
UE MANUF	0.3083	0.4166	0.5676	0.7174	0.6234	0.5564	0.5392
UE SERVICES	0.3684	0.4631	0.6042	0.8538	0.6665	0.5117	0.4446
	UNEMPLOYMENT GOODS						
	T+3	T+2	T+1	T	T-1	T-2	T-3
UE MANUF	0.3989	0.5347	0.6994	0.8775	0.7085	0.5728	0.4748
UE SERVICES	0.4505	0.4972	0.5496	0.6191	0.5312	0.399	0.3287
	UNEMPLOYMENT SERVICES						
	T+3	T+2	T+1	T	T-1	T-2	T-3
UE MANUF	0.4516	0.4743	0.4976	0.5408	0.5019	0.3901	0.3524

Posterior Density DELTA (Simple Mix)

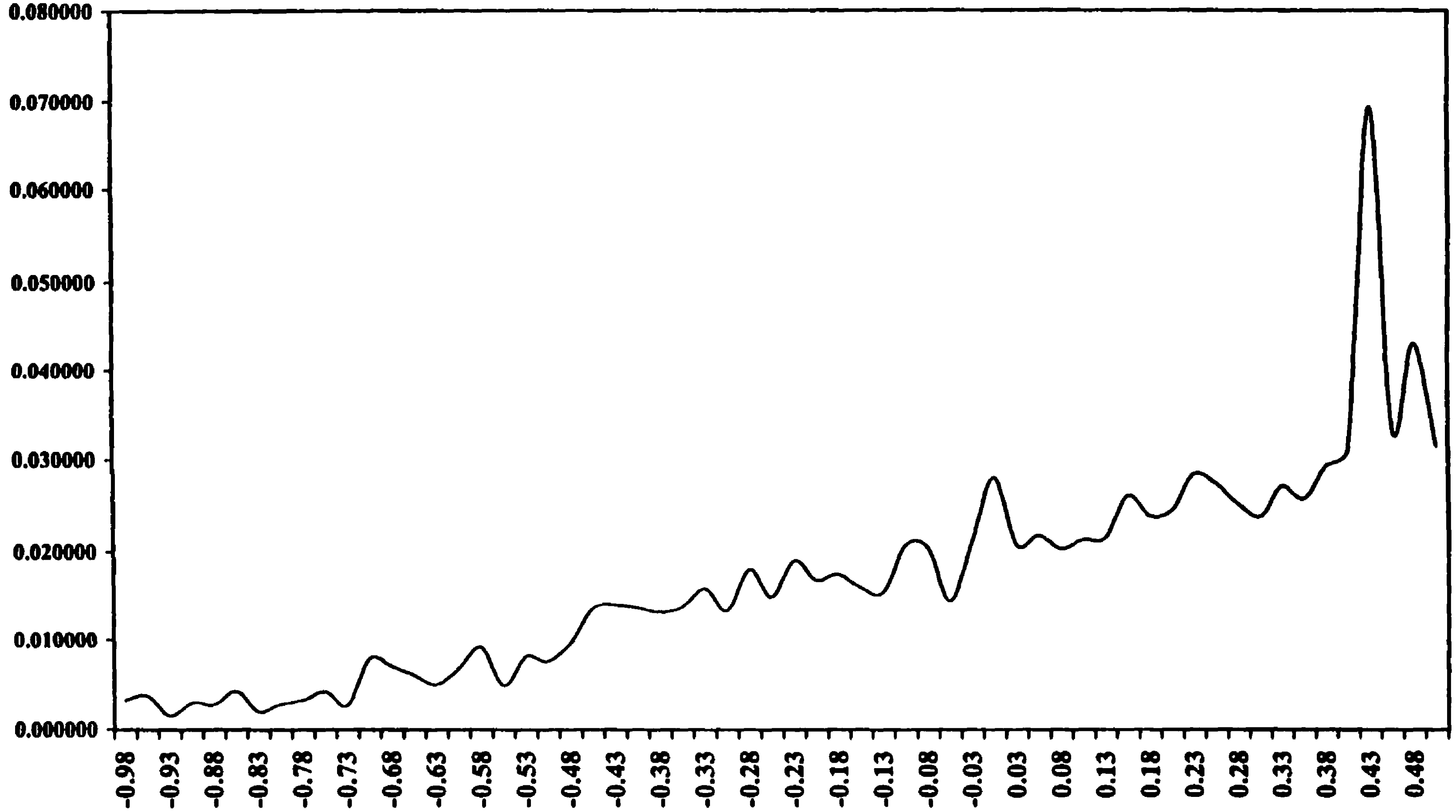
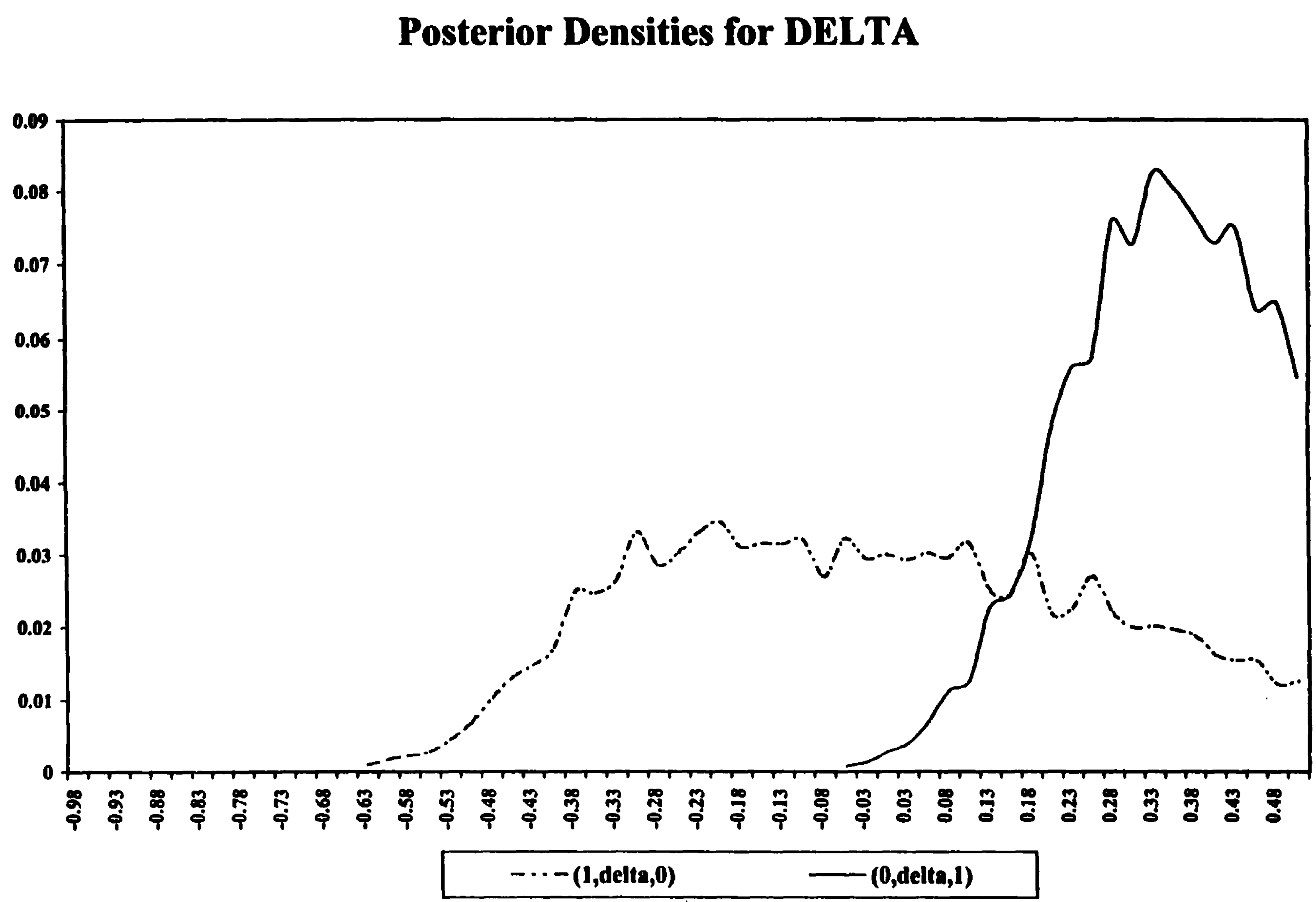
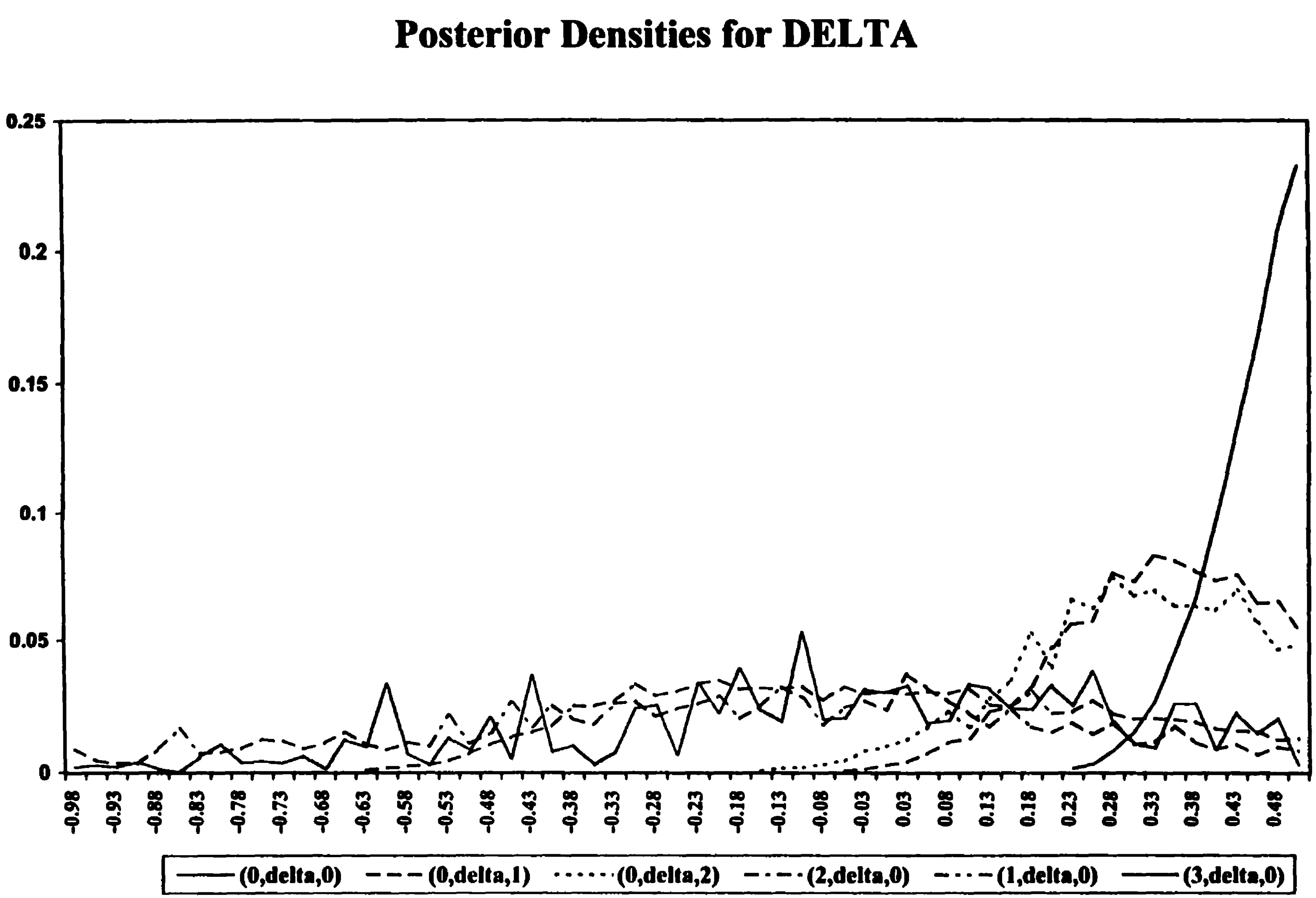


Figure 4.2



Posterior Densities for DELTA
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-0.98
-0.93
-0.88
-0.83
-0.78
-0.73
-0.68
-0.63
-0.58
-0.53
-0.48
-0.43
-0.38
-0.33
-0.28
-0.23
-0.18
-0.13
-0.08
-0.03
0.03
0.08
0.13
0.18
0.23
0.28
0.33
0.38
0.43
0.48
(1,delta,0)
(0,delta,1)

Figure 4.3



Posterior Densities for DELTA
0.25
0.2
0.15
0.1
0.05
0
-0.98
-0.93
-0.88
-0.83
-0.78
-0.73
-0.68
-0.63
-0.58
-0.53
-0.48
-0.43
-0.38
-0.33
-0.28
-0.23
-0.18
-0.13
-0.08
-0.03
0.03
0.08
0.13
0.18
0.23
0.28
0.33
0.38
0.43
0.48
(0,delta,0)
(0,delta,1)
(0,delta,2)
(2,delta,0)
(1,delta,0)
(3,delta,0)

Figure 4.4

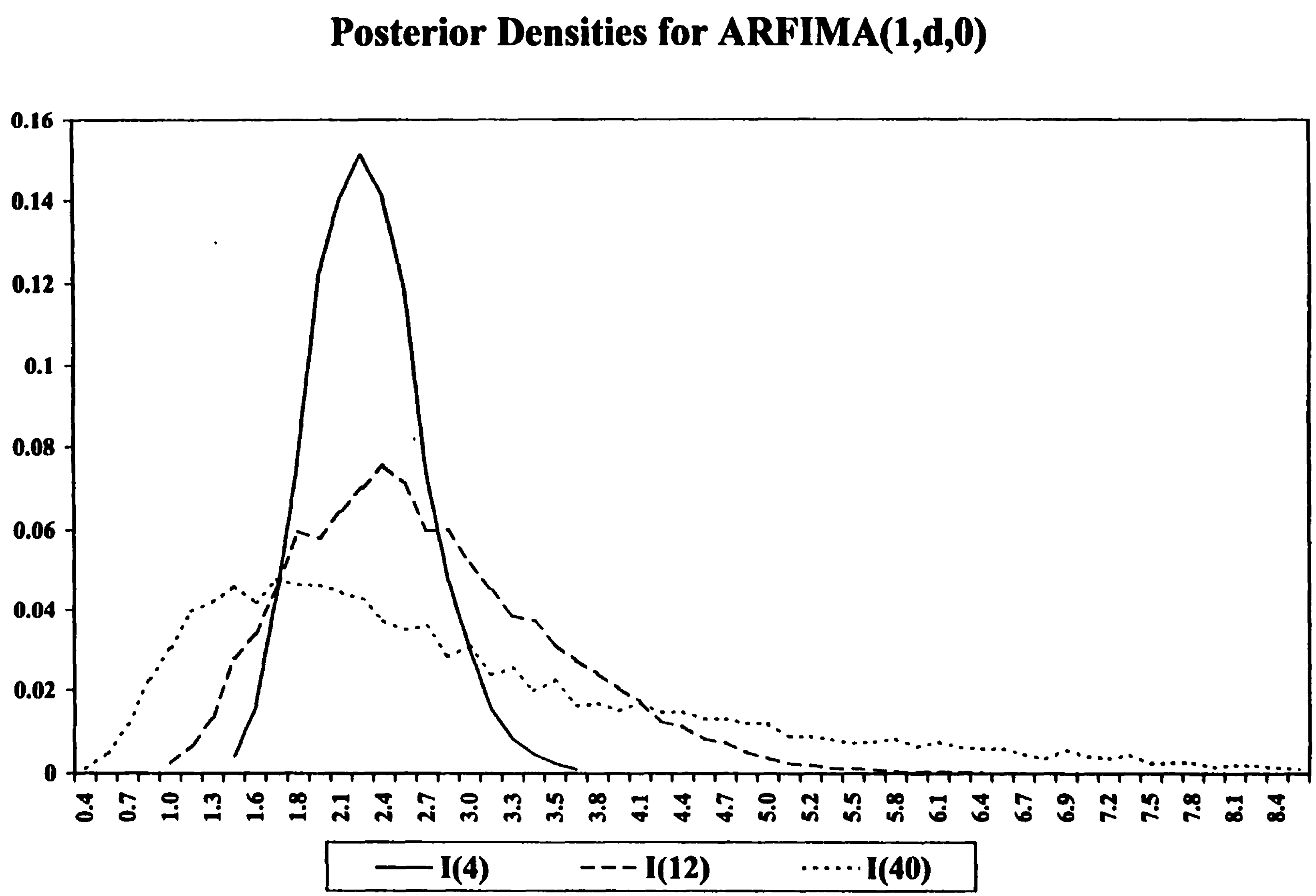
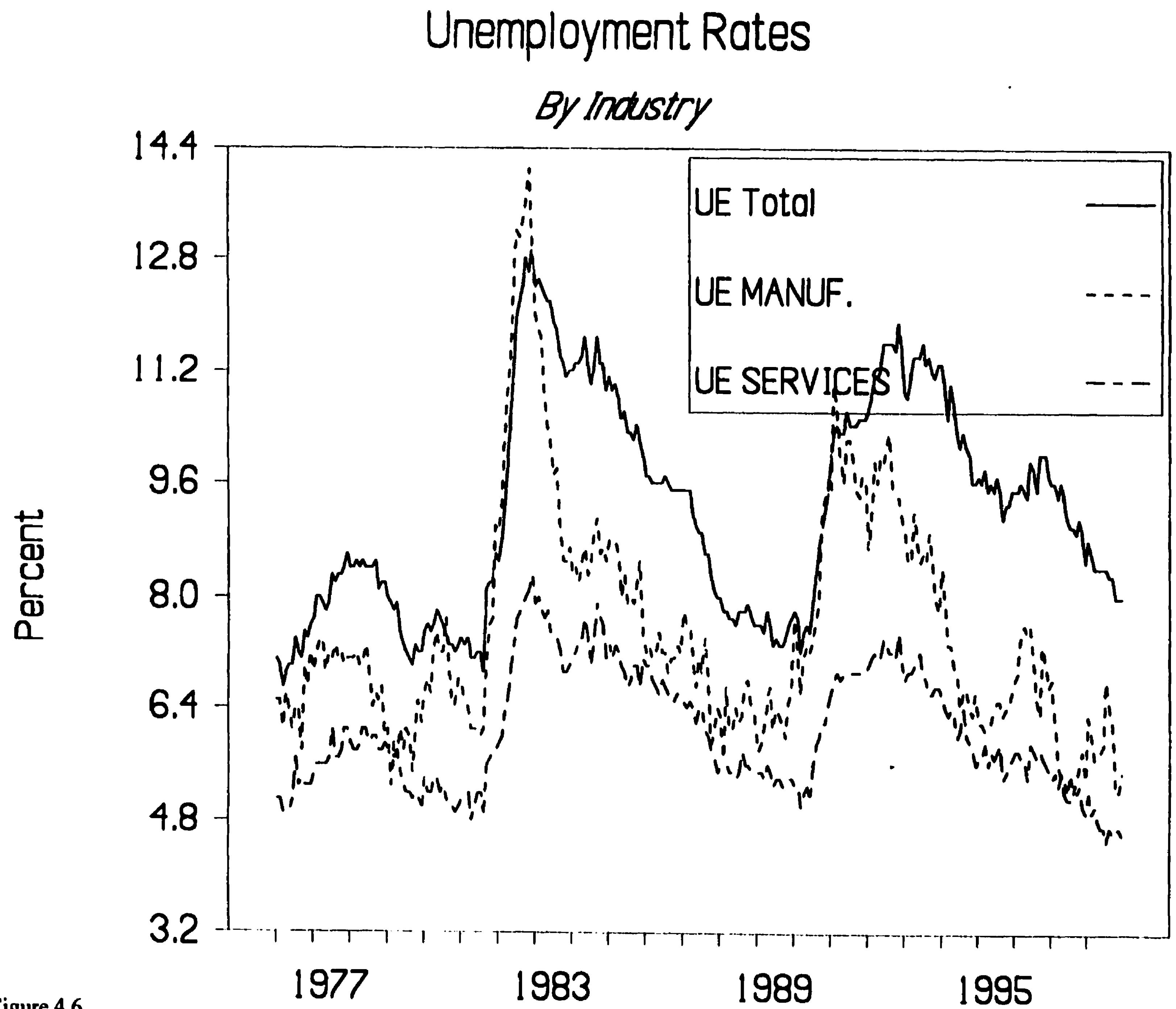
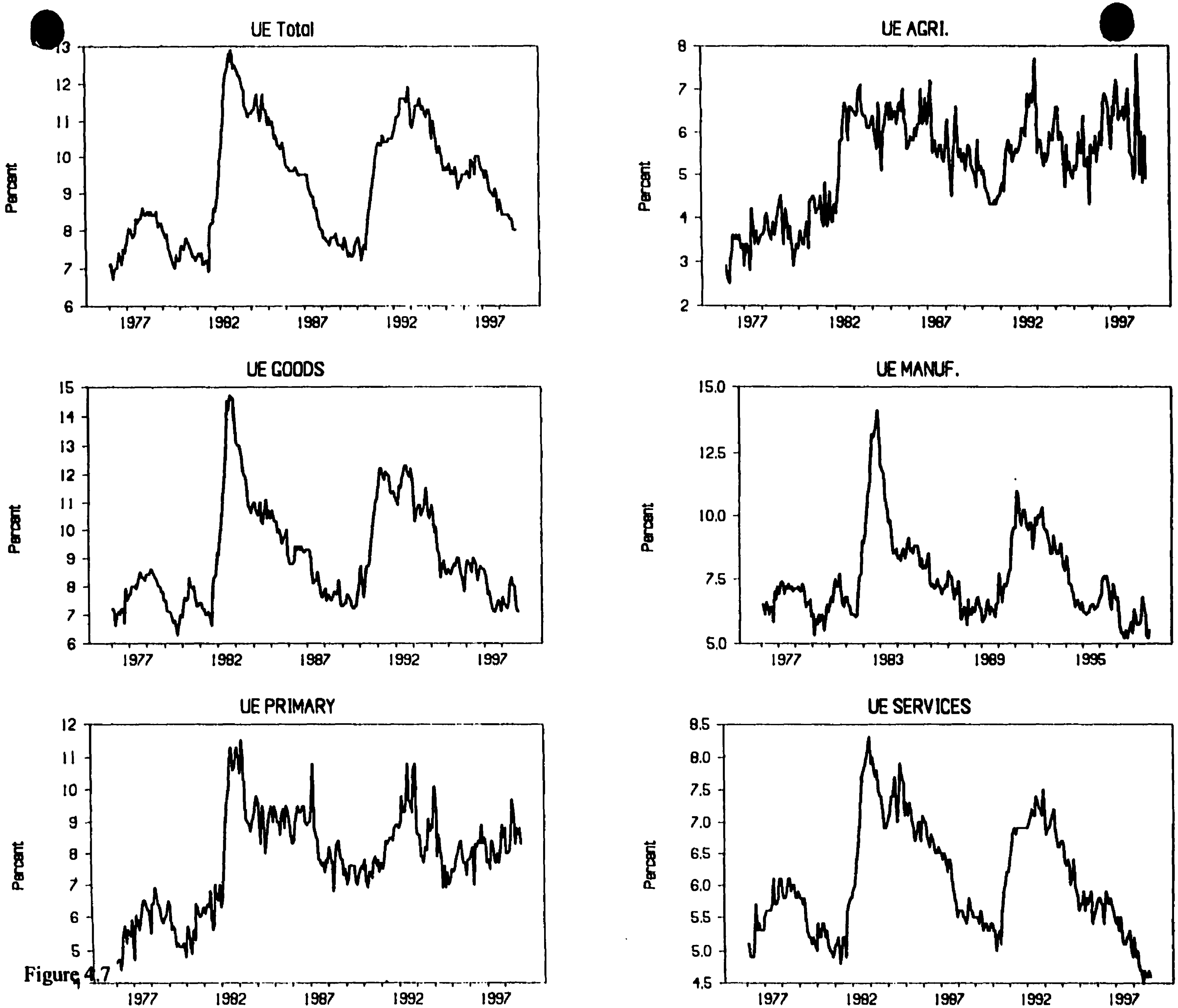

Posterior Densities for ARFIMA(1,d,0)
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0.4
0.7
1.0
1.3
1.6
1.8
2.1
2.4
2.7
3.0
3.3
3.5
3.8
4.1
4.4
4.7
5.0
5.2
5.5
5.8
6.1
6.4
6.7
6.9
7.2
7.5
7.8
8.1
8.4
I(4)
I(12)
I(40)

Figure 4.5



Unemployment Rates
By Industry
Percent
14.4
12.8
11.2
9.6
8.0
6.4
4.8
3.2
1977
1983
1989
1995
UE Total
UE MANUF.
UE SERVICES

Figure 4.6


UE Total
UE AGRI.
UE GOODS
UE MANUF.
UE PRIMARY
UE SERVICES
Percent
1977
1982
1987
1992
1997
1983
1989
1995
Figure 4.7

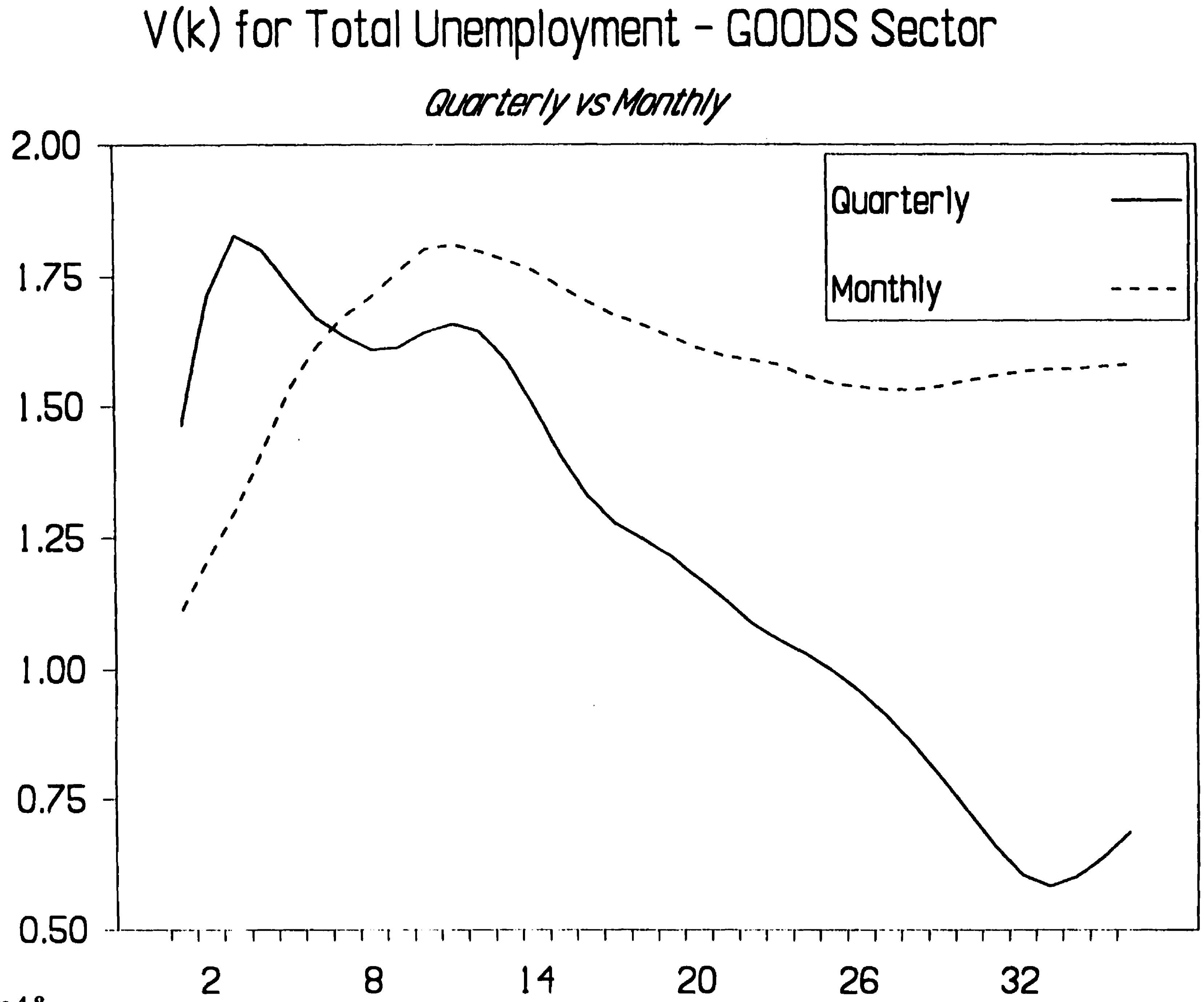

V(k) for Total Unemployment - GOODS Sector
Quarterly vs Monthly
Quarterly
Monthly
2.00
1.75
1.50
1.25
1.00
0.75
0.50
2
8
14
20
26
32

Figure 4.8

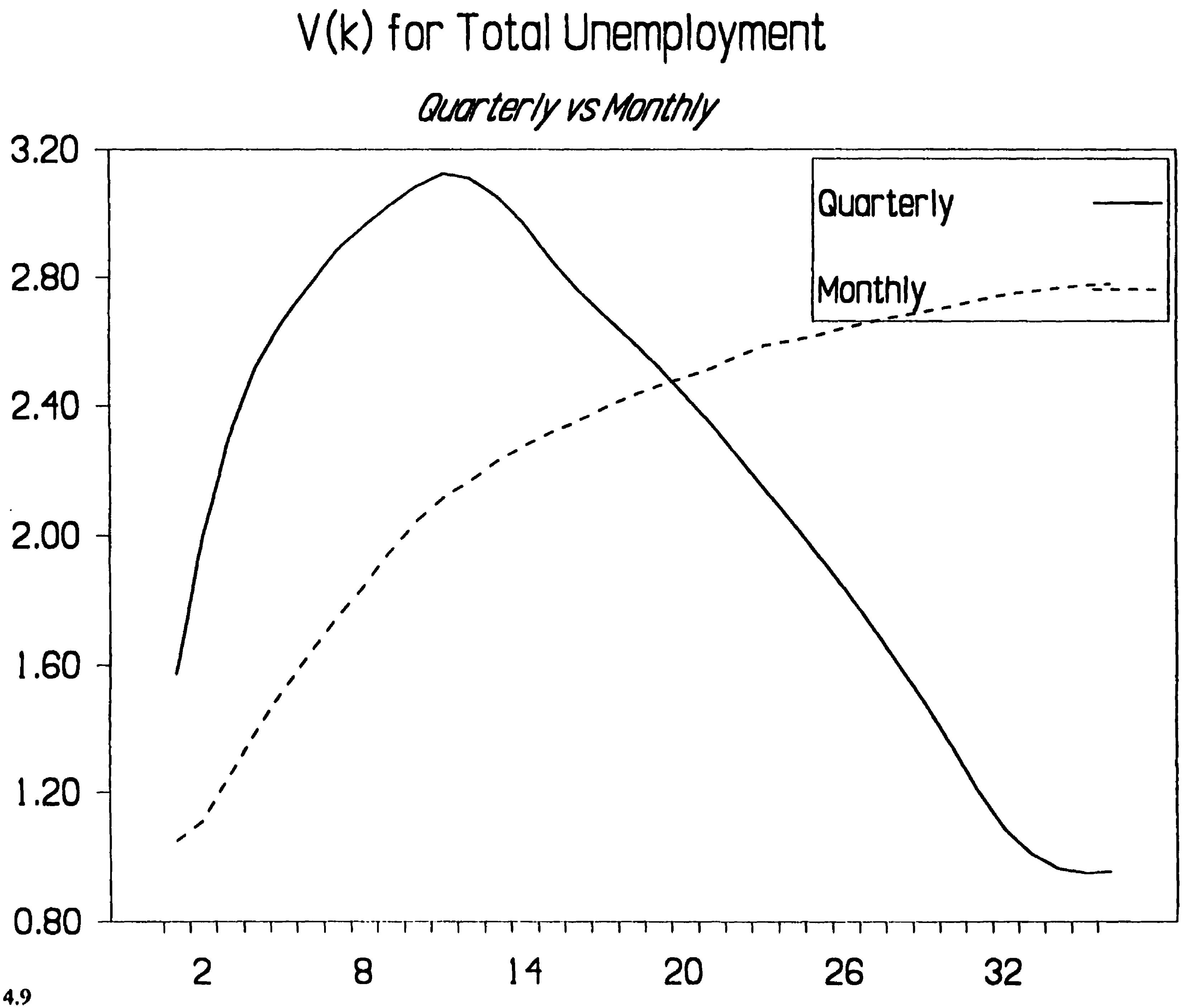

V(k) for Total Unemployment
Quarterly vs Monthly
Quarterly
Monthly
3.20
2.80
2.40
2.00
1.60
1.20
0.80
2
8
14
20
26
32

Figure 4.9

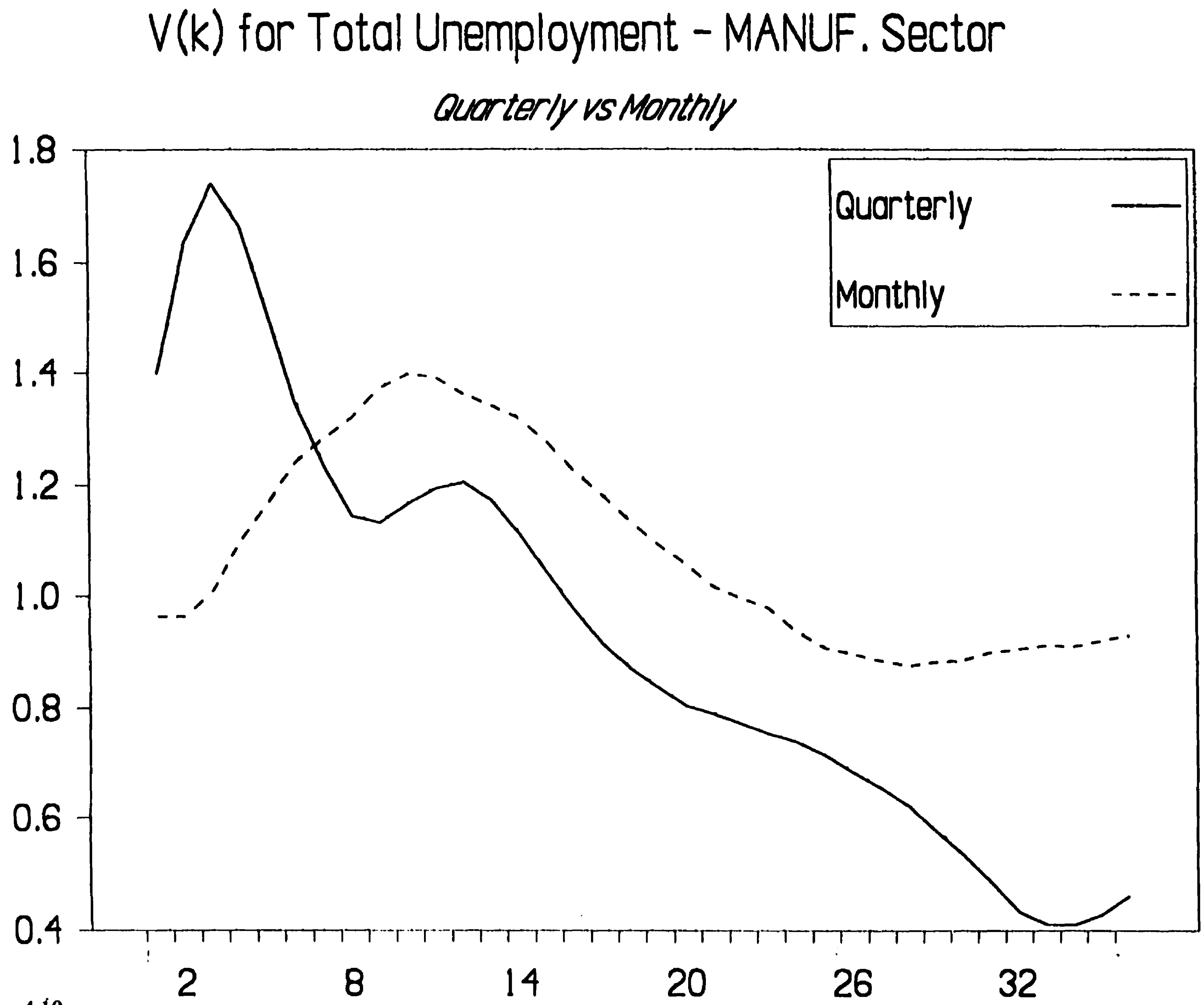
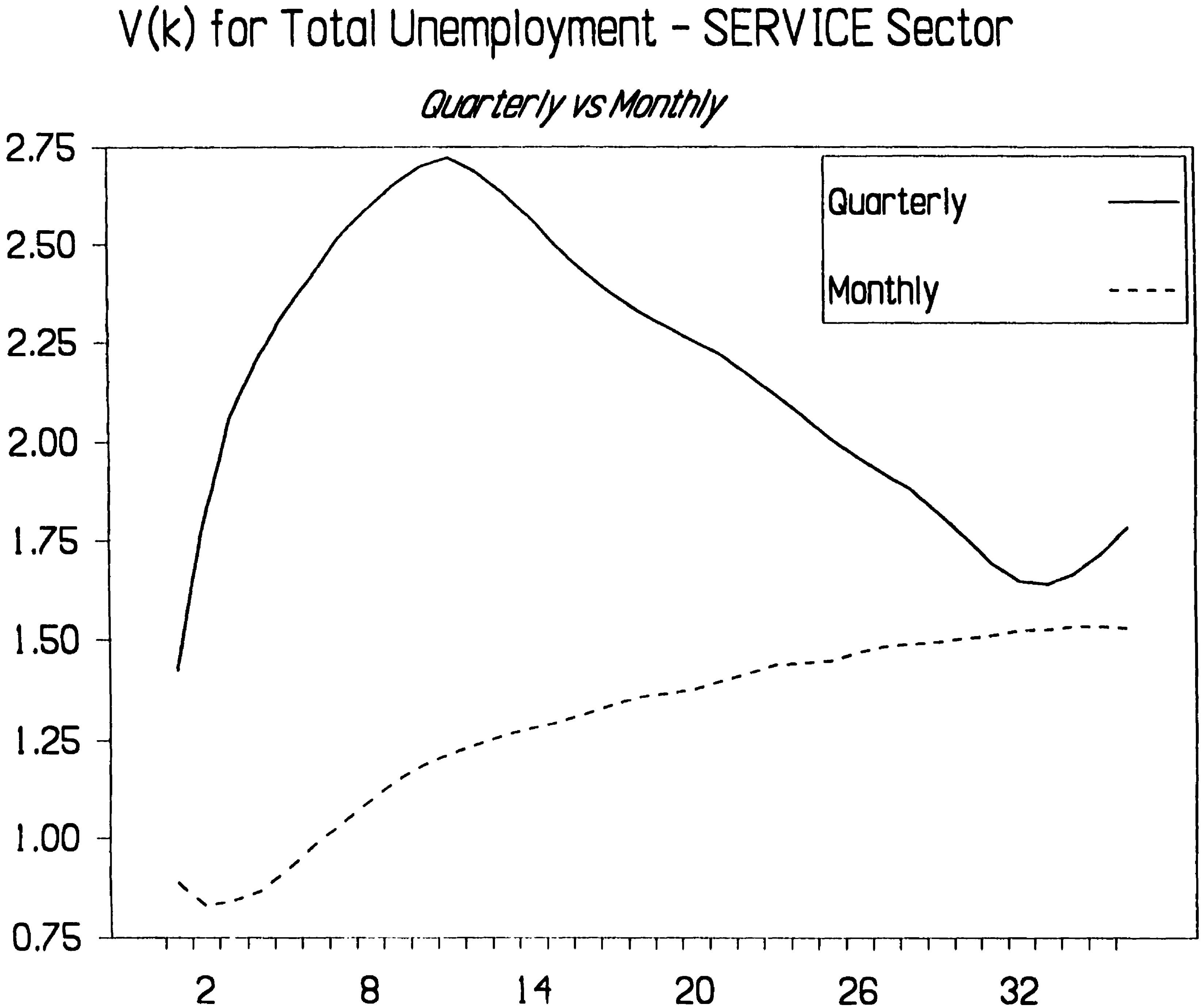

V(k) for Total Unemployment - MANUF. Sector
Quarterly vs Monthly
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
2
8
14
20
26
32
Quarterly
Monthly

Figure 4.10



V(k) for Total Unemployment - SERVICE Sector
Quarterly vs Monthly
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.75
2
8
14
20
26
32
Quarterly
Monthly

Figure 4.11

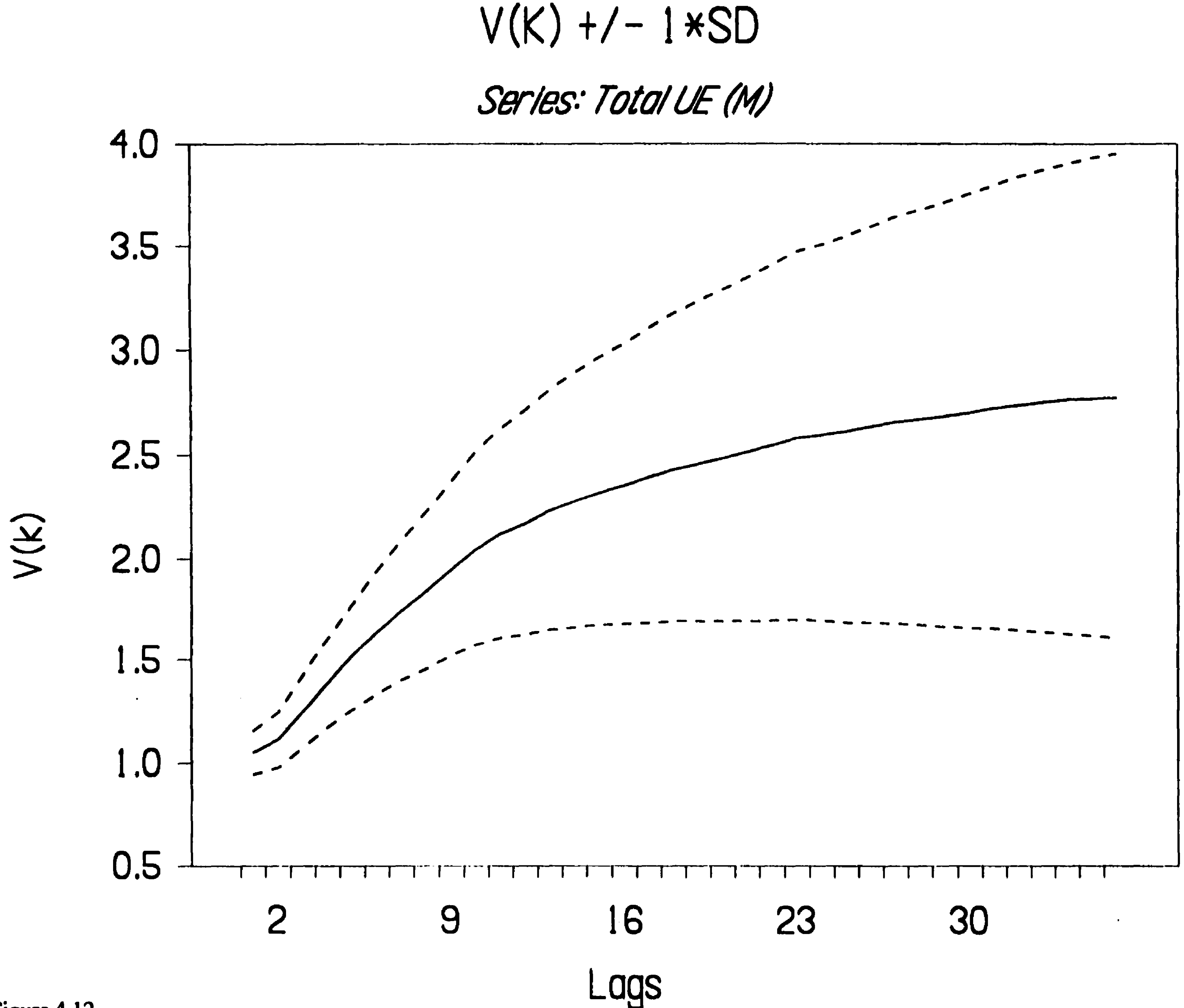


Figure 4.12

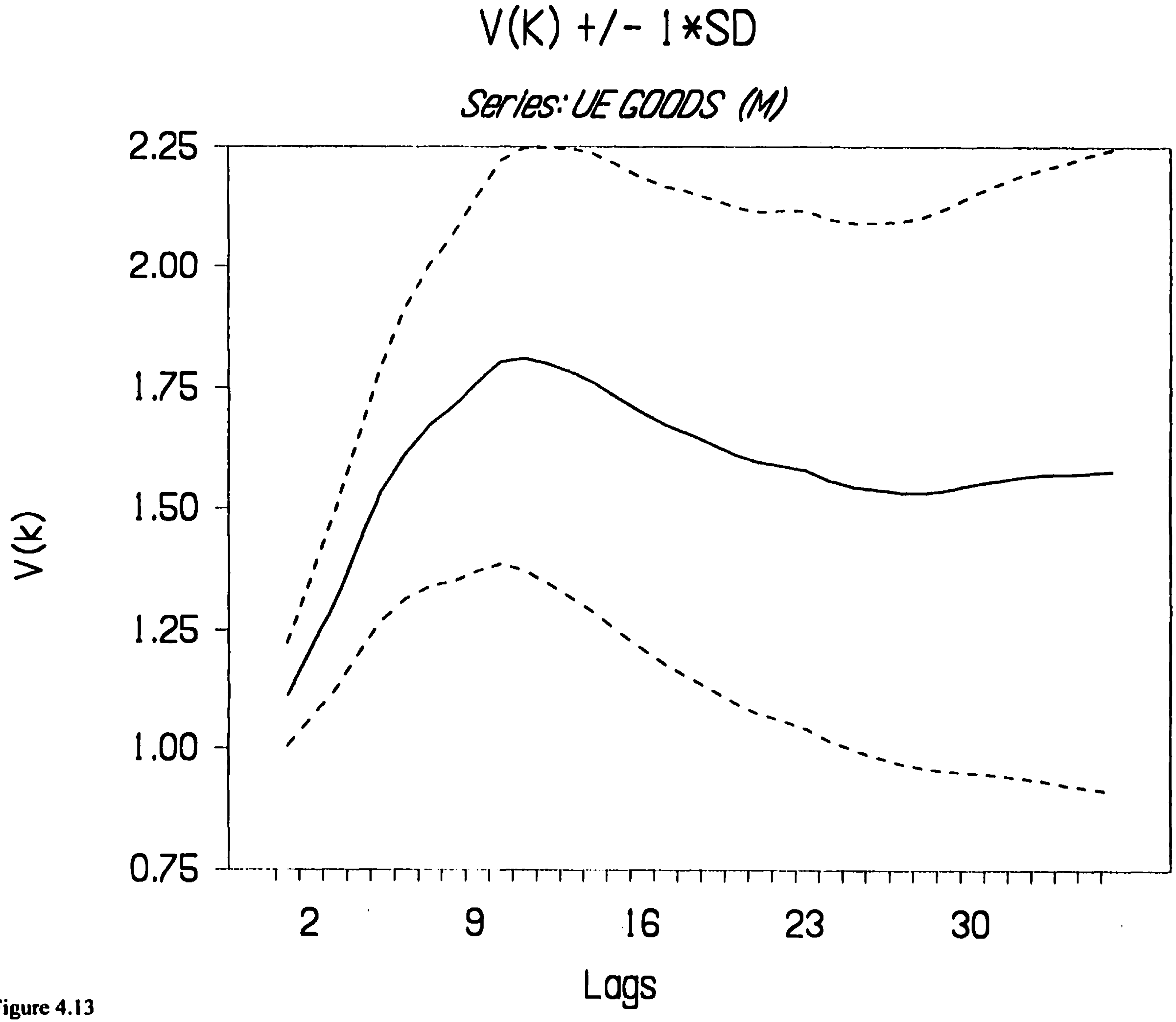

V(K) +/- 1*SD
Series: UE GOODS (M)
2.25
2.00
1.75
1.50
1.25
1.00
0.75
V(k)
2
9
16
23
30
Lags

Figure 4.13

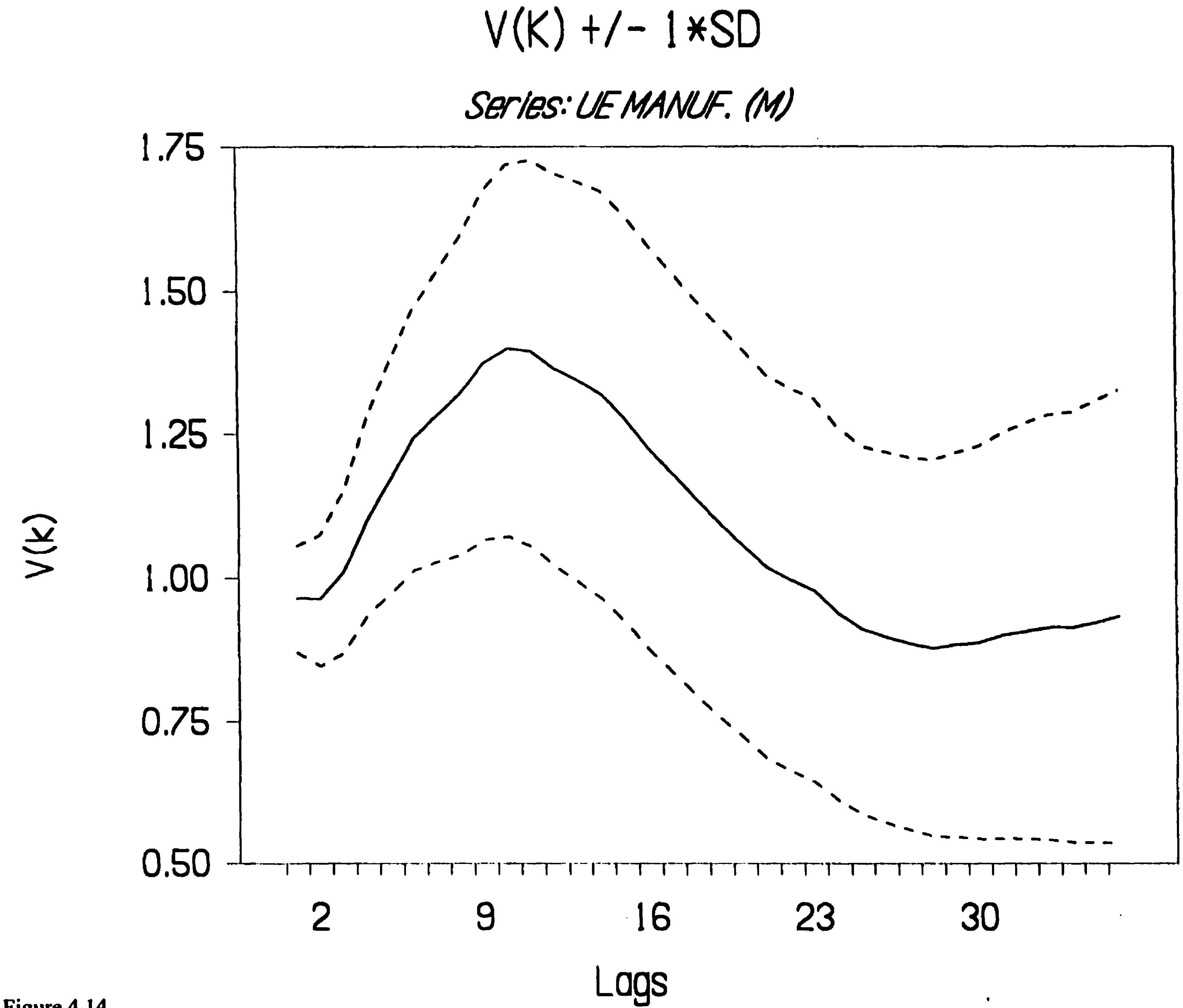

V(K) +/- 1*SD
Series: UE MANUF. (M)
1.75
1.50
1.25
1.00
0.75
0.50
V(k)
2
9
16
23
30
Lags

Figure 4.14

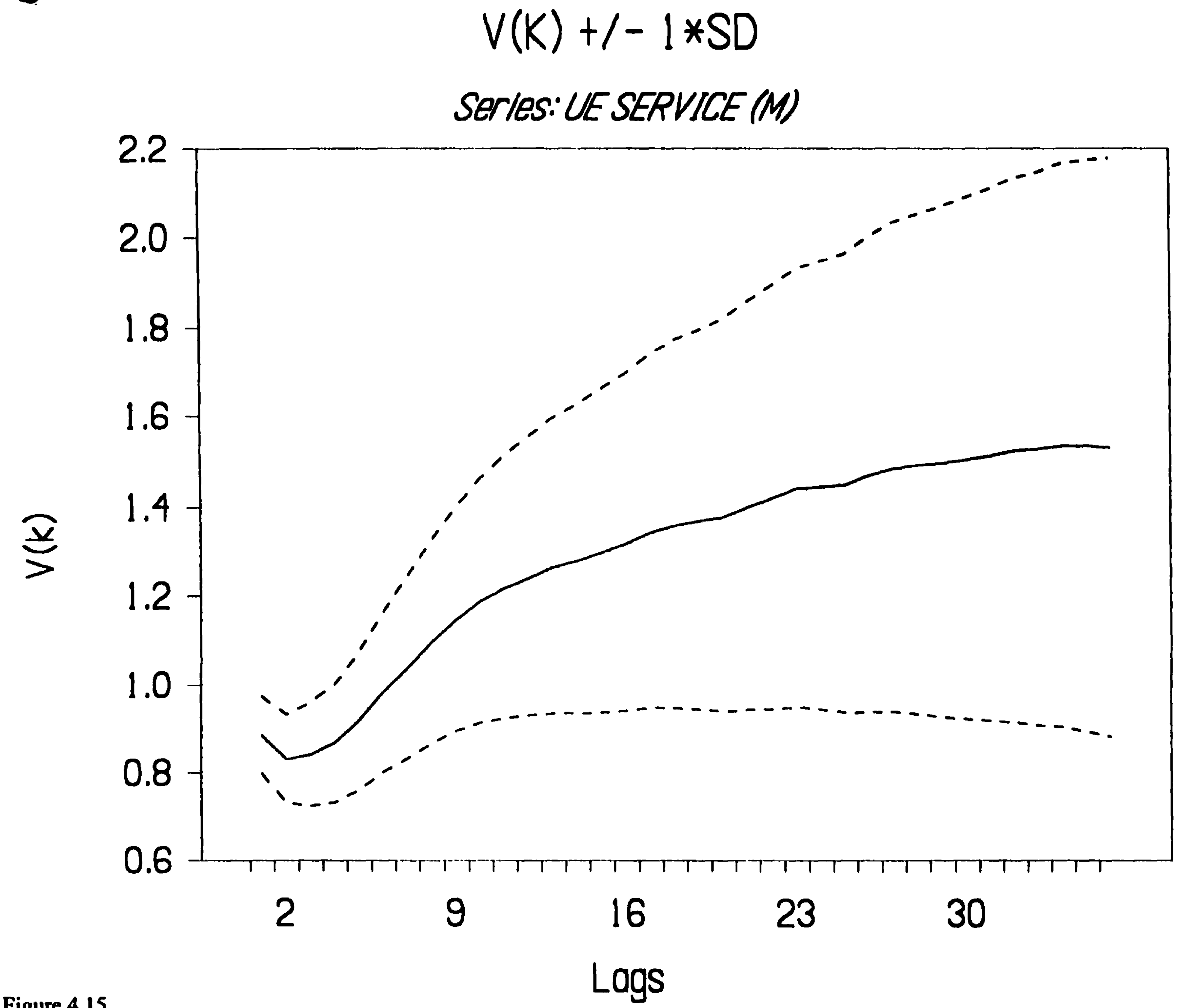

V(K) +/- 1*SD
Series: UE SERVICE (M)
V(k)
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
2
9
16
23
30
Lags

Figure 4.15

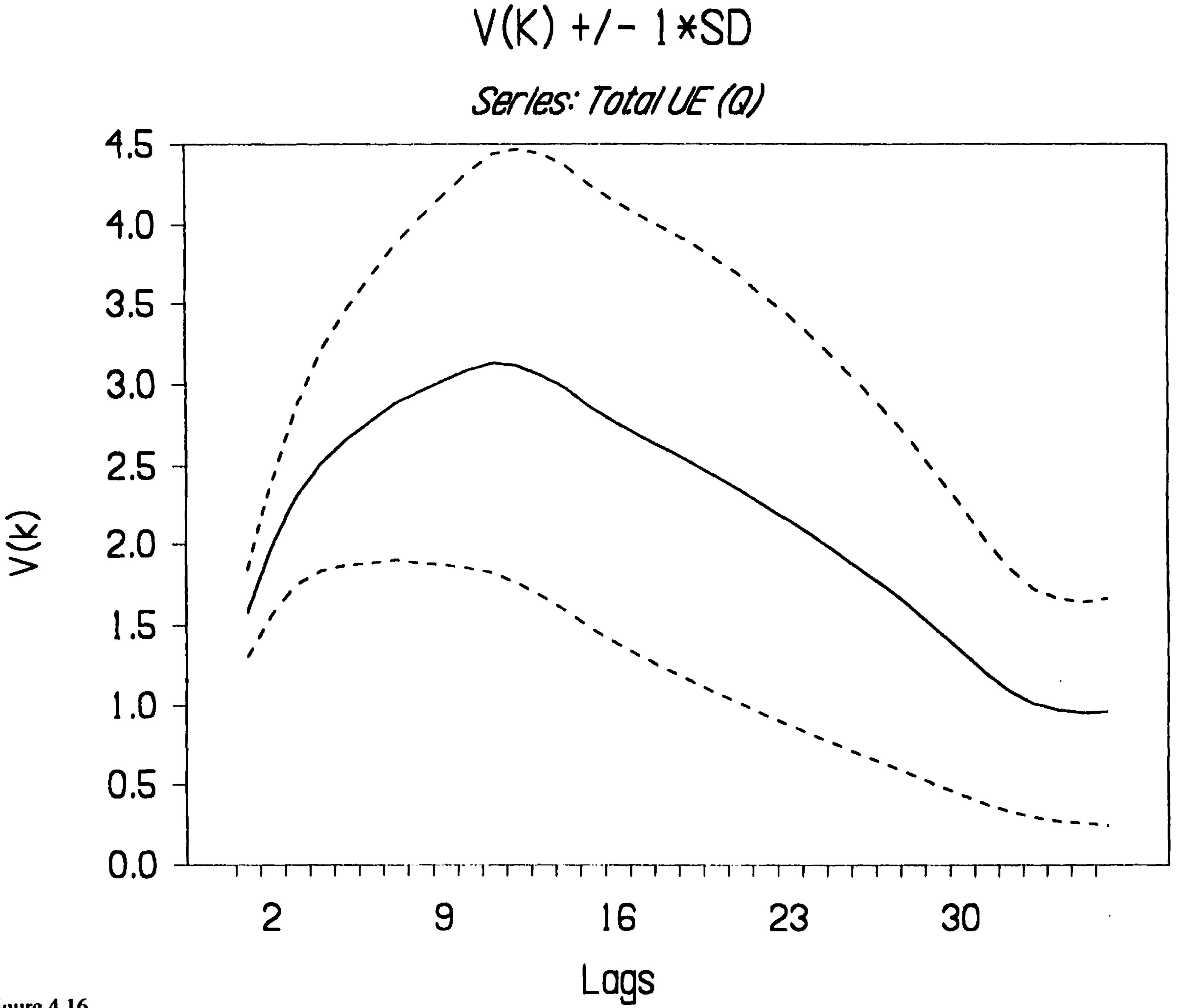

V(K) +/- 1*SD
Series: Total UE (Q)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
V(k)
2
9
16
23
30
Lags

Figure 4.16

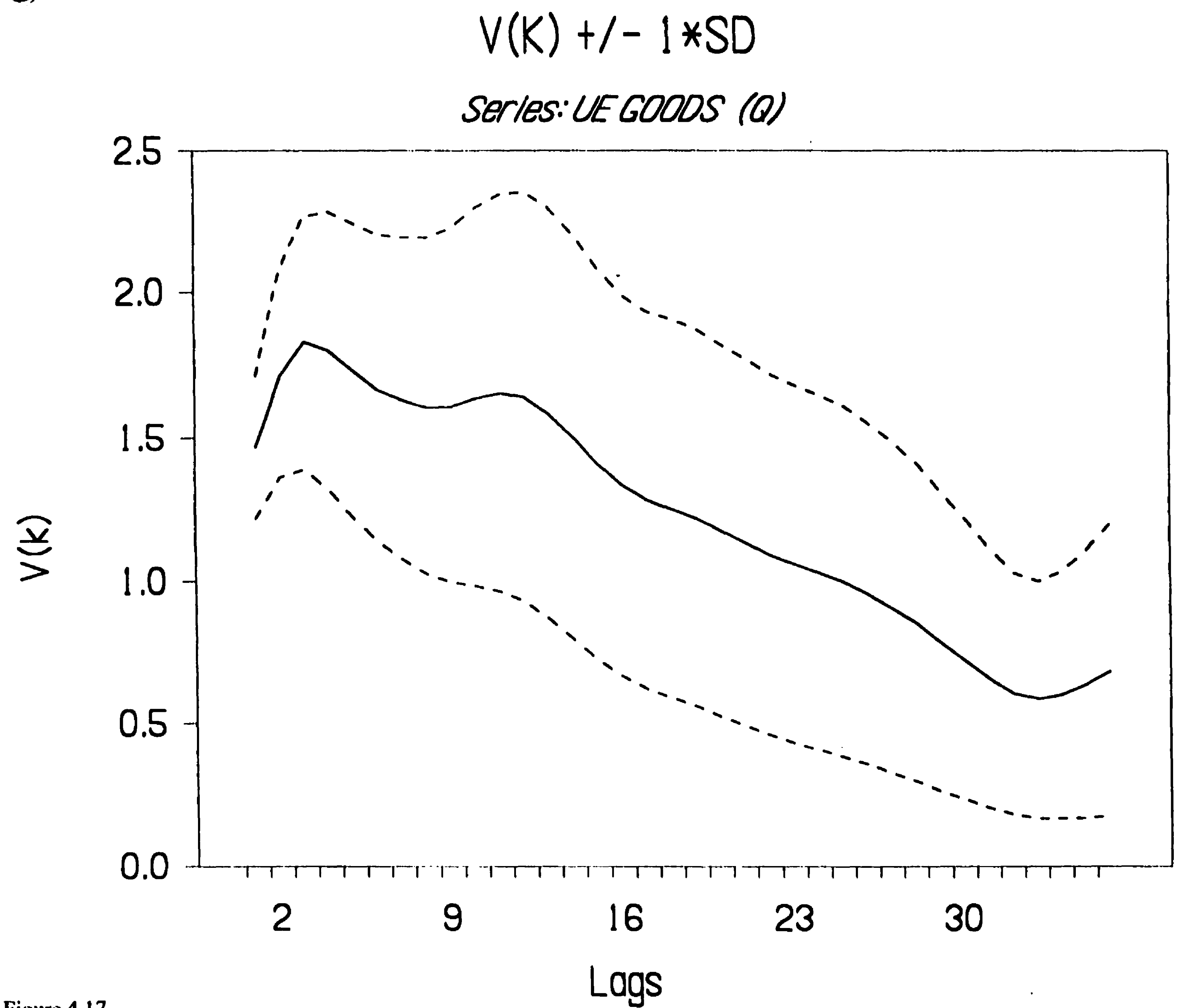


Figure 4.17

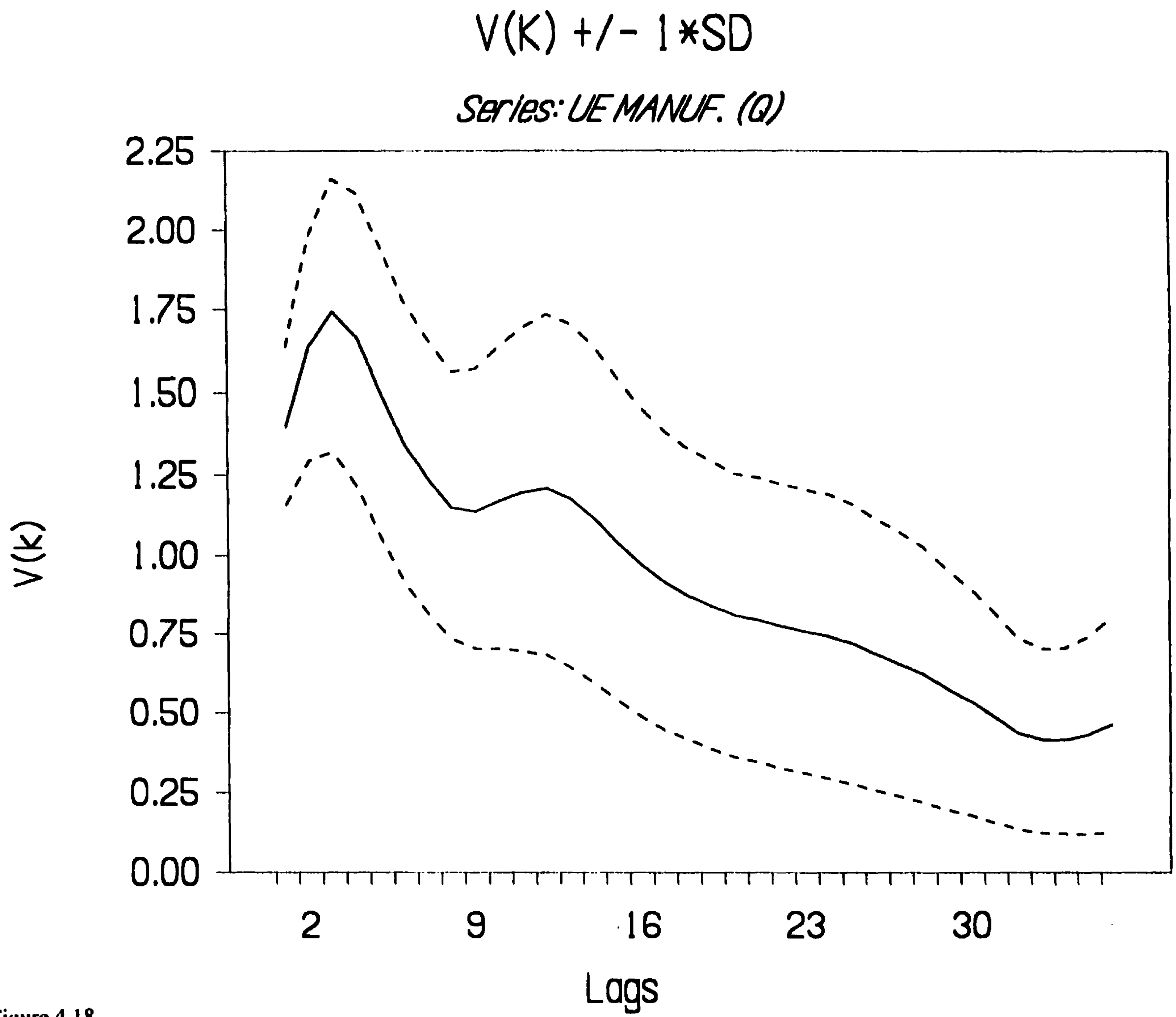

V(K) +/- 1*SD
Series: UE MANUF. (Q)
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
V(k)
2
9
16
23
30
Lags

Figure 4.18

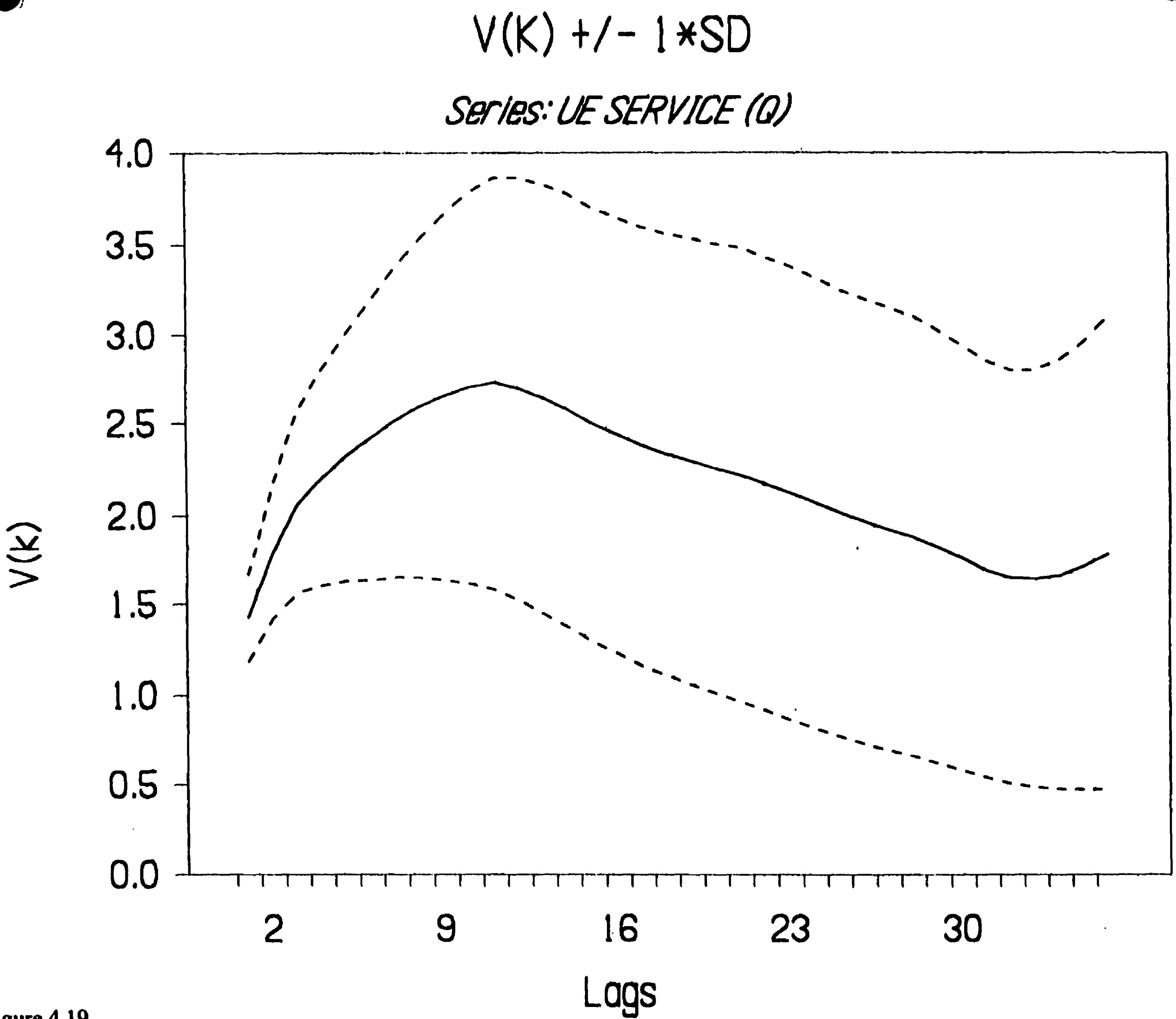

V(K) +/- 1*SD
Series: UE SERVICE (Q)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
V(k)
2
9
16
23
30
Lags

Figure 4.19

Chapter 5

Vector Auto-Regression (VAR) and Sectoral Canadian Data

This chapter investigates the effects of a sectoral shock on Canadian employment using two approaches: a Classical and a Bayesian Vector Auto-Regressive (VAR).

5.1 Introduction

VAR models are dynamic models which postulate that all the variables in the system of equations are endogenous. Formally, the VAR approach writes each variable as a linear function of its own lagged values and the lagged values of all the other variables in the system, leading to a linear system of equations. The rationale for focusing on linear systems is that, since monthly and quarterly macroeconomic time series are usually well approximated by linear processes (see Brock and Sayers (1988)), non-linearity in the conditional mean is of marginal interest unless one examines higher-frequency data.

Proposed as an alternative to large structural models,[1] VAR models are useful because they answer the following questions. How does one assess the in-sample additional predictive content of one variable for another? How does one assess the in-sample effect of a typical shock on the rest of the system by using impulse response functions and variance decompositions? What are the effects of policy changes on out-of-sample unconditional and conditional forecasts? Here, the purpose of VAR modeling is to learn about the historical dynamics of the behaviour of sectoral unemployment, specifically the interaction between total employment, manufacturing employment and services employment. Another important issue is to investigate the presence of 'economic persistence'. Does a sectoral reallocation shock generate 'economic persistence' in total employment?

In this chapter, we estimate and report the results for two bivariate Classical VAR models and three (two bivariate and one trivariate) Bayesian VAR models. Each Classical VAR is identified using the Blanchard-Quah and the Bernanke-Sims identification approaches. The Blanchard-Quah identification used in this thesis is adopted from that in Blanchard and Quah (1989). It is *slightly* different to the one proposed in Blanchard and Quah (1989) and we will refer to it as the B-Q identification. The Bayesian VAR models are identified with the Bernanke-Sims method.

The two Classical VAR models are as follows. Model C-I is a bivariate VAR between the growth rate of total employment and a measure of manufacturing sectoral reallocation. Model C-II is a bivariate VAR between the growth rate of total em-

[1] See section 5.4.4 for details.

ployment and a measure of services sectoral reallocation. For the identifying schemes used here, a trivariate VAR is arduous in terms of the economic restrictions to impose on the system. The Tri-variate VAR is estimated using the Bayesian approach with different variables.

The three Bayesian VAR models are as follows. Model B-I is a bivariate VAR between total employment and manufacturing employment. Model B-II is a bivariate VAR between total employment and services employment. Finally, model T-III is a trivariate VAR that encompass all of the three employment series. For sensitivity purposes, each model is run under five different parameter specifications for a total of 15 sub-models. Note that, for model B-I, total employment is defined as all employment minus manufacturing employment. For model B-II, total employment is defined as all employment minus services employment. In other words, model B-I (B-II) investigates the dynamic relationship between manufacturing (services) employment and the rest of employment. For model T-III, total employment is defined as all employment minus both manufacturing and services employment. Model T-III examines the dynamic behaviour between manufacturing employment, services employment, and the rest of employment.

The purpose of this chapter is to understand and to report Canadian employment dynamics at the sectoral level. All results are conditional on the model specifics (i.e., assumptions and identification method). Notably, the aim is to produce data driven impulse responses for sectoral employment and most importantly to investigate the evidence (if any) for economic persistence. For the Bayesian VAR models, the 'best' model - among many specifications - based on the Theil U statistic criterion for in-sample forecasts is chosen. Once the best model is chosen, its forecast error decomposition/impulse responses are compared with the ones reported from the Classical VAR models and the RBC models (Chapter 6) and a final conclusion is drawn.

5.2 Mathematical derivations

This section presents the mathematical derivation[2] of VAR models. It draws heavily on Canova's (1995, pp. 74-79) notation.

The building block in the analysis of VAR is the Wold theorem. Using properties of Hilbert spaces, one can decompose any stochastic vector process of dimension m into the sum of two orthogonal components: one which is linearly predictable based on the information available at time $t-1$ while the other is linearly unpredictable. For this purpose, let ξ_t be the information set available at time t and note that $\xi_t = \xi_{t-1} \oplus \zeta_t$, where ξ_{t-1} is the information set available at time $t-1$, ζ_t is the space spanned by new information, and $\oplus$ indicates a direct space sum. Because ξ_{t-1} is orthogonal to ζ_t, we can write

$$y_t = P[y_t \mid \xi_t] = P\left[y_t \mid \xi_{t-1}\right] + P[y_t \mid \zeta_t] \tag{5.1}$$

where P is the linear projection operator and y_t has a zero mean. Note that the equivalence between the first two expressions comes from the fact that y_t is adapted to ξ_t. Since, at each t, ξ_t can be decomposed into the sum of two orthogonal components, one containing information available one period earlier and the other containing new

[2] For details on the mathematical derivations, see Rozanov(1967), Brockwell and Davis(1989) and Quah(1993).

information, equation (5.1) can be solved backward to obtain

$$y_t = P\left[y_t \mid \xi_{-\infty}\right] + \sum_{j=0}^{\infty} P\left[y_t \mid \zeta_{t-j}\right] \tag{5.2}$$

where the first term on the right hand side of equation (5.2) is the linearly deterministic part of y_t (the part that is predictable given the infinite past, where $\xi_{-\infty} \equiv \cap_{j=0}^{\infty}\xi_{t-j}$) and the second term is the linearly regular part. Since P is a linear operator, one can write $P\left[y_t \mid \zeta_{t-j}\right] = B_{jt}\varepsilon_{t-j} \quad (\forall j)$, where ε_{t-j} is defined by $\varepsilon_{t-j} \equiv y_{t-j} - P_{t-j}\left[y_{t-j} \mid \xi_{t-j-1}\right]$. The innovation sequence $\{\varepsilon_t\}_{t=0}^{\infty}$ is a white noise process (i.e., $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_{t-s}^T) = \Sigma_t$ if $s = 0$ and zero otherwise) and the coefficients of the projection satisfy $\sum_{j=0}^{\infty} B_{jt}^2 < \infty$ and $B_{j0} = I$ (i.e., square summable).

Usually one assumes that y_t is a zero mean process so that the linearly deterministic component of equation (5.2) is omitted. If y_t is assumed to be covariance stationary (i.e., $E(y_t y_{t-s}^T)$ depends on s but not on t) then the projections in equation (5.2) are independent of t. However, equation (5.2) holds regardless of the stationarity assumption. In general, most economic time series need a transformation to meet the covariance stationarity requirement (for example, if a unit root is present, then take the first difference). For a covariance stationary process, it is customary to rewrite equation (5.2) in an infinite moving average (∞-MA) form as

$$y_t = Dw_t + B(L)\varepsilon_t \tag{5.3}$$

where w_t is a vector including all deterministic components of the process, D is a vector of coefficients, $w_t \in \xi_{-\infty}$, $B(L) = I + B_1 L + B_2 L^2 + \ldots$, with $L\varepsilon_t \equiv \varepsilon_{t-1}$, and each B_j matrix $j = 1, 2, \ldots\infty$ is of dimension $m \times m$.

Two issues come to mind regarding equation (5.3). The first is the issue of fundamentalness and the second is the issue of renormalization. The former issue is concerned with the possibility of representing y by equation (5.3). The latter focuses on the properties of ε_t. However, a VAR must be identified before one moves to draw conclusions from its structural form. Identification of a VAR is analogous to the procedure of recovering the structural parameters from a reduced form in a simultaneous equations system. Structural innovations can be recovered using three techniques: first, a semi-automatic (SA) normalization scheme which imposes a recursive structure on the contemporaneous innovations (a Wold Causal Chain); second, by using economic restrictions such as homogeneity on real variables in the long-run; third, by imposing information delay restrictions on the long-run (cointegration) and short-run system dynamic behaviour. The first method involves the use of the Cholesky decomposition of the variance-covariance matrix of the errors Σ (described later). In this chapter, I will address the Blanchard-Quah and the Bernanke-Sims identification approaches based on economic restrictions.

In summary, to compute the impulse responses and the variance decomposition, one needs to write the VAR as an ∞-MA. A covariance stationary VAR can be written in the ∞-MA form (issue of fundamentalness). Once inverted, the errors of the ∞-MA are not orthogonal (issue of renormalization). The advantage of working with orthogonalized errors is the usefulness of examining the effects of a shock to a single variable in isolation.

5.2.1 Issue of fundamentalness

For any non-singular matrix $H(L)$ such that $H(z)$ has no poles (singularities) for $|z| \leq 1$ and satisfying $H(L)H^T(L^{-1}) = I$, where $H^T(L^{-1})$ defines the transpose (and possibly complex conjugate) of $H(L^{-1})$, there exists an infinite MA representation for y_t of the form:

$$y_t = Dw_t + \widetilde{B}(L)\widetilde{\varepsilon}_t \tag{5.4}$$

where $\widetilde{B}(L) \equiv B(L)H(L)$ and $\widetilde{\varepsilon}_t \equiv H^T(L^{-1})\varepsilon_t$. Note that $E(\widetilde{\varepsilon}_t\widetilde{\varepsilon}_t^T) = E(\varepsilon_t\varepsilon_t^T)$. Therefore, the two representations (systems (5.3) and (5.4)) are equivalent from the point of view of the autocovariance function of y_t. $H(L)$ are labelled Blaschke factors and are of the form:

$$H(L) = \prod_{r=1}^{R} k_r Q(\lambda_r, L) \tag{5.5}$$

where λ_r are the roots of $B(L)$, $|\lambda_r| \leq 1$, $k_r k_r^T = I$, and, for each r, $Q(\lambda_r, L)$ is given by.

$$Q(\lambda_r, l) = \begin{bmatrix} 1 & 0 & \ldots & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & \frac{l-\lambda_r}{1-\lambda_r^{-1}L} & \ldots & \ldots & 0 \\ 0 & 0 & \ldots & \ldots & 1 \end{bmatrix} \tag{5.6}$$

For different sets of coefficients in $B(L)$, one can produce a different MA presentation. Among the class of equivalent MA representations for y_t, it is typical to consider the one which is 'fundamental', i.e., the one for which $|B_0 E_t \varepsilon_t \varepsilon_t^T B_0|$ is maximal. Fundamental representations, also called Wold representations, are identified by the requirement that the completion of the space spanned by linear combinations of the y_t's has the same amount of information as the completion of the space spanned by linear combinations of ε_t's. Let system (5.3) be such a representation.

5.2.2 Issue of renormalization

This issue is concerned with renormalizing the system to obtain errors that are contemporaneously uncorrelated. Since the covariance matrix of the ε's is - in general - non-diagonal (i.e., correlated), it is useful to transform system (5.3) to have innovations which are contemporaneously uncorrelated. This representation is obtained by renormalizing the system and is equivalent to the system from the point of view of the autocovariance function of y_t. To obtain such a representation, let Σ be the covariance matrix of ε_t in system (5.3) and decompose Σ such that $\Sigma \equiv ZVZ^T$, where V is a diagonal matrix.[3] Therefore the system

$$y_t = Dw_t + \widehat{B}(L)\widehat{\varepsilon}_t \tag{5.7}$$

is equivalent to system (5.3) for $\widehat{B}(L) \equiv B(L)Z$ and $\widehat{\varepsilon}_t \equiv Z^{-1}\varepsilon_t$ and $V \equiv E(\widehat{\varepsilon}_t\widehat{\varepsilon}_t^T)$.

When the polynomial $B(z)$ has all its roots greater than one in modulus (this is ensured by the restrictive condition that $\{B_j\}_{j=0}^{\infty}$ is square summable,[4] i.e., $\sum_{j=0}^{\infty} B_j^2 < \infty$), it is invertible and there exists an autoregressive (AR) representation which expresses ε_t as a linear combination of current and past values of y_t as in,

$$A(L)^* y_t = F(L)w_t + \varepsilon_t \tag{5.8}$$

where $A(L)^* \equiv (B(L))^{-1}$, and $F \equiv (B(L))^{-1}D$ and $A(0)^* \equiv I$. Moving lagged terms in y's on the right hand side and grouping, we obtain a vector autoregressive (VAR)

[3] Note that $V \equiv Z^{-1}\Sigma(Z^{-1})^T$.

[4] Absolute summability ($\sum_{j=0}^{\infty} \mid B_j \mid < \infty$) is a slightly stronger condition than square summability ($\sum_{j=0}^{\infty} B_j^2 < \infty$). The usefulness of these coefficients' restrictions is the following. A square summable sequence of coefficients implies that the MA presentation of the process generates a mean square convergent random variable. Note that absolute summability implies square summability, but the reverse is not true. Absolute summability implies also that the process is ergodic for the mean. Ergodicity for the mean is satisfied whenever the time average $\overline{y}$ of a covariance stationary time series y_t converges in probability to $E(Y_t)$ as $t \to \infty$. See Hamilton (1994, pp. 46-47) for the definition.

representation

$$y_t = F(L)w_t + A(L)y_{t-1} + \varepsilon_t \tag{5.9}$$

where $A(L) \equiv [L^{-1}A(L)^*]_+$ and the notation $[.]_+$ indicates the annihilator operator (e.g., Sargent (1987, p. 452)). In general, the polynomials $F(L)$ and $A(L)$ will have finite length for any reasonable specification of the polynomial $B(L)$.

5.3 First-Order Bivariate VAR

This section presents the derivation of a first-order bivariate VAR. The purpose is to highlight the dynamics and the identification issue which is readily translated into higher order VAR models (see Enders (1995, p. 294)). For example, we show the necessary derivations for estimating the VAR using the Blanchard-Quah identification. This section explains the identification schemes used in this thesis within a first order context. Section 5.4 builds on the identification approaches presented here, using higher order lags.

Let y_{1t} and y_{2t} represent the two variables under consideration in the structural VAR. The 'first-order' label refers to the maximum number of lags present in the VAR. Formally, the two structural (primitive) equations are written as,

$$y_{1t} = b_{10} - b_{12}y_{2t} + \gamma_{11}y_{1t-1} + \gamma_{12}y_{2t-1} + \varepsilon_{y_{1t}} \tag{5.10}$$

$$y_{2t} = b_{20} - b_{21}y_{2t} + \gamma_{21}y_{1t-1} + \gamma_{22}y_{2t-1} + \varepsilon_{y_{2t}} \tag{5.11}$$

where, by assumption,[5]

$$\begin{bmatrix} \varepsilon_{y1t} \\ \varepsilon_{y2t} \end{bmatrix} \backsim \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\varepsilon_{y1t}} & 0 \\ 0 & \sigma^2_{\varepsilon_{y2t}} \end{bmatrix} \right) \tag{5.12}$$

Rewrite the system in matrix format as,

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y1t} \\ \varepsilon_{y2t} \end{bmatrix} \tag{5.13}$$

or in compact form as,

$$B \cdot y_t = \Gamma_0 + \Gamma_1 \cdot y_{t-1} + \varepsilon_t \tag{5.14}$$

Now this system is estimated using a reduced form VAR, such as,

$$y_t = B^{-1} \cdot \Gamma_0 + B^{-1} \cdot \Gamma_1 \cdot y_{t-1} + B^{-1} \cdot \varepsilon_t \tag{5.15}$$

Let $A_0 \equiv \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} \equiv B^{-1} \cdot \Gamma_0$, $A_1 \equiv \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \equiv B^{-1} \cdot \Gamma_1$, and $e_t \equiv \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \equiv B^{-1} \cdot \varepsilon_t$

$$a_1 = \frac{b_{10} + b_{12} b_{20}}{1 - b_{12} b_{21}} \tag{5.16}$$

$$a_{11} = \frac{\gamma_{11}}{1 - b_{12} b_{21}} \tag{5.17}$$

$$a_{12} = \frac{b_{12} \gamma_{22}}{1 - b_{12} b_{21}} \tag{5.18}$$

$$a_2 = \frac{b_{20} + b_{21} b_{10}}{1 - b_{12} b_{21}} \tag{5.19}$$

$$a_{21} = \frac{b_{21} \gamma_{11}}{1 - b_{12} b_{21}} \tag{5.20}$$

$$a_{22} = \frac{\gamma_{22}}{1 - b_{12} b_{21}} \tag{5.21}$$

Rewrite the reduced form system in a compact from, such as,

$$y_t = A_0 + A_1 \cdot y_{t-1} + e_t \tag{5.22}$$

[5] See the discussion after equation (5.56).

The $\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$ are serially uncorrelated and each is with a constant variance. The relationship between the residuals of the reduced form and the residuals from the structural form is summarized as follows,

$$e_{1t} = \frac{\varepsilon_{y_{1t}} - b_{12}\varepsilon_{y_{2t}}}{1 - b_{12}b_{21}} \tag{5.23}$$

$$e_{2t} = \frac{\varepsilon_{y_{2t}} - b_{21}\varepsilon_{y_{1t}}}{1 - b_{12}b_{21}} \tag{5.24}$$

Therefore, $E(e_{1t}) = 0$ and $E(e_{2t}) = 0$. Also,

$$Ee_{1t}e_{1t-i} = \frac{E\left[\left(\varepsilon_{y_{1t}} - b_{12}\varepsilon_{y_{2t}}\right)\left(\varepsilon_{y_{1t-i}} - b_{12}\varepsilon_{y_{2t-i}}\right)\right]}{(1 - b_{12}b_{21})^2} = 0 \qquad (i \neq 0) \quad \text{(5.25a)}$$

$$Ee_{2t}e_{2t-i} = \frac{E\left[\left(\varepsilon_{y_{2t}} - b_{21}\varepsilon_{y_{1t}}\right)\left(\varepsilon_{y_{2t-i}} - b_{21}\varepsilon_{y_{1t-i}}\right)\right]}{(1 - b_{12}b_{21})^2} = 0 \qquad (i \neq 0) \quad \text{(5.25b)}$$

$$E(e_{1t}^2) = \frac{\sigma_{y_{1t}}^2 + b_{12}^2\sigma_{y_{2t}}^2}{(1 - b_{12}b_{21})^2} \quad \text{(5.26a)}$$

$$E(e_{2t}^2) = \frac{\sigma_{y_{2t}}^2 + b_{21}^2\sigma_{y_{1t}}^2}{(1 - b_{12}b_{21})^2} \quad \text{(5.26b)}$$

Equations (5.25) show that the errors are serially uncorrelated.[6] The two equations (5.26) imply that the variances of the reduced form residuals are time-independent. The contemporaneous relationship between the reduced form residuals is,

$$E(e_{1t}e_{2t}) = \frac{E\left[\left(\varepsilon_{y_{1t}} - b_{12}\varepsilon_{y_{2t}}\right)\left(\varepsilon_{y_{2t}} - b_{21}\varepsilon_{y_{1t}}\right)\right]}{(1 - b_{12}b_{21})^2} = -\frac{\left(b_{21}\sigma_{y_{1t}}^2 + b_{12}\sigma_{y_{2t}}^2\right)}{(1 - b_{12}b_{21})^2} \tag{5.27}$$

Let D denote the variance-covariance matrix of the reduced form residuals.

$$D \equiv \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \tag{5.28}$$

[6] The equations are showing the autocovariances.

Due to the feedback inherent in the system, the structural system of the equations can not be estimated directly. The reason is that y_{1t} is correlated with $\varepsilon_{y_{2t}}$ and y_{2t} is correlated with $\varepsilon_{y_{1t}}$. Therefore, standard estimation techniques will yield inefficient parameters. At best, one can estimate 9 parameters from the reduced form VAR. These parameters are: $a_{10}, a_{20}, a_{11}, a_{12}, a_{21}, a_{22}, \sigma_{e_1}, \sigma_{e_2}$ and $\sigma_{e_1e_2}$. The problem is that there are 10 structural form parameters and they are non-linear functions of the reduced form parameters. These parameters are: $b_{10}, b_{20}, \gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22}, b_{12}, b_{21}, \sigma_{y_{1t}}$ and $\sigma_{y_{2t}}$.

The issue of identification is whether one can recover all the information present in the structural system. In our setup, if there are no restrictions on the structural parameters, then the system is underidentified. If there is only 1 restriction, then the system is just identified. Finally, if there are more than one restrictions then the system is overidentified.

5.3.1 Cholesky Identification

One way to identify the model is to use the Cholesky identification which relies on setting $b_{21} = 0$. This implies that y_{1t} has no contemporaneous effect on y_{2t}. The structural shocks $\varepsilon_{y_{1t}}$ and $\varepsilon_{y_{2t}}$ affect y_{1t}, but $\varepsilon_{y_{2t}}$ affects only y_{2t}. $\varepsilon_{y_{1t}}$ has no direct effect on y_{2t}. $\varepsilon_{y_{1t}}$ has an indirect effect on y_{2t} in the sense that within the second equation, the lagged values of y_{1t} affect the contemporaneous value of y_{2t}. The key issue of Cholesky is the imposed asymmetry on the structural system, which implies an ordering of the variables. When $b_{21} = 0$, it is implied that y_{2t} is a 'prior'[7] to y_{1t}.

[7] In a general, non-Bayesian sense.

In this setup,

$$Var(e_{1t}) = \sigma^2_{y_{1t}} + b_{12}^2\sigma^2_{y_{2t}} \quad (5.29)$$

$$Var(e_{2t}) = \sigma^2_{y_{2t}} \quad (5.30)$$

$$Cov(e_{1t}, e_{2t}) = -b_{12}\sigma^2_{y_{2t}} \quad (5.31)$$

$e_{1t} = \varepsilon_{y_{1t}} - b_{12}\varepsilon_{y_{2t}}$ and $e_{2t} = \varepsilon_{y_{2t}}$. The observed residuals from the second equation are the estimates of the $\{\varepsilon_{y_{2t}}\}$ sequence. The observed values for e_{2t} are completely attributed to 'pure' shocks to the $\{y_{2t}\}$ sequence. This decomposition of the model into a triangular form is called the Cholesky decomposition (see Sims (1980)). The Cholesky decomposition provides a minimal set of assumptions that can be used to identify the primitive model in the spirit of Sims' argument against the "incredible identifying restrictions".

Note that under the assumption that $\sigma^2_{y_{1t}} = \sigma^2_{y_{2t}}$, the residuals $e_{1t} = \varepsilon_{y_{1t}} + \rho(e_{1t}, e_{2t})\varepsilon_{y_{2t}}$ and $e_{2t} = \varepsilon_{y_{2t}}$ imply an ordering of the variables. In this identification scheme, the importance of ordering depends on the value of $\rho(e_{1t}, e_{2t})$. As a rule of thumb (Enders (1995, p. 309)), if $|\ \rho(e_{1t}, e_{2t})\ | \leq 0.2$ then ordering is immaterial. However, if $|\ \rho(e_{1t}, e_{2t})\ | > 0.2$, then ordering is significantly important. In the latter case, one compares the results of the impulse response functions under different ordering specifications. If the results are quite different in their implications then additional investigation into the relationship between the variables in the VAR is necessary.

In this context of a first order two variables VAR system, the impulse response function of the reduced form is based on the moving average (∞-MA) representation of the system,

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \overline{y_{1t}} \\ \overline{y_{2t}} \end{bmatrix} + \sum_{k=0}^{\infty} \begin{bmatrix} c_{11}(k) & c_{12}(k) \\ c_{21}(k) & c_{22}(k) \end{bmatrix} \begin{bmatrix} \varepsilon_{y_{1t-k}} \\ \varepsilon_{y_{2t-k}} \end{bmatrix} \tag{5.32}$$

$$C_k \equiv \begin{bmatrix} c_{11}(k) & c_{12}(k) \\ c_{21}(k) & c_{22}(k) \end{bmatrix} \equiv \frac{\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^k \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}}{1 - b_{12}b_{21}} \tag{5.33}$$

where $c_{ij}(k)$ denotes the elements of C_k. Plotting $c_{ij}(k)$ against k represents the impulse response function. $c_{ij}(0)$ are the impact multipliers. For example, $c_{12}(0)$ is the instantaneous impact of a one-unit change in $\varepsilon_{y_{2t}}$ on y_{1t}. $c_{11}(1)$ and $c_{12}(1)$ are the one period responses to a change in $\varepsilon_{y_{1t-1}}$ and $\varepsilon_{y_{2t-1}}$, respectively on y_{1t}. The $\sum_{k=0}^{n} c_{12}(k)$ is the cumulated effect after n periods of $\varepsilon_{y_{2t}}$ on y_{1t}. If one lets $n \to \infty$, then $\sum_{k=0}^{\infty} c_{12}(k)$ is the long-run multiplier.

When the number of variables n in the system is higher then 2, it is often not practical to try $n!$ ordering alternatives. In general, it is rare to find all variables with low residual correlations in the system. After all, the variables in the VAR were selected on the basis of a priori comovement. In the case where there are many variables in the system with high residual correlations, an alternative identification is recommended. In our case, we will explore both the Blanchard-Quah and the Bernanke-Sims decompositions.

5.3.2 The Blanchard and Quah Identification

Blanchard and Quah (1989) proposed an identifying assumption based on a long-run economic description of the VAR system. In this setup, both variables must be in stationary form. Re-write the system in its infinite Moving Average (∞-MA) notation as,

$$y_{1t} = \sum_{k=0}^{\infty} c_{11}(k)\, \varepsilon_{y_{1t-k}} + \sum_{k=0}^{\infty} c_{12}(k)\, \varepsilon_{y_{2t-k}} \tag{5.34}$$

$$y_{2t} = \sum_{k=0}^{\infty} c_{21}(k)\, \varepsilon_{y_{1t-k}} + \sum_{k=0}^{\infty} c_{22}(k)\, \varepsilon_{y_{2t-k}} \tag{5.35}$$

or equivalently in its compact matrix form,

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{12}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{y_{1t}} \\ \varepsilon_{y_{2t}} \end{bmatrix} \tag{5.36}$$

where $\begin{bmatrix} \varepsilon_{y_{1t}} \\ \varepsilon_{y_{2t}} \end{bmatrix}$ ~independent White Noise with $\Sigma_\varepsilon \equiv \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

$C_{ij}(L)$ are polynomials in the lag operator L such that the individual coefficients of $C_{ij}(L)$ are denoted by $c_{ij}(k)$. For example,[8] the second coefficient of $C_{21}(L)$ is $c_{21}(2)$. The coefficients of $C_{11}(L)$ represent the impulse responses of a $\varepsilon_{y_{1t}}$ shock on y_{1t}. For convenience, the shocks' variances are normalized to 1. $E(\varepsilon_{y_{1t}}, \varepsilon_{y_{2t}}) = 0$ implies that both structural shocks are uncorrelated. The key underlying argument is that one assumes that $\varepsilon_{y_{1t}}$ is the portion of the (economic) shock that does not change (orthogonal to) in response to a change in $\varepsilon_{y_{2t}}$, and vice versa. Since $E(\varepsilon_{y_{1t}}, \varepsilon_{y_{2t}}) = 0$, one interprets $\varepsilon_{y_{2t}}$ as a shock (or the portion of a shock) that is unaffected by a total

[8] In general, $C_{11}(L) = c_{11}(0) + c_{11}(1)L + c_{11}(2)L^2 + \ldots$

employment shock, i.e., 'pure' sectoral shock. For a similar discussion, see Blanchard and Quah (1989, p. 671).

Since y_t is stationary, neither shock has a long-run effect on y_t. Also, assuming that $\varepsilon_{y_{2t}}$ has no effect on the long-run *level* of y_{1t} amounts to setting $\sum_{k=0}^{\infty} c_{12}(k) = 0$.

In Blanchard and Quah (1989, p. 657), y_{1t} and y_{2t} referred to the growth rate of GNP and the unemployment rate, respectively. $\varepsilon_{y_{1t}}$ and $\varepsilon_{y_{2t}}$ denoted aggregate demand and aggregate supply shocks, respectively. They assumed that aggregate demand shocks have no long-run effect on the *level* of GNP. Formally, they set $\sum_{k=0}^{\infty} c_{11}(k) = 0$. A similar restriction was used by Schmidt-Grohé (2001, p. 1147) and by Davis and Haltiwanger (1999, p. 1244) wherein it was labeled as the 'Neutrality Restriction'.

In our study for the Classical VAR, y_{1t} and y_{2t} refer to the following notation:

	First Variable: Total Employment	Second Variable: Sector Employment
Model C-I	$y_{1t} \equiv$ EMP T	$y_{2t} \equiv$ EMP M/T
Model C-II	$y_{1t} \equiv$ EMP T	$y_{2t} \equiv$ EMP S/T

For our analysis, y_{1t} refers to employment growth. Employment is defined as total employment. Also, we estimated the same models (C-I and C-II) using another definition of total employment, namely wherein total employment is defined as the rest of employment. The results were similar in terms of economic persistence. However, the initial effect of a sectoral shock is different. To investigate the Blanchard-Quah identification scheme, we were inclined to use total employment rather than the rest of employment for the long-run restriction to be meaningful. y_{2t} refer to the log of the square of the growth of employment share in a given sector.

Formally, $y_{2t} = \ln[(s_t - s_{t-1})/s_{t-1}]^2 = 2\ln[|s_t - s_{t-1}|/s_{t-1}]$, where s_t denotes the share of sectoral employment. We consider y_{2t} as a proxy for employment sectoral reallocation. As labour is reallocated across sectors, a decrease in the share of employment in one sector implies an increase in the share of employment of other sectors. y_{2t} is computed as $2\ln[|s_t - s_{t-1}|/s_{t-1}]$. We bound $|s_t - s_{t-1}|$ from below by 10^{-8} to avoid instances of constant employment share. This functional form is arbitrary. We tried different variables transformation and similar results were concluded, e.g., $y_{2t} = \ln[(s_t - s_{t-1})^2/s_{t-1}]$, $y_{2t} = (s_t - s_{t-1})/s_{t-1}$ and $y_{2t} = s_t$.

For all Classical VAR models, total employment ($y_{1t} \equiv$ EMP T) refers to the growth rate of total employment computed as the difference in logs. In model C-I, $y_{2t} \equiv$ EMP M/T, refers to the square of the growth rate of the fraction of manufacturing employment relative to total employment. y_{2t} is meant to capture manufacturing reallocation shocks. In model C-II, $y_{2t} \equiv$ EMP S/T, refers to the square of the growth rate of the fraction of service employment relative to total employment. Here, y_{2t} is meant to capture service reallocation shocks. Note that y_{2t} treats percentage decreases in the sector's employment share symmetrically with increases. This is a reasonable first approximation. For example, Campbell and Fisher (2000, p. 1329) argued that using a symmetric per-job adjustment costs, yields reasonable results in their simulations. In Chapter 6, we symmetrically treat increases and decreases in the sector's share of employment.

All series are the annualized growth rates of quarterly data. Model C-I refers to a bivariate VAR in EMP T and EMP M/T. Model C-II refers to a bivariate VAR in

EMP T and EMP S/T.

To explain the usefulness of the square term, note the bivariate first-order VAR outlined in section 5.3.

$$y_{1t} = b_{10} - b_{12}y_{2t} + \gamma_{11}y_{1t-1} + \gamma_{12}y_{2t-1} + \varepsilon_{y_{1t}} \quad (5.37)$$

$$y_{2t} = b_{20} - b_{21}y_{2t} + \gamma_{21}y_{1t-1} + \gamma_{22}y_{2t-1} + \varepsilon_{y_{2t}} \quad (5.38)$$

Reallocation of labour in response to a 'pure' sectoral shock occurs whenever manufacturing's share in total employment either increases or decreases. By squaring the growth rate of s_t, it is implicitly assumed (at least as an approximation) that increases and decreases in s_t have symmetric effects on employment. That is, the adjustment cost of moving employment into manufacturing is roughly the same as the adjustment cost of moving labour out of manufacturing and into another sector.

$\varepsilon_{y_{1t}}$ and $\varepsilon_{y_{2t}}$ denote 'aggregate' and 'pure' sectoral shocks, respectively. $\sum_{k=0}^{\infty} c_{12}(k) = 0$ is equivalent to assuming that 'pure' sectoral shocks have no long-run effect on the level of total employment. A 'pure' sectoral shock - when combined with labour adjustment costs in terms of moving workers across sectors - redistributes employment across sectors and does not affect the total employment level in the long-run.

Since the total employment and the 'pure' sectoral shocks are not observed, the issue is to recover them from the VAR estimation. The reduced form of the VAR is

$$y_t = A(L)y_{t-1} + e_t \quad (5.39)$$

where $A(L)$ is a 2x2 matrix with elements equal to the polynomials $A_{ij}(L)$ with coefficients denoted by $a_{ij}(k)$. e_{1t} is the one-step ahead forecast error for y_{1t}, i.e.,

$e_{1t} = y_{1t} - E_{t-1}y_{1t}$. From the ∞-MA representation, the one-step ahead forecast error for y_{1t} is $c_{11}(0)\varepsilon_{y_{1t}} + c_{12}(0)\varepsilon_{y_{2t}}$. Therefore,

$$e_{1t} = c_{11}(0)\varepsilon_{y_{1t}} + c_{12}(0)\varepsilon_{y_{2t}} \tag{5.40}$$

and similarly for y_{2t}. In compact form,

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} c_{11}(0) & c_{12}(0) \\ c_{21}(0) & c_{22}(0) \end{bmatrix} \begin{bmatrix} \varepsilon_{y_{1t}} \\ \varepsilon_{y_{2t}} \end{bmatrix} \tag{5.41}$$

If the coefficients $c_{ij}(0)$ were known, it would be possible to recover $\varepsilon_{y_{1t}}$ and $\varepsilon_{y_{2t}}$ from the regression residuals e_{1t} and e_{2t}.

Blanchard and Quah (1989) showed that using (5.41) and the long-run restriction $(\sum_{k=0}^{\infty} c_{11}(k)\varepsilon_{y_{1t-k}} = 0)$, there are four restrictions to be used to exactly identify the four $c_{ij}(0)$ coefficients. The four restrictions are,

$$\begin{aligned} Var(e_1) &= c_{11}(0)^2 + c_{12}(0)^2 && (5.42a) \\ Var(e_2) &= c_{21}(0)^2 + c_{22}(0)^2 && (5.42b) \\ E(e_1e_2) &= c_{11}(0)c_{21}(0) + c_{12}(0)c_{22}(0) && (5.42c) \\ \sum_{k=0}^{\infty} c_{11}(k)\varepsilon_{y_{1t-k}} &= 0 && (5.42d) \end{aligned}$$

The system (5.42) is four equations in four $c_{ij}(0)$ unknowns. Therefore, one can recover the coefficients and exactly identify the VAR.

For our analysis here, the fourth restriction is replaced by $\sum_{k=0}^{\infty} c_{12}(k)\varepsilon_{y_{2t-k}} = 0$. To transform this restriction into its VAR representation, the following algebraic derivation must be carried. First, rewrite the VAR as,

$$y_t = A(L)Ly_t + e_t \tag{5.43}$$

Next, some transformations are necessary,

$$[I - A(L)L]\, y_t = e_t \tag{5.44}$$

$$y_t = [I - A(L)L]^{-1}\, e_t \tag{5.45}$$

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \frac{\begin{bmatrix} 1 - A_{22}(L)L & A_{12}(L)L \\ A_{21}(L)L & 1 - A_{11}(L)L \end{bmatrix}}{\mid I - A(L)L \mid} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5.46}$$

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \frac{\begin{bmatrix} 1 - \sum_{k=0}^{\infty} a_{22}(k)L^{k+1} & \sum_{k=0}^{\infty} a_{12}(k)L^{k+1} \\ \sum_{k=0}^{\infty} a_{21}(k)L^{k+1} & 1 - \sum_{k=0}^{\infty} a_{11}(k)L^{k+1} \end{bmatrix}}{\mid I - A(L)L \mid} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5.47}$$

$$y_{1t} = \frac{\left(1 - \sum_{k=0}^{\infty} a_{22}(k)L^{k+1}\right) e_{1t} + \left(\sum_{k=0}^{\infty} a_{12}(k)L^{k+1}\right) e_{2t}}{\mid I - A(L)L \mid} \tag{5.48}$$

$$y_{1t} = \frac{\begin{bmatrix} \left(1 - \sum_{k=0}^{\infty} a_{22}(k)L^{k+1}\right) \left(c_{11}(0)\varepsilon_{y_{1t}} + c_{12}(0)\varepsilon_{y_{2t}}\right) \\ + \left(\sum_{k=0}^{\infty} a_{12}(k)L^{k+1}\right) \left(c_{21}(0)\varepsilon_{y_{1t}} + c_{22}(0)\varepsilon_{y_{2t}}\right) \end{bmatrix}}{\mid I - A(L)L \mid} \tag{5.49}$$

Making the assumption that $\varepsilon_{y_{2t}}$ has no long-run effect on the log level of employment implies,

$$0 = \left(1 - \sum_{k=0}^{\infty} a_{22}(k)L^{k+1}\right) c_{12}(0)\varepsilon_{y_{2t}} + \left(\sum_{k=0}^{\infty} a_{12}(k)L^{k+1}\right) c_{22}(0)\varepsilon_{y_{2t}} \tag{5.50}$$

Setting the long-run restriction $\sum_{k=0}^{\infty} c_{12}(k)\varepsilon_{y_{2t-k}}$ equals 0, yields

$$0 = \left(1 - \sum_{k=0}^{\infty} a_{22}(k)\right) c_{12}(0) + \left(\sum_{k=0}^{\infty} a_{12}(k)\right) c_{22}(0) \tag{5.51}$$

The last equation presents the fourth restriction needed for our identification. Equations (5.42a), (5.42b), (5.42c) and (5.51) are four equations in four unknowns used to identify the coefficients $c_{11}(0)$, $c_{12}(0)$, $c_{21}(0)$ and $c_{22}(0)$.

The method proceeds by estimating the reduced VAR, then computing the variance-covariance matrix of the residuals. Once computed, one calculates the sums $\sum_{k=0}^{p} a_{22}(k)$ and $\sum_{k=0}^{p} a_{12}(k)$ then proceed to compute the $c_{ij}(0)$ coefficients. Using these coefficients and the VAR residuals (e_{1t}, e_{2t}), one can identify the entire sequences of $\varepsilon_{y_{1t-k}}$ and $\varepsilon_{y_{2t-k}}$,

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} c_{11}(0) & c_{12}(0) \\ c_{21}(0) & c_{22}(0) \end{bmatrix} \begin{bmatrix} \varepsilon_{y_{1t}} \\ \varepsilon_{y_{2t}} \end{bmatrix} \tag{5.52}$$

Finally, proceed with impulse response function analysis. For the Bayesian approach to the Blanchard-Quah identification see Koop (1992, p. 409). Applying the Blanchard-Quah technique to the Bayesian VAR models proposed here is beyond the scope of my focus in this thesis. In my view, the Classical approach provides fertile ground for imposing economic restrictions on the VAR system. As proposed in section 5.4.4, the Bayesian VAR is used to highlight empirical regularities. Our aim is to understand the dynamics of sectoral reallocation in the Canadian data.

5.4 Structural / Reduced Form Models and Identification

Based on information criteria for lag selection, a first order VAR is rarely chosen for estimation. This section expands the first-order bivariate VAR system presented in section 5.3 to a higher order bivariate VAR. Using matrix notation, this section presents and explains the restrictions imposed on the variance-covariance matrix of the reduced form estimates of the residuals under different identification schemes in higher order VAR. Let the structural (primitive) VAR be,

$$By_t = \Gamma_0 + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{5.53}$$

and the reduced form VAR be,

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t \tag{5.54}$$

with

$$\varepsilon_t \sim (0, \Sigma) \qquad \text{and} \qquad e_t \sim (0, D) \tag{5.55}$$

where

$$\Sigma \equiv \begin{bmatrix} \sigma^2_{\varepsilon_1} & 0 \\ 0 & \sigma^2_{\varepsilon_2} \end{bmatrix} \qquad \text{and} \qquad D \equiv \begin{bmatrix} \sigma^2_{e_1} & \sigma_{e_1 e_2} \\ \sigma_{e_2 e_1} & \sigma^2_{e_2} \end{bmatrix} \tag{5.56}$$

The assumption that the covariance of structural shocks is zero, implies that we are treating these shocks as 'pure' structural shocks (Enders (1995, p. 325)). We assume that the structural shocks are uncorrelated at all leads and lags. The same assumption was made by Blanchard and Quah (1989, p. 659). Similarly, the assumption that the two disturbances are uncorrelated does not restrict the channels through which 'pure' structural shocks affect y_t. We refer to 'pure sectoral' shock as the component of the shock that is orthogonal to the 'pure aggregate' shock. This is similar to Schmidt-Grohé (2001, p. 1147). This interpretation is reasonable and useful in understanding the dynamics of sectoral reallocation shocks.

Starting with the reduced form VAR , the innovations of the reduced form can be written in terms of uncorrelated structural error terms,

$$e_t = Ge_t + \varepsilon_t \tag{5.57}$$

where G is a matrix with zeros on the diagonal. Let $B = I - G$ and $A = B^{-1}$. Therefore, the relationship between D and Σ can be presented as follows. $\Sigma = BDB^T$ and $D = A\Sigma A^T$.

5.4.1 The Cholesky approach

Using the Cholesky decomposition of symmetric positive semi-definite matrices, one decomposes D into PP^T, where P is a lower triangular matrix. $P = B^{-1}\Sigma^{1/2}$. Therefore, $D = B^{-1}\Sigma\,(B^{-1})^T$ and $B = \left(P\left(\Sigma^{1/2}\right)^{-1}\right)^{-1}$.

5.4.2 The Blanchard-Quah approach

One decomposes D into PP^T, where $P = C(1)^{-1}G$. Here, $C(1)$ is the long-run multiplier sum of the ∞-MA coefficients. G is the lower Cholesky decomposition of $C(1)D(C(1))^T$. In this setup, $B = P^{-1}$ and Σ is the identity matrix. Here, we assume that the 'pure' sectoral shock has no long-run effect on the level of the aggregate variable. A 'pure' sectoral shock has short-run effects on the level of employment because of the adjustment costs of moving labour across sectors, but the level of the long-run employment is unaffected.

5.4.3 The Bernanke-Sims approach

One decomposes D into $B^{-1}\Sigma(B^{-1})^T$. In this setup, one chooses - based on economic theory - to set certain non-diagonal elements of B equal to zero. For example, if one assumes that no contemporaneous relationship between the two variables exists, then B collapses to the identity matrix. In this case, one expects the relationship between the two variables to take effect with a delay of at least one period. For sensitivity analysis regarding the identification scheme, we assume that a 'pure' sectoral shock does not effect the 'aggregate' variable instantaneously. We also assume that an 'aggregate' shock does not effect the 'sectoral' variable instantaneously and we test for over-identification. We adopt the Bernanke-Sims identification as an approach to emphasis sensitivity analysis regarding the Blanchard-Quah identification.

5.4.4 Identification and Reality

A model is identifiable if all its possible structures are identifiable, i.e., each structure is associated with a different distribution. A simple dynamic multi-equation provides a statistical distribution for the variables involved. The problem is that many (unknown) models could have been the true data generating process of these variables of interest. To understand the purpose and the development of identification, we present the traditional 'Cowles Commission', the LSE and the VAR approaches to identification.

The traditional approach to macroeconometric modelling - referred to as the 'Cowles Commission' approach - aims at the quantitative evaluation of the impact of changes in the exogenous variables in the system on the endogenous ones. Policy-controlled variables are considered as exogenous while final goals variables are portrayed as endogenous. The policy experiment consists of assessing the impact on final goal variables by modifying the exogenous ones. Identification in these models is achieved by imposing coefficient restrictions (e.g., zero value for the coefficient) on the structural equation to ensure that the rank condition is satisfied. In this approach, the inclusion of exogenous variables increases the chances for the model to be identified. Three stages are upheld in this tradition: 1) specification and identification of the theoretical model, 2) estimation of the relevant parameters and 3) simulation of the effects of exogenous variables on the final goal ones. Note that the identified structure is estimated without testing if the implied probability structure of the model properly describe the data.

The traditional approach broke down in the 1970s after the well-known critiques of Lucas (1976) and Sims (1980). Lucas' critique emphasized that the coefficients of the structural equations that describe the impact of a policy, depend on the policy regime under which they were estimated. No model estimated under a specific regime can be used to assess a different policy regime. Given that many parameters are expectations-dependent, it is natural that a model based on optimizing agents is a better framework for policy evaluation. Note that deep parameters (i.e., expectations-independent parameters such as taste and technology) are estimated by traditional econometric methods. Lucas' critique pointed out that the traditional 'Cowles Commission' approach do not take explicit account for expectations, so that these models are unstable across different policy regimes.

Sims' critique paralleled that of Lucas's. Sims focused on the ad hoc exogeneity of some variables in the traditional model to achieve identification. In a forward-looking world, agents' behaviour depends on the solution of an intertemporal optimization problem and therefore, no variable is exogenous. By incorrectly assuming exogeneity, these models induce spurious effects.

The LSE approach was developed by Denis Sargan[9] and advocated by his students,[10] e.g., David Hendry (1995). Based on the theory of reduction (i.e., simplification process), the LSE approach evolved to correct the failures of the traditional approach. It interprets the econometric model as a simplified representation of the unobserved data generating process (DGP). For the representation to be 'congruent[11] ' the information lost in the specification process must be irrelevant to the problem at hand, e.g., omission of relevant variables. One can test the model adequacy by analysing the reduced form. The approach here reverses the one used in the traditional case (see Spanos (1990, p. 90)). In the traditional case, the statistical baseline model describes structural relationships and the reduced form is then derived. Here, one starts by specifying and identifying a general reduced form model. The reduced form model should be sufficiently general to produce a congruent representation of the underlying unknown DGP. The LSE approach emphasizes the lack of validation of the reduced form that existed within the traditional approach. This lack of validation is interpreted as a lack of credibility in the structural model estimates. The system is

[9] Denis Sargan (1924-1996) was a leading British econometrician. He played a central role in establishing a basis for modern time series econometrics. For a biographical history of Denis Sargan's career and review of his contribution to econometrics, see Ericsson, Maasoumi and Mizon (2001).
[10] For the list of Sargan's students, see Ericsson, Maasoumi and Mizon (2001, Table 2, p. 20).
[11] 'Congruent' is used here as in Hendry's terminology to mean 'valid'.

validated by applying an extensive number of tests. The absence of mis-specification symptoms are viewed as success, e.g., in rejecting residuals non-normality and autocorrelation. A series of diagnostic tests are undertaken to verify the congruency of the baseline model. The general criterion for assessment is that congruent models should feature true random residuals. Any departure from this criterion is viewed as a sign of mis-specification. Once the baseline is validated, one reduces the dimensionality of the reduced form by eliminating the equations for those variables for which the null hypothesis of exogeneity is not rejected. Another stage in the simplification process is to impose rank reduction restrictions based on cointegration vectors (see the Blanchard-Quah identification in the previous section). The final product of this simplification process is a statistical model for the data and a structural model that is identified and estimated. Finally, the structural model is used to perform forecasting and policy evaluation. In this thesis, we use the LSE approach to discover the dynamic relationships between a sectoral reallocation shock and total employment. The long-run structure is discussed in relation to the Blanchard-Quah identification.

Sims' critique led to the development and estimation of VAR models. The VAR approach to modelling rejects the Cowles Commission identifying restrictions as 'incredible' for reasons similar to the LSE approach. However, the VAR approach focus on and try to answer a different question from the one proposed within the LSE approach. This approach emphasizes a new role for empirical analysis, that is to provide stylized evidence to include in the theoretical model adopted for policy analysis.

Using a VAR approach, the estimates provide empirical evidence on the response of macroeconomic variables to impulses in order to discriminate between alternative theoretical models of the economy.[12] Briefly, using theory-free restrictions and taking into account the potential endogeneity of the variables in the system, VAR models concentrate on shocks, and provide a theory-independent dynamics that serve as criteria for general equilibrium model evaluation (see Favero (2001, p. 266)). Corroboration of the theoretical general equilibrium model is achieved when the responses of variables to shocks in the theoretical model match the stylised facts derived from the empirical VAR.

To conform with Sims' methodology, we estimate the Bayesian VAR models in levels. We assume that the variables are non-stationary and center the prior of each own lag variable around the value 1. A *priori*, one suspects that the level variables - total and setoral employment - are cointegrated. Such a relation is examined within the Classical VAR combined with the Blanchard-Quah identification. In this identification, the long-run behaviour of sectoral reallocation shocks provide acceptable restrictions to be compared to our Real Business Cycle models of Chapter 6. The long-run restriction of zero impact on total employment is stated in terms of a cointegration relationship and in terms of the cumulative impulse response function. The Cholesky decomposition is another identification approach that depends on the ordering of variables. It is a recursive economic structure.

However, imposing the wrong cointegrating restrictions on the system leads to the inconsistency of the estimates. Sims, Stock and Watson (1990) argued that a VAR

[12]For example, Christiano, Eichenbaum and Evans (1996a, 1996b) applied the VAR approach to derive a set of 'stylised facts' on the effect of a contractionary policy shock and concluded that plausible models should be consistent with their findings. The point here is that, their findings or rather their 'stylised facts' are solely qualitative in nature and rely primarily on the implied behaviour of the variables by impulse responses function, e.g., the aggregate price level initially responds very little to the monetary shock.

in levels in the presence of cointegration is over-parametrized. This characteristic implies that the estimates of the parameters of interest are inefficient, but consistent. One has to weight the risk of inefficiency against inconsistency. We choose to explore both. Assuming that the imposed cointegration relationship on the Classical VAR is wrong - as shown by the Blanchard-Quah identification - the models will exhibit inconsistency. However, the Bayesian VAR models in levels will exhibit inefficiency.

Impulse response functions are used to make statements about structural systems. To make such statements, one needs an identification scheme. There is no known method to mechanically choose the identification scheme. However, it is always reasonable to use an identification that represents one's understanding of the relationship.

Hamilton (1994, pp. 335-336) emphasized that "Even so, it must be recognized that convincing identifying assumptions are hard to come by. For example, the ordering ... is clearly somewhat arbitrary, and the exclusion restrictions are difficult to defend. Indeed, if there were compelling identifying assumptions for such a system, the fierce debates among macroeconomists would have been settled long ago! Simultaneous equations bias is very pervasive in the social sciences, and drawing structural inferences from observed correlations must always proceed with great care. We surely cannot always expect to find credible identifying assumptions to enable us to identify the causal relations among any arbitrary set of n variables on which we have data."

The LSE and VAR approaches would reject the 'Cowles Commission' identifying restrictions as 'incredible' (See Favero (2001, p. 164)). Here, we investigate both these approaches. Prior to undertaking identification, we tested for Granger-causality[13] between y_{1t} and y_{2t}. Briefly, the test investigates whether the lags of one variable enter into the equation for another variable. y_{1t} does not Granger cause y_{2t} if and only if all the coefficients of $A_{21}(L)$ in equation (5.54) are equal zero. Thus if y_{1t} does not improve the forecasting performance of y_{2t}, then y_{1t} does not Granger cause y_{2t}. Note that this test is a weaker condition than the condition for exogeneity wherein the current and past values of y_{1t} do not affect y_{2t}. For the details of the test, see Enders (1995, pp. 315-316) and the Appendix of this chapter. The following table reports the results of the Granger causality tests,

Null Hypothesis	**P-value**
EMP T does not Granger-cause EMP M/T	0.0395
EMP M/T does not Granger-cause EMP T	0.9240
EMP T does not Granger-cause EMP S/T	0.1289
EMP S/T does not Granger-cause EMP T	0.7222

At the 5 percent significance level, the test result rejects the null; EMP T does not Granger-cause EMP M/T. If one attempts to identify the VAR using a Cholesky scheme, then EMP T should be ordered first. Our other tests do not reject the null at the 5 percent significance level. Here, we interpret Granger-causality as a statement regarding the importance of a variable in forecasting another variable. Given the result that EMP T does not Granger-cause EMP S/T, we attempt to pursue the VAR estimation of model C-II so as to investigate the 'economic persistence' effect only as illustrated by the impulse responses.

We computed the Granger-causality test statistic for different lags. As expected, the results of the test proved to be sensitive to the lag length of the VAR model. See

[13]The Granger-causality test is outlined in the Appendix of this chapter.

Hamilton (1994, p. 305) for the discussion relating the lag length to the Granger-causality test statistic. We found that the shorter the lag, the higher was the p-value. Consequently, we reject the test and conclude that there is evidence of causality. However, one conclusion can be drawn from the lag sensitivity issue: sectoral reallocation variables do reject the null - of not Granger-causing EMP T - under any lag length. This is strong evidence of the importance of sectoral reallocation variables in forecasting EMP T. Finally, to assess the relative merits of the chosen lag length in the VAR, we tested both VAR models for lag exclusions. The results of the lag exclusion tests are discussed in subsection 5.6.1 and reported in Tables 5.2 and 5.7 for models C-I and C-II, respectively.

In the following, we advance the arguments for the choice of the Blanchard-Quah and Bernanke-Sims identification schemes. We view shocks affecting y_{1t} as 'aggregate' shocks that impinge directly on employment growth. However, these shocks can also indirectly influence y_{2t}. For example, an inflow into the labour force will increase total employment in the first instance. This inflow of new workers will feed into the sectoral labour markets. Also, a favourable aggregate technology shock will shift the labour demand in all the sectors. Therefore, we assume the existence of an indirect channel - equally distributed across sectors - that transmits the effect of an aggregate shock into sectoral employment growth.

We also propose that 'pure' sectoral shocks that influence y_{2t} have an indirect influence on y_{1t}. For example, sectoral taste shocks can display such an impulse. For instance, the demand for more nutritious food products at the beginning of the 1980s increased relative to the demand for other food products. This relative increase for the product of one sector relative to others shifted the firms' derived demand for factor inputs, such as labour. The demand for labour in declining industries decreased. Also, relative technological shocks across industries will produce a similar pattern in the labour market. A favourable sector-specific technology shock can spill over to other sectors by rendering their products obsolete. As discussed in Chapter 6, these shocks are combined with adjustment costs of moving labour across industries.

Whenever labour is immobile and costly to move across sectors, aggregate employment will fall. Therefore, we assume the existence of an indirect influence on aggregate employment. This influence is transitory and reflects the time it takes labour to fully adjust across sectors. These effects are typical of models with adjustment costs (See Sargent (1986, p. 399)). Therefore, in the long run, we assume that a 'pure' sectoral shock to y_{2t} have no long-run effects on the log level of total employment. Similar to Blanchard and Quah (1989), these two assumptions - that the structural shocks are uncorrelated and the structural shocks to y_{2t} have no long-run effect on the level of employment - exactly identifies the model.

The existence of a propagation mechanism that delays the adjustment of the variables to a shock can be captured by the lags in a structural VAR model. Similar to Blanchard and Quah (1989, p. 671), we interpret the 'pure' sectoral shock as a shock (or the portion of a shock) that is unaffected by a total employment shock. Given the assumptions that both shocks are uncorrelated and that a 'pure' sectoral shock has no long-run effect on the level of employment, we proceeded to estimate a structural VAR using the Blanchard-Quah identification. Also, we investigated the argument of contemporaneous dichotomy between the growth rate of employment and the growth rate of sectoral employment; the effects of an aggregate (pure sectoral) shock will take at least one period to reach the sectoral (aggregate) variable. Note that if total employment is defined as total employment minus manufacturing employment, then this assumption is plausible whenever the frequency of data collection (measurement) is different. To examine the dynamic implications of this view and to serve as sensitivity analysis for the Blanchard-Quah identification, we estimate the VAR using the Bernanke-Sims identification scheme under the assumption of independent shocks.

5.5 Specification and Estimation

Sims (1980) suggested formulating unrestricted VAR models, treating all variables as endogenous at a first stage in order to avoid infecting the model with spurious or false identifying restrictions. Statistical procedures determine the lag length, the form of transformation (log or difference) and the appropriate de-trending procedures (if any). Then, OLS is consistent and efficient under the normality of errors. Since our interest revolves around two variable systems, this section will use the finite order bivariate (BVAR) model of order p of the form (similar in notation to the system (5.9))

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} F_{11}(L) & F_{12}(L) \\ F_{21}(L) & F_{22}(L) \end{pmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} + \begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{5.58}$$

where y_{1t} and y_{2t} are vectors of dimensions $m_1 \times 1$ and $m_2 \times 1$, respectively, with $m \equiv m_1 + m_2$. In our application, $m_1 = m_2 = 1$. Here, the added dimensionality is useful in explaining the Johansen approach to determine the order of integration and cointegration of the system (see subsection 5.5.1). The matrix $F(L)$ contains the coefficients on $w_t^T = [w_{1t}, w_{2t}]^T$, which include all deterministic components in the two blocks of equations. $\varepsilon_t^T = [\varepsilon_{1t}, \varepsilon_{2t}]^T$ are white noise, conditional on ξ_t, with covariance matrix Σ_ε. ξ_t represents the information set available at time t and $A_{ij}(L) = A_{ij1+}A_{ij2}L + ... + A_{ijp}L^{p-1}$, $(\forall i, j)$, where L is the lag operator.

For a covariance stationary process, the system (5.58) can be written in its MA representation as,

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} D_{11}(L) & D_{12}(L) \\ D_{21}(L) & D_{22}(L) \end{pmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} + \begin{pmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{5.59}$$

where $C(L) \equiv (I - A(L)L)^{-1}$ and $D(L) \equiv C(L)F(L)$.

The four approaches to specification and estimation differ in the types of restrictions placed on the $A(L)$ matrix in system (5.58). As outlined by Canova (1995, p. 79), the four specifications are:

1) Specification using Classical Statistical Theory.

2) Specification using Bayesian Statistical Theory.

3) Specification based on dynamic economic theory.

4) VAR as index models.

Here, I will address only the first and the second approaches for reasons discussed below. Before exploring these, we investigate the presence of non-stationary variables.

5.5.1 VAR, Unit Roots, Differencing and Detrending

In specifying the VAR model, one has to account for non-stationary variables or structural breaks in the time series. Because testing hypotheses on the coefficients of integrated variables require nonstandard asymptotic theory, determining the order of integration (to make the time series stationary) is crucial for correct inference.

Different modelling strategies have been proposed to deal with the problem of estimating a VAR that is plagued by variables suffering from non-stationarity. Examples are:

1) Conduct univariate unit roots tests, then difference the series if found non-stationary. This method leads to a loss of information.

2) Engle & Granger (1987) 'two step procedure'. They suggested checking for the presence of cointegration restrictions to avoid univariate unit root procedures that end up generating many unit roots. First, test for the presence of a stochastic trend in each variable, then take the OLS estimates of the coefficients of the long run relationships as if they were the true ones, then transform the VAR into a stationary vector error correction model (VECM) and proceed with standard estimation and inference.

3) Johansen's (1988) approach determines the order of integration and cointegration of the system using standard unit root and cointegration tests and models the VAR in the space of integrated processes of order I(0). In this method, first choose the VECM form, then distinguish between the three cases listed below.

Let Π be the matrix containing the factor loadings for the cointegration vectors, then check the rank of Π. If

a) the rank of Π equals m, then all variables in the system are I(0), where m is defined on page 210.

b) the rank of Π equals 0, then all variables are stationary in the first difference, i.e., I(1).

c) intermediate case: there are some linear combinations of the variables which act as a common statistical trend. In this case, one can factor Π into $\Pi = \alpha\beta'$ and jointly estimate the cointegrating factor and the coefficients of the VAR model under the rank restrictions on Π with a maximum likelihood technique. Because restrictions are imposed on the coefficients in the $A(L)$ matrix, one needs a system-wide method such as FIML for efficient estimation. King (1992) and Giannini (1992) provided useful insights on the economic interpretation of the β' vector in the factorization. Also, Sims, Stock and Watson (1990) provided a solution to testing the problem in the context of VARs with polynomial functions of time and one or more unit roots.

Sims (1980) and Doan (1992) argued against differencing. Their argument was as follows. If the aim of using a VAR is to determine the interrelationships among the variables and *not* to focus on the structural parameter estimates, then differencing a time series included in the VAR leads to a loss of information. On the issue of detrending, they argued that a Bayesian approach to estimate the parameters that relies on the 'Minnesota Prior'[14] is best.

However, the majority view, specifically within the classical framework is to focus on the structural VAR estimates, their properties and the underlying economic assumptions.

In conclusion, if one is to estimate a VAR, then one is bound to test for stationarity before moving to the estimation of the reduced VAR. Since I will apply both (Classical and Bayesian) specification approaches, I will correct for non-stationarity in

[14]The 'Minnesota Prior' is described in the 'Bayesian Specification' section of this chapter.

the Classical approach prior to estimation. Note also that using the Blanchard-Quah identification imposes a long-run cointegrating relationship.[15] Within the Bayesian approach, - specifically, the Minnesota prior used here - it is required that the VAR variables be in their original state. Since the Minnesota prior assumes that the variable is a random walk, there is no need to correct for stationarity prior to estimation. This is the main reason for using different transformations on the variables under both approaches. The Classical VAR uses the growth rates whereas the Bayesian VAR uses the level series. Note that the main goal is understanding the dynamics.

5.5.2 Specification using Classical Statistical Theory

In general, economic theory, empirical observations and experience is used to select the variables included in y_t. The steps and the choices concern:

1) The variables to include in y_t from economic theory or experience.

2) The lag length p of the autoregression.

3) The type of the deterministic component to be included in w_t.

4) The approach to follow if a unit root exists in the $A(L)$ matrix.

The lag length p of the autoregression

There exist two issues in choosing the lag: the degree of dimensionality and the correct specification of the model. A trade-off between overparametrization and oversimplification is at the heart of the selection criteria in choosing p. Note that since the number of parameters increases with the number of lags of the system, and since the number of degrees of freedom in a VAR depends on the total number of free parameters appear-

[15]Favero (2001, pp. 169-170) outlines the interpretation of the Blanchard-Quah identification as a cointegrating relation imposed on the impulse response function.

ing in the system, moderately sized systems become highly overparametrized relative to the number of observations, leading to insignificant or inefficient estimates of short run parameters. On the other hand, a short lag length will leave serial correlation in the ε's, and consequently induces spurious significance and inefficient estimates.

Sims (1977,1980a) suggested a procedure in which the number of parameters is a function of the sample size. Berk (1974) suggested that the number of parameters be chosen according to the rule $mp = T^{1/3}$, where m is the dimension of the time series and T is the sample size.

The choice of the lag length in VAR is a subject to debate. Formal selection criteria to determine the order p in univariate and multivariate autoregression are well documented. The mechanics of the procedure are straightforward. Given a sample size T, the value $\bar{p}$ is chosen if the mean square error of the system due to the addition of the $\bar{p}+1$ lag is larger than the mean square error induced by the lag $\bar{p}$. One chooses $\bar{p}$ to minimize (any of) the following criteria over j alternatives, i.e., $p_j \in \{0, 1, ..., p_{\max}\}$

AIC (Akaike Information Criterion)(1974)	$\log \mid \widehat{\Sigma}_\varepsilon(p_j) \mid + \frac{2N^2 p_j}{T}$	
SIC (Schwartz Information Criterion)(1978)	$\log \mid \widehat{\Sigma}_\varepsilon(p_j) \mid + \frac{N^2 p_j \log(T)}{T}$	
HQ (Hannan and Quinn Criterion)(1979)	$\log \mid \widehat{\Sigma}_\varepsilon(p_j) \mid + \frac{2N^2 p_j \log(\log(T))}{T}$	
MLR (Modified Likelihood Ratio) Sims (1980)	$(T-\gamma) \mid \log \det \widehat{\Sigma}_\varepsilon(p_j) \mid$	
FPE (Final Prediction Error)	$\frac{SSR_k}{t} \frac{T+K-1}{T-K-1}$	$k = 1, 2 \ldots p^*$

where N denotes the number of parameters estimated, T is the sample size, γ is a correction factor, and $\widehat{\Sigma}_\varepsilon(p_j)$ is the estimated covariance matrix of the residuals for a given specification of lag length p_j.

Estimation

Here, I will briefly discuss different methods of estimation within the classical framework.

1) The **OLS estimates** of the coefficient matrix $A(L)$ are consistent. Since only predetermined variables and deterministic functions appear on the RHS and $E(\varepsilon_t \varepsilon_{t-s}^T) = E(\varepsilon_t y_{t-s}^T) = 0$, $(\forall s)$, OLS estimates are consistent. Criticisms of the use of the OLS estimates focus on the following. Since all variables enter the system with the same lag length, that may reduce the efficiency of the estimates. The OLS is an 'all variables in the system and all variables are in equal length' approach.

2) **Hsiao's sequential procedure** is a 'specific to general' approach. By combining Akaike's FPE approach for univariate autoregression with Granger-causality testing to decide which variables should enter each autoregression and what number of lags should be used, this approach reduces the number of parameters to be estimated. Many critics of this procedure voiced three major concerns. First, the approach relies on separating the mechanical specification step and the rational tests of economic hypothesis. Second, the second stage hypothesis testing may be sensitive to type I errors committed at the first stage. Finally, the same variables do not appear in all equations, so that system-wide methods, such as full information maximum likelihood (FIML), are needed for efficient estimation of the parameters.

3) **Unrestricted VAR**: Given all available information, we need to select an unrestricted 'congruent' VAR. Congruent is defined as (a) it captures the dynamics

of the relationships existing in the data, (b) it is free from specification errors, and (c) it has constant parameters. Once such a model is found, then the dimensionality of the VAR is reduced by purging insignificant lags using t-tests and F-tests.

In summary, VAR specification and estimation under the classical approach involve two general mechanic steps:

1) One chooses a model which is dynamically well specified (in terms of functional forms, variables included, lag length, non-correlation, and possibly the normality of residuals), extracts as much information as possible from the data, and tests for the presence of unit roots and cointegrating restrictions, taking into account the possibility of regime shifts, segmented trends, etc.

2) Then one transforms the system and estimate a VAR using the two step procedure of Engle and Granger, or estimate the original VAR model under a rank restriction using the ML approach of Johansen. Then testing hypotheses on the coefficients of the transformed system can be undertaken by standard asymptotic theory.

Note that the tests of economic hypotheses are conditional on the results of testing for the model specification (i.e., integration, cointegration and lag length). In other words, inference depends on the procedure used to select the model.

5.5.3 Specification Using Bayesian Methods

Litterman (1980; 1986a; 1986b) and Todd (1984) suggested a Bayesian perspective to the VAR specification. Within such a framework, one attempts to filter as much information from the data prior to the model specification, using a symmetrical 'atheoretical' prior - to decide which variable at which lag should be included - on all variables, so as to compromise the trade-off between the overparametrization and oversimplification of the model. Too many (few) lags lead to over parametrization (oversimplification).

One reason - advanced by Litterman (1980, 1986) - for such an approach is that economic data suffer from a very low signal-to-noise ratio, which leaves little confidence about the useful economic structure at hand. In general, this depends on the type of data and the type of conclusions one tries to infer.

Bayesians claim that the prior on the lag coefficients acts as an antenna and, when appropriately specified, may clarify the signal. The prior is characterized by a small number of parameters. The prior is non-standard from the point of view of Bayesian analysis and is 'objective' in the sense that it is based on experience and has no economic interpretation.

In general, a Bayesian VAR is composed of two sets of equations

$$y_t = C_t(L)w_t + A_t(L)y_{t-1} + \varepsilon_t \tag{5.60}$$

$$\beta_t = G\beta_{t-1} + F\bar{\beta} + u_t \tag{5.61}$$

where β_t is a stacked version of $A_t(L)$ and $C_t(L)$, $\bar{\beta}$ is the unconditional mean of β, G and F are $mp \times mp$ matrices, and u_t is a white noise process with covariance matrix Ω_t.

Note that this is the same as system (5.9) except that the coefficients are allowed to be time variant. In equation (5.60), the coefficients are allowed to be time varying. Equation (5.61) represents the prior law of motion of the coefficients and usually is very broadly formulated. Special cases of this system are:

1) If $G = 0$ and $F = I$, then the coefficients are random around the unconditional mean.

2) If $G = I$ and $F = 0$, then the coefficients are random walks.

3) If $\Omega_t = 0$, then the coefficients deterministically evolve over time and the system collapses to system (5.9).

4) If $G = 0$, $F = I$ and $\Omega_t = \Omega$, the unconditional distribution of the β_t's are constant. In this setup, one needs to specify the $3m^2(p+1)(m^2(p+1)+1)$ parameters contained in the matrices G, F, Ω and $\bar{\beta}$.

This approach relies on making the parameters of these matrices depend on a low dimensional vector of parameters θ which indexes various extraction filters.

The commonly used 'Minnesota Prior' specification is

$$G = \theta_0 I \tag{5.62}$$

$$F = I - G \tag{5.63}$$

$$\bar{\beta}_{ijl} = \left\{ \begin{array}{ccc} 1 & if & i = j, l = 1 \\ 0 & & otherwise \end{array} \right\} \tag{5.64}$$

$$\Omega_{0ijl} = \theta_1 f(i,j) h(l) \frac{\sigma_i}{\sigma_j} \tag{5.65}$$

$$\Omega_t = \theta_2 \Omega_0 \tag{5.66}$$

Equations (5.62) and (5.63) imply that the coefficients are AR(1) processes with some decay toward the mean. Equation (5.64) implies that the time zero mean is one for the first own lag coefficient and zero otherwise. Equation (5.65) assumes that the time zero variance of the coefficients shrinks with lags. l denotes the lag. The function $h(l)$ is typically chosen to have a geometric decay of the form $h(l) = 1/l$. The variance is smaller for coefficients of other variables in each equation $(f(i,j) < f(i,i), \quad \forall i \neq j)$, and is scaled by the ratio of standard deviations of x_i and x_j. It is also regulated by a tightness parameter θ_1. Equation (5.66) assumes that the covariance matrix of the coefficients at each t is a fixed (scaled) function of the covariance matrix at time zero. In this formulation, the VAR coefficients are time varying. The vector $\theta \equiv (\theta_0, \theta_1, \theta_2)$ describes the time invariant structure of the system.

There is no reason to suggest a particular restriction on the coefficients of a dynamic structure such as the one used in the polynomial distributed lag models. No 'hard shape' restriction on the coefficients seems theoretically sound. To deal with this problem, shrinkage estimators (on the lag coefficients) have been suggested and are more suitable for the analysis here. Dropping a lag from the dynamic structure is equivalent to forcing its coefficient to zero. Rather than adopting a lag or no lag approach, it seems reasonable that coefficients on longer lags are likely to be closer to zero than on shorter lags and one can use this in the prior specification. However, if the data show significant evidence of a long lag, one must allow for it. In brief, using a Bayesian framework in the dynamic structure allows the data to determine the lag structure.

Litterman (1986) and Todd (1984) suggested a Bayesian framework for the VAR specification. Within such an approach, one attempts to filter as much information from the data prior to the model specification, and lets the data decide on the lag specification in the system. Using a symmetrical 'atheoretical' prior to decide which variable at which lag should be included will balance the trade-off between the over-parametrization and oversimplification of the model. The prior reflects ignorance and has no economic interpretation. In this specification process, using the VAR in levels amounts to ignoring the long-run structure of the reduced form, this step is skipped only at the risk of loss in efficiency (See Favero (2001, p. 95)). In this Bayesian VAR approach, our focus is on the dynamics.

Rewrite the VAR model as

$$y_t = Cons + \Phi_1 . y_{t-1} + \Phi_2 . y_{t-2} + ... + \Phi_p . y_{t-p} + \varepsilon_t \tag{5.67}$$

where,

$$\Phi_j = \begin{pmatrix} \phi_{11}^{(j)} & \cdots & \phi_{1m}^{(j)} \\ \vdots & \ddots & \vdots \\ \phi_{m1}^{(j)} & \cdots & \phi_{mm}^{(j)} \end{pmatrix} \qquad j = 1, ..., p \tag{5.68}$$

m denotes the number of variables and p denotes the number of lags in each equation. The coefficient $\phi_{ik}^{(j)}$ gives the relation between y_{it} and $y_{k,t-j}$ $(i, k = 1, ..., m.\ \ j = 1, ..., p)$. Note that y_t is a m-dimensional vector $y_t = (y_{1t}, ..., y_{mt})^T$ and ε_t is also a m-dimensional vector $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{mt})^T$. In our context, $y_t = (y_{1t}, y_{2t})^T$.

Write the VAR system in the form of a multivariate regression model as,

$$y_t = \Phi^T z_t + \varepsilon_t \tag{5.69}$$

where $\varepsilon_t \sim IN(0, \Sigma)$. $z_t = (1, y_{t-1}^T, y_{t-2}^T, \cdots, y_{t-p}^T)^T$ and $\Phi = (c, \Phi_1, \Phi_2, \ldots, \Phi_p)$. y_t, z_t and Φ are of dimension $m \times 1, (mp+1) \times 1$ and $(mp+1) \times m$, respectively. The matrix version of this system is,

$$Y = Z\Phi + E \tag{5.70}$$

Throughout this chapter E is assumed to follow $E \sim MN_{T\times m}(0, \Sigma \otimes I)$. MN denotes a matricvariate normal distribution as defined in Bauwens et al. (1999, p. 301) and reported in the Appendix of this chapter.

Also, the VAR model can be cast in the form of a SURE model, which is a set of regression equations whose error terms are correlated. The SURE model can be written as

$$Y_i = Z_i \Phi_i + E_i \qquad i = 1, ..., m. \tag{5.71}$$

where Y_i, Z_i and Φ_i are of dimension $T \times 1$, $T \times k_i$ and $k_i \times 1$, respectively. In compact matrix format,

$$Y = Z\Phi + \Xi \tag{5.72}$$

where

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_m \end{bmatrix} \qquad \Phi = \begin{bmatrix} \Phi_1 \\ \Phi_2 \\ \vdots \\ \vdots \\ \Phi_m \end{bmatrix} \qquad \Xi = \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ \vdots \\ E_m \end{bmatrix} \tag{5.73}$$

$$Z = \begin{bmatrix} Z_1 & 0 & 0 & \cdots & 0 \\ 0 & Z_2 & & & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & & & \ddots & \vdots \\ 0 & 0 & \cdots & \cdots & Z_m \end{bmatrix} \tag{5.74}$$

Here, it is assumed that $\Xi \sim N_{Tm}(0, \Sigma \otimes I_T)$. Note that in this formulation, $\Xi = vec(E)$. For the properties of the vec operator,[16] see Hamilton (1994, p. 265). The

[16]The vec operator is obtained by stacking the columns of a matrix A, one below the other, with the columns ordered from left to right. For example, if $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, then $vec(A) = \begin{bmatrix} a_{11} \\ a_{21} \\ a_{12} \\ a_{22} \end{bmatrix}$.

usefulness in writing the system in this form is apparent when one derives the posterior distributions of the parameters.

One can relax the assumption of normality and homoscedasticity along the lines of Geweke (1993) to allow for heteroscedasticity or fat-tailed marginal distributions for ε_t for some priors. This line of investigation will not be pursued here.

The following notation will be used (following Kadiyala and Karlsson (1997)), $\tilde{}$ (tilde) and $\bar{}$ (bar) denote the parameters of the prior and the posterior distribution, respectively. The OLS estimates of Φ and ϕ are denoted by $\widehat{\Phi}$ and $\widehat{\phi}$. The likelihood function is given[17] by (see also Zellner 1971, p. 22)

$$L(\phi, \Sigma) \propto |\Sigma|^{-T+m+1/2} \exp\left\{\frac{-tr\left[(Y - Z\Phi)^T \Sigma^{-1}(Y - Z\Phi)\right]}{2}\right\} \tag{5.75}$$

$$\propto |\Sigma|^{-T+m+1/2} \exp\left\{\begin{array}{c} -\frac{1}{2}(\phi - \widehat{\phi})^T(\Sigma^{-1} \otimes Z^T Z)(\phi - \widehat{\phi}) \\ -\frac{1}{2}tr\left[\Sigma^{-1}(Y - Z\widehat{\Phi})^T(Y - Z\widehat{\Phi})\right] \end{array}\right\} \tag{5.76}$$

$$\propto |\Sigma|^{-k/2} \left\{\begin{array}{c} \exp\left\{-\frac{1}{2}(\phi - \widehat{\phi})^T(\Sigma^{-1} \otimes Z^T Z)(\phi - \widehat{\phi})\right\} \\ \times |\Sigma|^{-(T-k)/2} \exp\left\{-\frac{1}{2}tr\left[\Sigma^{-1}(Y - Z\widehat{\Phi})^T(Y - Z\widehat{\Phi})\right]\right\} \end{array}\right\} \tag{5.77}$$

$$\propto \left\{\begin{array}{c} N\left(\phi|\widehat{\phi}, \Sigma \otimes (Z^T Z)^{-1}\right) \\ \times iW\left(\Sigma|(Y - Z\widehat{\Phi})^T(Y - Z\widehat{\Phi}), T - k - m - 1\right) \end{array}\right\} \tag{5.78}$$

Therefore, the likelihood function is proportional to the product of an inverse Wishart density for Σ and a normal density for ϕ conditional on Σ.

Using different priors, one ends with different posterior distribution. The following table is a summary of different priors and their respective posterior distributions.

[17] With some modifications to Kadiyala and Karlsson (1997, p. 101) and Bauwens et al. (1999, p. 266, see also theorem A.19, p. 307-308).

	Prior	Posterior
Minnesota	$\phi_i \sim N(\bar{\phi}_i, \bar{\Sigma}_i)$ Σ fix and diagonal	$\phi_i \| y \sim N(\bar{\phi}_i, \bar{\Sigma}_i)$ with $\bar{\Sigma}_i = (\bar{\Sigma}_i^{-1} + \sigma_{ii}^{-1} Z^T Z)^{-1}$
Diffuse (Jeffrey's)	$p(\phi, \Sigma) \propto \| \Sigma \|^{-(m+1)/2}$	$\Phi \| y \sim MT(Z^T Z, (Y - Z\hat{\Phi})^T)$ $\times (Y - Z\hat{\Phi}), \hat{\Phi}, T - k)$
Normal-Wishart	$\phi \| \Sigma \sim N(\bar{\phi}, \Sigma \otimes \bar{\Omega})$, $\Sigma \sim iW(\bar{\Sigma}, \alpha)$	$\Phi \| y \sim MT(\bar{\Omega}^{-1}, \bar{\Sigma}, \bar{\Phi}, T + \alpha)$

Source: Kadiyala and Karlsson (1997, p. 103)
For the distributions, please refer to the Appendix of this Chapter.

Kadiyala and Karlsson (1997) examined the forecasts' properties under different prior assumptions for two VAR models, large and small. They concluded that mixed evidence exists in terms of forecast performance. Different results are reported and are sensitive to the prior used. They emphasized that their preferred choice is the Normal-Wishart when the prior beliefs are of the Litterman type (1997, p. 129). However, the Minnesota prior reported acceptable results and in few instances was better than other priors for small VAR models. Here, we adopt the Minnesota prior.

Note that when using the Minnesota prior, one need not render the time series stationary. For example, see Kadiyala and Karlsson (1997, p. 113), where the level of the Swedish unemployment and the level of the logarithm of the industrial production index were used.

The Minnesota Prior

Litterman (1979, 1986), Sims (1980) and Doan, Litterman and Sims (1984) suggested using this prior to circumvent the "incredible identifying assumptions" made by the 'Cowles Commission' approach.

In this Bayesian approach, the residual variance-covariance matrix Σ, is taken to be fixed and diagonal. The likelihood function results in a product of independent normal densities for ϕ_i. The prior can be generalised by allowing for a non-diagonal Σ and/or unknown Σ. An additional assumption that can be made is that Σ has a fixed diagonal and an unknown non-diagonal element.

The Minnesota prior[18] is informative on all the coefficients of Φ_i matrices, and non-informative on the other parameters. The prior assumes that the VAR system consists of m random walks. The prior covariance matrix of all parameters in Φ_i is diagonal. This amounts to assuming that each equation in the system is a-priori uncorrelated with any other equation.

This Bayesian procedure is implemented by placing a normal prior with mean zero on the coefficients of the lags,[19] and allowing for a smaller standard deviation the longer the lag, i.e., the importance of lagged variables decreases with the lag length. Usually, a mean of one is placed on the first own lag, and means of zero on all other coefficients. This centers the prior around a random walk process. Formally, $\phi_{ii}^{(1)} = 1$ and all other $\phi_{ik}^{(j)} = 0 \quad (i \neq k, \quad j \neq 1)$ to characterize the mean of the prior

[18]The label 'Minnesota Prior' was given to this approach when both Sims and Litterman were at the University of Minnesota and working on the prior. The label was used to identify the specific prior proposed by Litterman (see McNees 1986, p. 5, Amisano et al. 1997, p. 9 and Bauwens et al. 1999, p. 269).

[19]Except the own first lag.

distribution of the coefficients. This is equivalent to assuming that for each variable in the VAR,

$$y_t = y_{t-1} + \varepsilon_t \tag{5.79}$$

Note that the prior assumes that the variables are $I(1)$ but not cointegrated. However, this prior and all extensions from it do not rule out cointegration. For a discussion of the Bayesian analysis of cointegrated VAR, see Bauwens and Lubrano (1994, p. 272), Dorfman (1995, p. 49) and Koop (1992b, p. 105).

Litterman assumed a diagonal variance-covariance matrix for the prior distribution, with γ referring to the standard deviation of the prior distribution for $\phi_{ii}^{(1)}$

$$\phi_{ii}^{(1)} \sim N(1, \gamma^2) \tag{5.80}$$

For the other coefficients, the standard deviation of the prior decays with respect to the lag.

$$\phi_{ik}^{(j)} \sim N(0, S^2(i,k,l)) \qquad for \quad i \neq k \tag{5.81}$$

Let k refer to the variables in the system ($k = E_0, E_1, E_2$) and i refer to the equation whose dependent variable is i. Define the standard deviation of the prior distribution for lag l of the variable k in equation i as

$$S(i,k,l) = \{\gamma . g(l) . f(i,k)\} \; \frac{s_i}{s_k} \tag{5.82}$$

where $f(i,i) = g(1) = 1.0$ such that $\phi_{ii}^{(1)} \sim N(1, \gamma^2)$, as above. γ is the degree of overall tightness and represents the confidence in the prior information.

A value of $\gamma = 0.2$ means that one has a confidence of 95% that $\phi_{ii}^{(1)}$ is no smaller than 0.6 and no greater than 1.4 (the mean is equal to 1). s_i is the standard deviation of the residuals of a univariate autoregression on the dependent variable of equation i (OLS of y_{it} on a constant and own p lags). s_i/s_k represents a correction for different scales of the variables. In other words, it is an adjustment for the units in which the data are measured. In equation i, $f(i,k)$ is the tightness on variable k relative to variable i, while γ represents the overall tightness.

Standard functional forms for $g(l)$ and $f(i,k)$ are,

$$f(i,k) = symmetric \qquad \text{where} \qquad f(i,k) = \left\{ \begin{array}{ll} 1 & i = k \\ w & i \neq k \end{array} \right\} \tag{5.83}$$

where w is a weight parameter, and represents the relative tightness applied to all off-diagonal variables in the system. To have more confidence in the prior belief that $\phi_{ik}^{(j)} = 0$ than the prior belief that $\phi_{ii}^{(1)} = 0$, w should be less than one. A common choice in applied economic time series is $w = 0.5$ and $\gamma = 0.2$. As w goes to zero, the system reduces to a set of univariate autoregressions. In other words, it forces coefficients on other than own lags toward zero. $g(l)$ is the tightness on lag l relative to lag 1. It captures how the standard deviation changes with increasing lags. The $g(l)$ lag decay function is

$$g(l) = \left\{ \begin{array}{ll} harmonic & g(l) = l^{-d} \\ geometric & g(l) = d^{l-1} \end{array} \right\} \tag{5.84}$$

where d is the lag decay parameter for the harmonic (geometric) function. A large (small) value for d reflects a tighter (looser) prior. Note that the lag decay function $g(l)$ is a bad choice when one is faced with seasonal data. In brief, a low tightness forces the system to a VAR, while a high tightness forces it to an OLS.

Many criteria for choosing the parameters of the prior are discussed in the literature. Among others, one can use the log determinant of the covariance matrix of out-of-sample forecast errors or use a forecast performance statistic such as the Theil U statistic (the ratio of the root mean square error of the model to the root mean square error of the naive forecast of no change in the dependent variable). The latter is used here. The Theil U statistic is a unit free measure, and provides a comparison with the naive (no change over time) forecast. A value higher than one (of the statistic) means that the model is doing worse than the naive one.

The Bayesian approach is very flexible. It allows different lags for different equations. There is neither a restriction on lags, nor specification restrictions. The presence of trending variables does not cause any particular problems in this framework. Inference is based on the likelihood principle. The approach requires normality of residuals and 'good' priors, but is invariant to the size of the dominant root of the system. Estimation is carried out numerically, passing through the sample recursively with the Kalman filter algorithm.

When Σ_ε and the coefficients on lags are not time varying parameters, the system of equations (5.60) and (5.61) forms a VAR model with a set of uncertain linear restrictions on the linear coefficients. The unconditional distributions of the coefficients are constants. If equation (5.61) is regarded as a dummy observation appended to the system, the estimation of the model can be carried out with mixed-type estimation. The result is a restricted estimator which shrinks the data toward the information contained in the prior restriction. This interpretation of the VAR is similar to the single equation ridge regressions: whenever the noise in the data is influential, the set of uncertain linear restrictions acts as a constraint on the filter extracting information from the data.

One might ask if this method will introduce an alternative source of bias such as shrinking the model to an incorrect parameter vector. A solution to this bias is to specify a prior distribution over different trend specifications, trying different distributional assumptions on the innovation of the VAR model, and computing pairwise posterior odd ratios using numerical integration.

5.5.4 Impulse responses and variance decomposition

This section discusses the usefulness of the VAR approach. Once the parameters of the primitive VAR are recovered, one computes the impulse responses and the variance decomposition. Both are methods of describing the dynamic properties of the model following certain shocks and both are in-sample forecasting exercises. They are similar with respect to the information they report about the model under investigation. The former is used for better economic understanding, while the latter is used for economic testing. They describe the effect on the system of equations of a 'typical' shock to a variable, where 'typical' is used in the sense of a one standard error shock.

In general terms, suppose that y_t is a covariance stationary process (possibly after some transformation) with MA representation.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} D_{11}(L) & D_{12}(L) \\ D_{21}(L) & D_{22}(L) \end{pmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} + \begin{pmatrix} B_{11}(L) & B_{12}(L) \\ B_{21}(L) & B_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{5.85}$$

For such a y_t, Σ_ε is in general non-diagonal. One can use a Cholesky decomposition to transform the system in such a way that the shocks to each equations are uncorrelated. Given that Σ_ε is a real symmetric positive definite matrix, let Z be a non-singular lower triangular orthogonal matrix with ones on the main diagonal and let V be a diagonal matrix. If we decompose $\Sigma_\varepsilon \equiv Z^{-1}V(Z^{-1})^T$, the system can be normalized as,

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} D_{11}(L) & D_{12}(L) \\ D_{21}(L) & D_{22}(L) \end{pmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} + \begin{pmatrix} G_{11}(L) & G_{12}(L) \\ G_{21}(L) & G_{22}(L) \end{pmatrix} \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} \tag{5.86}$$

where $G(L) = B(L)Z$ and $v_t = Z^{-1}\varepsilon_t$. Because Z is lower triangular, so is $G(L)$ and innovations in the variable i do not contemporaneously affect variable k if variable k precedes variable i in the list of elements of y_t. Note that $Z^{-1}V^{1/2}$ has the standard deviation of ε_t along its principal diagonal. Thus, a shock of one unit to v_t is equivalent to a shock of one standard deviation to ε_t.

The VAR system (5.86) has a so-called Wold causal chain form. This orthogonalization procedure is not unique and depends on the ordering of the variables, i.e., the position of each variable in the y_t vector (simply interchanging the rows or columns in Σ_ε, will yield a different Cholesky factor).

The variables on the top of the triangle contemporaneously feed into all the other variables and the variables on the bottom of the triangle contemporaneously affect only themselves. Our interest in both concepts (impulse responses and variance decomposition) arises due to their advantages.

1) Variance decomposition tells us how much of the average squared forecast error variance of one variable at the kth step ahead is associated with surprise movements in each variable of the model.

2) The impulse response function traces out the moving average representation of the system and describes how one variable responds over time to a single shock

increase in itself or in any other variable. The impulse response measures the responses of the system to a particular initial shock.

Whenever the system is correctly identified, the impulse response function (IRP) interpretation is straightforward. It describes the response of the system y_t to a shock in the innovations. If the errors have a common component which can not be identified with any specific variable, then the IRP will reflect the response to the innovation shock and to the common component. One has to treat the results with caution since the results are conditional on the assumptions used for structural identification.

IMPULSE RESPONSE

The matrix $G(L)$ in system (5.86) represents the impulse response functions and is useful in examining the effects of typical shocks to the variables of the system in the short and long run. The ∞-MA representation of the VAR is the complete set of impulse responses. The standard deviations for the estimated impulse responses are usually carried out through bootstrap resampling technique or by normal density approximation.[20] There are few methods for computing confidence intervals for impulse responses. These are the delta-method, the bootstrap, the bias-adjusted bootstrap, the asymptotic parametric inference methods and the Bayesian Monte-Carlo integration method. Wright's new proposal is a size-adjusted delta based method. In an attempt to overcome the low coverage of traditional methods that compute confidence

[20]See Runkle (1987) for a detailed analysis and see Ripley (1987, p. 175) for the properties of the standard errors of the impulse responses estimates using bootstrap methods. Fachin and Bravetti (1996) examined the performance of bootstrap and asymptotic parametric inference methods. They concluded that the bootstrap delivered superior results in terms of both length of the confidence interval and coverage when the variance of the forecast error is considered. See Fachin and Bravetti (1996, p. 339) for details.

intervals for the impulse responses in a vector autoregression, Wright (2000) proposed a new approach. This approach relies on the Normality assumption of the innovations and the lag order. His proposed confidence interval controls for coverage and addresses the coverage versus width trade-off. For our study here, we adopt the bootstrap method (Runkle 1987) in the Classical VAR. As mentioned, Sims, Stock and Watson (1990) argued that a VAR in levels in the presence of cointegration implies that the estimates of the parameters of interest are inefficient, but consistent.

For the Classical VAR, we bootstrap the residuals 1000 times for each impulse response. We choose the residuals at the same time period for each equation to preserve the contemporaneous relationship. Then we simulate the system using the new residuals, the coefficients and the actual series as initial values. We estimate the VAR and compute the impulse responses. We repeat this exercise 1000 times, then we calculate the 95 percent coverage (i.e., the 2.5 and the 97.5 percentiles) of the impulse responses. This method uses the percentile approach described in Mooney and Duval (1993, pp. 36-37) and Stine (1990, pp. 249-250).

Each G_j describes the response of the vector y_t to innovations j periods ago. The kth row of each G_j measures the responses of y_{kt} to innovations in the system which occurred j periods ago, $j = 0, 1, 2, \ldots$. Finally, the hth element of the kth row of $G(1)$ measures the cumulative effect on y_{kt} of an innovation in y_{ht} that occurred j periods ago, where $j \to \infty$.

From a Bayesian point of view, the posterior density function of the impulse response function is defined as follows (Koop (1992a, p. 398)),

$$p(I_i(y_k, \varepsilon_{y_k})) = \left\{ \begin{array}{c} p(y_{k,T+i}|y, \varepsilon_{y_k,T+1} = 1, \varepsilon_{y_k,T+2} = 0, ..., \varepsilon_{y_k,T+j} = 0) \\ -p(y_{k,T+i}|y, \varepsilon_{y_k,T+j} = 0, \varepsilon_{y_k,T+j} = 0) \end{array} \right\} \qquad (j = 1, ..., i) \tag{5.87}$$

where k denotes the variable of interest. $I_i(y_k, \varepsilon_{y_k})$ is the response, i periods later, of the variable y_k to a shock ε_{y_k}. The shock occurs at period $T+1$. Therefore, the probability density function is conditioned on observed data and the shock. A criticism arises here regarding model uncertainty. A Bayesian approach offers the possibility and recommends averaging the impulse responses across several different models using weights the posterior probability that each model is true. However, such exercise requires that one adopt an informative proper prior, which is relatively difficult to defend in Bayesian analysis.

VARIANCE DECOMPOSITION

From system (5.86), one computes the variance decomposition of y_t,

$$var(y_t) = G(1)Ev_tv_t'G(1)' \tag{5.88}$$

For the special case where[21] $m_1 = m_2 = 1$, the variance of y_{1t} has two components. One component is due to the impact of its own innovations from time t to time $t-j, \quad j = 1, 2, ...,$ and the other one is due to innovations in y_{2t} from time t to time $t-j$. If y_{2t} is shocked at time $t-j$ and left unperturbed afterward, then one can examine how much of the variability of y_t at time t is due to that innovation, for all j. As seen from equation (5.88) the variance decomposition represents the contribution of the shock to each variable's forecast error variance.

[21]See page 210 for the definitions of m_1 and m_2.

5.6 Data Analysis

This section reports the results of the VAR estimation for the Canadian industry-level (goods sector, manufacturing sector and services sector) data on employment level. All series are quarterly Canadian data covering the period from 1976 to 1998. The reform of the Canadian system of unemployment insurance was introduced in the early 1970s. Mixing two different policy regimes induces parameter instability, therefore we concentrate on a single regime. To circumvent the effect of the change in policy on the data, we used post-1976 data. The variables used in the Classical VAR are defined on page 193.

5.6.1 Classical VAR Results

Prior to estimating the VAR models, we used the multivariate AIC and Schwarz criteria to select the lag length for both models. On this basis, we estimated the VAR model at lag 8. In each model, two dummy variables were added to the list of exogenous variables in the VAR to account for the structural breaks identified by the graphs. We added these dummy variables to remove the outliers.[22]

Using the Likelihood Ratio test, we tested for 1 lag and 4 lags exclusions. Both model C-I (Table 5.2) and model C-II (Table 5.7) significantly rejected the null of excluding the last lag and the last four lags. The former exclusion tests the null hypothesis that the last lag is zero. The latter exclusion tests jointly the null; the that the last four lags equal zero. For models C-I and C-II, each hypothesis was

[22]Outliers are defined as observations generating observed residuals of a magnitude exceeding, in absolute value, three times the standard deviation of fitted residuals. See Favero (2001, p. 142) for the definition.

rejected at the 5% level.

Tables 5.1 to 5.5 report the results for model C-I and Tables 5.6 to 5.10 report the results for model C-II. We report the results of the Bernanke-Sims as sensitivity analysis to the Blanchard-Quah identification.

Model C-I Results

Table 5.1 reports the Jarque-Bera normality test, the Lagrange-multiplier serial autocorrelation test and the Lagrange-multiplier ARCH test for the reduced form VAR residuals.[23] Evidence of deviations from normality appears only for EMP M/T, where normality is rejected. The residuals of the reduced form are serially uncorrelated and no evidence of conditional heteroskedasticity is found. Table 5.2 presents some statistics of interest regarding the estimated reduced form VAR.[24]

Table 5.3 reports the VAR results under two identification schemes; Bernanke-Sims and Blanchard-Quah. The matrices notation B, $D^{0.5}$ and $B^{-1}D^{0.5}$ are used to be consistent with the notation in section 5.4. Note the difference in matrix D across the identifications. From the matrices, the initial effect of a one standard deviation structural shock on the variables is computed from $B^{-1}D^{0.5}$. Focusing on the Blanchard-Quah results, the initial effect of a one percent standard deviation 'pure' sectoral shock on the growth rate of total employment is negative. The growth of total employment decreases whenever a 'pure' sectoral shock occurs. This result suggests the presence of adjustment costs that impinge on labour mobility. The

[23]As defined in the literature, all tests are outlined in the Appendix.

[24]The value of $\rho(EMP\ T, EMP\ M/T) = -0.024$, which indicates that ordering is unimportant if one assumes the Cholesky decomposition.

usefulness of normalized variables[25] in the VAR lies in the easier interpretation of the impulse response figures. For example, the first point of the impulse response curve is given by $B^{-1}D^{0.5}$.

From the matrix $B^{-1}D^{0.5}$, (Table 5.3), in the initial period of the shock for the Blanchard-Quah identification, a one standard deviation structural 'aggregate' shock leads to 60.8 percent increase in employment growth and to 20.4 percent increase in the square of the manufacturing employment growth rate. In the initial period of the shock, a one standard deviation structural 'pure' manufacturing shock leads to 86.4 (84) percent - using the Bernanke-Sims (Blanchard-Quah) - increase in the square of the manufacturing employment growth rate. A 'pure' sectoral shock decreases the employment growth rate by 16.4 percent in the initial period. Note that by identifying assumption, the initial effect is nil in the Bernanke-Sims case.

The accumulated responses to a structural shock (one standard deviation) for MA(16) and MA(∞)are,[26]

$$y_{1t} = \sum_{k=0}^{16} c_{11}(k)\ \varepsilon_{y_{1t-k}} + \sum_{k=0}^{16} c_{12}(k)\ \varepsilon_{y_{2t-k}} \tag{5.89}$$

$$y_{2t} = \sum_{k=0}^{16} c_{21}(k)\ \varepsilon_{y_{1t-k}} + \sum_{k=0}^{16} c_{22}(k)\ \varepsilon_{y_{2t-k}} \tag{5.90}$$

$$y_{1t} = \sum_{k=0}^{\infty} c_{11}(k)\ \varepsilon_{y_{1t-k}} + \sum_{k=0}^{\infty} c_{12}(k)\ \varepsilon_{y_{2t-k}} \tag{5.91}$$

$$y_{2t} = \sum_{k=0}^{\infty} c_{21}(k)\ \varepsilon_{y_{1t-k}} + \sum_{k=0}^{\infty} c_{22}(k)\ \varepsilon_{y_{2t-k}} \tag{5.92}$$

[25]Each VAR is re-run using normalized variables. A normalized variable is defined as the ratio of the deviation from the mean relative to its standard deviation.
[26]$k = 16$ is arbitrary and is computed for comparison purposes.

	MA($k=16$)	MA($k=\infty$)
Bernanke-Sims	$y_{1t} = 3.145\ \varepsilon_{y_{1t-16}} + 0.813\ \varepsilon_{y_{2t-16}}$ $y_{2t} = -0.85\ \varepsilon_{y_{1t-16}} + 0.962\ \varepsilon_{y_{2t-16}}$	$y_{1t} = 3.141\ \varepsilon_{y_{1t-k}} + 0.841\ \varepsilon_{y_{2t-k}}$ $y_{2t} = -0.846\ \varepsilon_{y_{1t-k}} + 0.924\ \varepsilon_{y_{2t-k}}$
Blanchard-Quah	$y_{1t} = 3.229\ \varepsilon_{y_{1t-16}} - 0.027\ \varepsilon_{y_{2t-16}}$ $y_{2t} = -0.594\ \varepsilon_{y_{1t-16}} + 1.156\ \varepsilon_{y_{2t-16}}$	$y_{1t} = 3.232\ \varepsilon_{y_{1t-k}}$ $y_{2t} = -0.599\ \varepsilon_{y_{1t-k}} + 1.118\ \varepsilon_{y_{2t-k}}$

Source: Table 5.3.

The initial effect of a one standard deviation shock is given by the matrix $P \equiv B^{-1}D^{0.5}$. Note that PP^T is the variance covariance matrix of the residuals. To transform the initial impact to a structural shock of 1 - rather than a one standard deviation - one normalizes the $B^{-1}D^{0.5}$ matrix such that the sum of each row equals one. For the normalized variables, the effect of a 'pure' sectoral shock on employment growth is negligible after 4 years (16 steps in Table 5.3). By construction, in the long-run (∞-steps in Table 5.3), the accumulated influence of the Blanchard-Quah sectoral 'pure' shock is zero on the level of total employment.

For the Bernanke-Sims identification, the system is overidentified; the likelihood-ratio rejects at the 5% level the extra restriction imposed on the structural matrix. Therefore, we focus on the Blanchard-Quah identification for the rest of our analysis.

Table 5.4 reports the forecast error variance decomposition of a structural shock that equals one. It determines the proportion of the k-step ahead forecast error variance of the ith variable attributable to a shock to the jth variable. Each period in this table should be read as follows. The first (second) row of each cell refers to the variance of the first (second) variable. The first (second) element is the k-period variance proportion in the first variable attributable to a shock to the first (second) variable. Note that each row sums to 100 percent.

Regarding the Lilien hypothesis, after 12 periods and using the Bernanke-Sims identification, a shock to manufacturing reallocation (term used loosely to denote EMP M/T) is responsible for 11.95 percent variation in the growth rate of employment and for 89.81 percent of its own variability. As expected, since the Bernanke-Sims identification is more restrictive in terms of the shock effect in the initial period, all cross variables' forecast error variance decompositions are lower than their counterparts when using the Blanchard-Quah identification. When one assumes that there is no long-run effect on the level of employment following a 'pure' manufacturing shock (i.e., Blanchard-Quah identification), after 4 years, a manufacturing reallocation shock is responsible for 13.87 percent variance in the growth rate of employment. Assuming that the effect of the same shock is not felt immediately (i.e., Bernanke-Sims identification), it is responsible for 12.23 percent of employment growth variability after 4 years.

Table 5.5 reports the reduced form coefficients estimates. To compute the structural form coefficients, one has to multiply the reduced form coefficients by the respective rows of matrix $B^{-1}D^{0.5}$ (from Table 5.3).

Model C-II Results

Model C-II examines the reallocation shock to the service sector. Table 5.6 reports the Jarque-Bera normality test, the Lagrange-multiplier serial autocorrelation test and the Lagrange-multiplier ARCH test for the reduced form VAR residuals.[27] The residuals of the reduced can not reject normality. They are serially uncorrelated and no evidence of conditional heteroskedasticity is found. Table 5.7 presents few statistics of interest regarding the estimated reduced form VAR.[28]

Table 5.8 reports the VAR results under the two identification schemes; Bernanke-Sims and Blanchard-Quah. The initial effect of a one standard deviation structural shock on the variables is computed from $B^{-1}D^{0.5}$. In the initial period of the shock, a one standard deviation structural 'aggregate' shock leads to a 66.11 percent increase in employment growth and to a 29.17 percent decrease in the square of the service employment growth rate.

Using the Bernanke-Sims identification (Blanchard-Quah identification), in the initial period of the shock, a one standard deviation structural 'pure' service shock leads to 66.25 (59.49) percent increase in the square of the service employment growth rate. What is puzzling in the Blanchard-Quah identification is that a 'pure' reallocation shock to services increases employment growth by 23.28 percent in the initial period, then drops sharply to 2.3 percent after 4 years, while a one standard deviation aggregate shock reduces the reallocation of service employment by 29.17 percent in the initial period. We offer two reasons for this observation. First, it is due to the distinct nature of reallocation shocks to service employment. This sector of employment integrates into almost all the other sectors of the economy. Second, from the Granger-causality tests, EMP S/T does not Granger-cause EMP T and EMP T does

[27] As mentioned, all tests are outlined in the Appendix.

[28] $\rho(EMP\ T, EMP\ S/T) = -0.11$, so that ordering is unimportant if one assumes the Cholesky decomposition.

not Granger-cause EMP S/T. The inability of the tests to reject any of the hypothesis, leads one to believe that the information content in each variable is not useful for predicting the other. Changes in s_t are mostly due to changes in other sectors' employment.

In terms of employment dynamics, this relationship needs a VAR that includes other variables or simply an alternative approach to investigating it. Given the encouraging results of the C-I model, we drop further investigation into the dynamics of reallocation service shocks and focus on the quantitative effect to deduce evidence of the existence of persistence, if any.

The accumulated responses to a structural shock (one standard deviation) for MA(16) and MA(∞)are,

	MA(k=16)	MA($k=\infty$)
Bernanke-Sims	$y_{1t} = 3.171\ \varepsilon_{y_{1t-12}} - 1.108\ \varepsilon_{y_{2t-12}}$ $y_{2t} = -0.203\ \varepsilon_{y_{1t-12}} + 2.491\ \varepsilon_{y_{2t-12}}$	$y_{1t} = 3.146\ \varepsilon_{y_{1t-k}} - 1.163\ \varepsilon_{y_{2t-k}}$ $y_{2t} = -0.19\ \varepsilon_{y_{1t-k}} + 2.538\ \varepsilon_{y_{2t-k}}$
Blanchard-Quah	$y_{1t} = 3.479\ \varepsilon_{y_{1t-12}} + 0.057\ \varepsilon_{y_{2t-12}}$ $y_{2t} = -1.289\ \varepsilon_{y_{1t-12}} + 2.168\ \varepsilon_{y_{2t-12}}$	$y_{1t} = 3.48\ \varepsilon_{y_{1t-k}}$ $y_{2t} = -1.297\ \varepsilon_{y_{1t-k}} + 2.215\ \varepsilon_{y_{2t-k}}$

Source: Table 5.8.

Regarding the Lilien hypothesis, Table 5.9 reports the forecast error variance decomposition of a structural shock that equals one. After 16 periods and using the Bernanke-Sims identification, a shock to service' reallocation (term used to denote EMP S/T) is responsible for 4.34 percent variation in the growth rate of employment and for 84.64 percent of its own variability. For the same period, the same service shock is responsible for 13.11 percent of employment growth variability. The VAR system is overidentified with the Bernanke-Sims identification; the likelihood-ratio rejects at the 5% level the extra restriction imposed on the structural matrix. Hereafter, we focus on the results for the Blanchard-Quah identification.

When one assumes that there is no long-run effect on the level of employment following a 'pure' service shock (i.e., Blanchard-Quah identification), after 4 years, a service shock is responsible for 13.11 percent variance in the growth rate of employment.

Table 5.10 reports the reduced form coefficients' estimates. To compute the structural form coefficients, one has to multiply the reduced form coefficients by the respective rows of matrix $B^{-1}D^{0.5}$ (from Table 5.8).

Classical VAR Figures Results

The upper graphs of figures 5.1, 5.2 and 5.3 plot the HP detrended variables - EMP T, EMP M/T and EMP S/T, respectively - used in models C-I and C-II. The lower graphs plot the sample autocorrelation as well as the standard error band. The outliers present in all variables during the recessions of the early 1980s and the early 1990s pointed to us the need to include a dummy variable for each period.

Figures 5.4 to 5.7 illustrate the accumulated impulse responses to a shock with the Blanchard-Quah identification. The accumulated response of a shock to EMP M/T represents the effects of a manufacturing reallocation shock on the log of total employment (instead of the growth rate of employment). Similarly, the accumulated response for a shock to EMP S/T represents the effects of a service reallocation shock on the log of total employment. Figures 5.6 and 5.7 illustrate the impulse responses for normalized variables.

Figure 5.6 illustrates the accumulated impulse response to a reallocative manufacturing shock. The initial effect of the shock on employment is negative and equals 16.4 percent. Moving labour across sectors - combined with adjustment costs - implies a decrease in employment. Given the transitory nature of the shock, after 4 years, employment returns to its initial pre-shock level. In terms of persistence, the effect of the shock is felt for a minimum of 10 quarters. The initial negative effects last only for 2 quarters. After 6 quarters, employment overshoots its long-run steady state level and then returns to it after 9 quarters. The labour adjustment process from manufacturing to total employment lasts for 8 quarters. Coming out of a recession and following a decline in wealth (due to the loss of labour income), workers supply more labour during the adjustment and capital build up processes.

In conclusion, from the impulse response and the forecast variance decomposition, one can deduce that the variance of employment is influenced for at least 10 quarters. Given a transitory shock, employment returns to its initial pre-shock level after 4 years.

Figure 5.7 illustrates the accumulated impulse response to a reallocative service shock. The initial effect of the shock on employment is positive and equals 23.28 percent. This observation, combined with the results of the Granger-causality tests lead us to eschew modeling service employment in the next chapter. In terms of persistence, the effect of the shock is felt for a minimum of 10 quarters.

MODEL C-I

Table 5.1: Residual Analysis

	Jarque-Bera Normality Test JB(2)	Ljung-Box Residual Autocorrelation LB(24)	Lagrange Multiplier Residual ARCH ARCH (24)
EMP T	0.9526 [0.6211]	14.1949 [0.5842]	8.5763 [0.9984]
EMP M/T	6.1818 [0.0455]	22.2956 [0.1339]	26.0556 [0.3504]

[Significance]

MODEL C-I

Table 5.2

Reduced-Form Residuals		
σ (EMP T)	0.6305	
σ (EMP M/T)	0.8646	
ρ (EMP T, EMP M/T)	-0.0248	
Multivariate Normality		
Skewness	22.8451 [0.0000]	
Kurtosis	744.7952 [0.0000]	
Joint	767.6402 [0.0000]	
Log-Likelihood	-185.1554	
Log-Determinant of the Residual variance-covariance Matrix	-1.2142	
AIC	-0.2985	
BIC	0.8089	
Estimated Sum of the VMA(∞) coefficients And Standard Errors	2.0388 (0.6362)	0.4394 (0.5212)
	-0.5494 (0.2497)	0.4827 (0.2046)
LR Test for exclusion of the		
Last Lag $\chi(4)$	4.5230 [0.3398]	
Last 4 Lags $\chi(16)$	14.6581 [0.5498]	

[Significance]
(Standard Error)

MODEL C-I

Table 5.3

	Bernanke-Sims		Blanchard-Quah	
Matrix B	B, where D = inv(B)*SIGMA*inv(B)'		B, where D = inv(B)*SIGMA*inv(B)'	
	EMP T	EMP M/T	EMP T	EMP M/T
	1.0000	0.0000	0.9385	0.2023
	0.0000	1.0000	-0.2851	0.9385
Matrix $D^{1/2}$	1.5409	0.0000	1.4879	0.0000
	0.0000	1.9142	0.0000	1.8600
LR Test for Overidentification				
LR $\sim \chi(1)$	50.4139			
Significance Level	0.0000			
Matrix $B^{-1} D^{1/2}$	EMP T	EMP M/T	EMP T	EMP M/T
	1.5409	0.0000	1.4879	-0.4009
	0.0000	1.9142	0.4520	1.8600
Accumulated Effect of a Normalized Structural Shock = One Standard Deviation				
Out to 16 Steps	EMP T	EMP M/T	EMP T	EMP M/T
	3.14564	0.81386	3.22949	-0.02754
	-0.85054	0.96209	-0.59407	1.15616
Out to ∞ Steps	EMP T	EMP M/T	EMP T	EMP M/T
	3.14174	0.84116	3.23218	-0.00000
	-0.84660	0.92406	-0.59925	1.11819
Normalized Variables				
Matrix $B^{-1} D^{1/2}$	EMP T	EMP M/T	EMP T	EMP M/T
	0.6305	0.0000	0.6088	-0.1640
	0.0000	0.8646	0.2042	0.8401
Out to 16 Steps	EMP T	EMP M/T	EMP T	EMP M/T
	1.28709	0.33300	1.32140	-0.01127
	-0.38416	0.43455	-0.26832	0.52221
Out to ∞ Steps	EMP T	EMP M/T	EMP T	EMP M/T
	1.28549	0.34417	1.32250	0.00000
	-0.38239	0.41737	-0.27066	0.50505

MODEL C-I

Table 5.4

	Bernanke-Sims		Blanchard-Quah	
Forecast Error Variance Decomposition				
Period 0	1.00000 0.00000	0.00000 1.00000	0.93231 0.05576	0.06769 0.94424
Period 1	0.99570 0.05934	0.00430 0.94066	0.94313 0.11404	0.05687 0.88596
Period 2	0.99541 0.05625	0.00459 0.94375	0.94359 0.11218	0.05641 0.88782
Period 3	0.99041 0.05847	0.00959 0.94153	0.93947 0.11449	0.06053 0.88551
Period 4	0.97829 0.05983	0.02171 0.94017	0.93041 0.11563	0.06959 0.88437
Period 5	0.96995 0.06976	0.03005 0.93024	0.93119 0.12724	0.06881 0.87276
Period 6	0.92742 0.09232	0.07258 0.90768	0.90323 0.15808	0.09677 0.84192
Period 7	0.91092 0.09248	0.08908 0.90752	0.88975 0.15832	0.11025 0.84168
Period 8	0.89048 0.09731	0.10952 0.90269	0.87364 0.15946	0.12636 0.84054
Period 9	0.88247 0.09982	0.11753 0.90018	0.86566 0.16279	0.13434 0.83721
Period 10	0.88188 0.10048	0.11812 0.89952	0.86542 0.16294	0.13458 0.83706
Period 11	0.88085 0.10112	0.11915 0.89888	0.86415 0.16404	0.13585 0.83596
Period 12	0.88048 0.10186	0.11952 0.89814	0.86411 0.16458	0.13589 0.83542
Period 13	0.87823 0.10262	0.12177 0.89738	0.86225 0.16572	0.13775 0.83428
Period 14	0.87825 0.10206	0.12175 0.89794	0.86181 0.16541	0.13819 0.83459
Period 15	0.87843 0.10263	0.12157 0.89737	0.86198 0.16588	0.13802 0.83412
Period 16	0.87767 0.10276	0.12233 0.89724	0.86122 0.16615	0.13878 0.83385

MODEL C-I

Table 5.5

Model C-I
Reduced Form Coefficients Values

	EMP T	EMP M/T
1. EMP T{1}	0.49455	-0.31253
2. EMP T{2}	-0.12157	0.12191
3. EMP T{3}	0.01768	-0.03662
4. EMP T{4}	0.05490	-0.04470
5. EMP T{5}	0.19273	-0.10146
6. EMP T{6}	-0.05469	-0.13565
7. EMP T{7}	0.06917	-0.02125
8. EMP T{8}	-0.04663	0.08206
9. EMP M/T{1}	0.05899	-0.05755
10. EMP M/T{2}	-0.00936	-0.23199
11. EMP M/T{3}	0.07738	-0.01185
12. EMP M/T{4}	0.07122	-0.03441
13. EMP M/T{5}	0.06735	-0.04075
14. EMP M/T{6}	0.18015	-0.15871
15. EMP M/T{7}	0.07017	0.00516
16. EMP M/T{8}	-0.15738	-0.13333
17. DUM1	-4.92409	1.23483
18. DUM2	-3.64221	-2.25146
19. Constant	0.38133	3.83456

MODEL C-II

Table 5.6: Residual Analysis

	Jarque-Bera Normality Test JB(2)	Ljung-Box Residual Autocorrelation LB(24)	Lagrange Multiplier Residual ARCH ARCH (24)
EMP T	1.1464 [0.5637]	21.2679 [0.1684]	9.7828 [0.9954]
EMP S/T	3.2615 [0.1958]	18.2705 [0.3083]	17.9593 [0.8050]

[Significance]

MODEL C-II

Table 5.7

Reduced-Form Residuals		
σ (EMP T)	0.7009	
σ (EMP S/T)	0.6625	
ρ (EMP T, EMP S/T)	-0.1170	
Multivariate Normality		
Skewness	109.5324 [0.0000]	
Kurtosis	29736.1239 [0.0000]	
Joint	29845.6562 [0.0000]	
Log-Likelihood	-171.3079	
Log-Determinant of the Residual variance-covariance Matrix	-1.5479	
AIC	-0.6322	
BIC	0.4752	
	EMP T	EMP S/T
Estimated Sum of the VMA(∞) coefficients And Standard Errors	1.83668 (0.66210) -0.11124 0.48848	-0.74034 (1.04249) 1.61449 0.76912
LR Test for exclusion of the		
Last Lag $\chi(4)$	1.9819 [0.7391]	
Last 4 Lags $\chi(16)$	10.5523 [0.8362]	

[Significance]
(Standard Error)

MODEL C-II

Table 5.8

	Bernanke-Sims	**Blanchard-Quah**
Matrix B	B, where D = inv(B)*SIGMA*inv(B)' EMP T EMP S/T 1.0000 0.0000 0.0000 1.0000	B, where D = inv(B)*SIGMA*inv(B)' EMP T EMP S/T 0.8528 -0.3437 0.3653 0.8528
Matrix $D^{1/2}$	1.7131 0.0000 0.0000 1.5722	1.6158 0.0000 0.0000 1.4116
LR Test for Overidentification		
LR ~ $\chi(1)$	64.8082	
Significance Level	0.0000	
Matrix B^{-1} $D^{1/2}$	EMP T EMP S/T 1.7131 0.0000 0.0000 1.5722	EMP T EMP S/T 1.6158 0.5690 -0.6922 1.4116
Accumulated Effect of a Normalized Structural Shock = One Standard Deviation		
Out to 16 Steps	EMP T EMP S/T 3.17105 -1.10858 -0.20397 2.49111	EMP T EMP S/T 3.47908 0.05791 -1.28911 2.16895
Out to ∞ Steps	EMP T EMP S/T 3.14638 -1.16395 -0.19056 2.53829	EMP T EMP S/T 3.48018 0.00000 -1.29724 2.21576
Normalized Variables		
Matrix B^{-1} $D^{1/2}$	EMP T EMP S/T 0.7009 0.0000 0.0000 0.6625	EMP T EMP S/T 0.6611 0.2328 -0.2917 0.5949
Out to 16 Steps	EMP T EMP S/T 1.29748 -0.45359 -0.08595 1.04977	EMP T EMP S/T 1.42352 0.02370 -0.54324 0.91401
Out to ∞ Steps	EMP T EMP S/T 1.28739 -0.47625 -0.08030 1.06965	EMP T EMP S/T 1.42397 -0.00000 -0.54667 0.93374

MODEL C-II

Table 5.9

	Bernanke-Sims		**Blanchard-Quah**	
Forecast Error Variance Decomposition				
Period 0	1.00000	0.00000	0.88967	0.11033
	0.00000	1.00000	0.19383	0.80617
Period 1	0.99905	0.00095	0.89839	0.10161
	0.07871	0.92129	0.26193	0.73807
Period 2	0.98702	0.01298	0.89841	0.10159
	0.07899	0.92101	0.26274	0.73726
Period 3	0.97630	0.02370	0.88940	0.11060
	0.10379	0.89621	0.27360	0.72640
Period 4	0.97294	0.02706	0.88520	0.11480
	0.11597	0.88403	0.28755	0.71245
Period 5	0.97200	0.02800	0.88688	0.11312
	0.12740	0.87260	0.29208	0.70792
Period 6	0.97217	0.02783	0.88602	0.11398
	0.12621	0.87379	0.29122	0.70878
Period 7	0.97129	0.02871	0.88391	0.11609
	0.14642	0.85358	0.31585	0.68415
Period 8	0.96509	0.03491	0.87731	0.12269
	0.14661	0.85339	0.31576	0.68424
Period 9	0.95893	0.04107	0.87111	0.12889
	0.15034	0.84966	0.31562	0.68438
Period 10	0.95769	0.04231	0.87018	0.12982
	0.15227	0.84773	0.31602	0.68398
Period 11	0.95767	0.04233	0.87016	0.12984
	0.15236	0.84764	0.31607	0.68393
Period 12	0.95765	0.04235	0.87001	0.12999
	0.15223	0.84777	0.31600	0.68400
Period 13	0.95764	0.04236	0.86996	0.13004
	0.15274	0.84726	0.31648	0.68352
Period 14	0.95735	0.04265	0.86942	0.13058
	0.15274	0.84726	0.31650	0.68350
Period 15	0.95668	0.04332	0.86888	0.13112
	0.15359	0.84641	0.31632	0.68368
Period 16	0.95660	0.04340	0.86887	0.13113
	0.15355	0.84645	0.31628	0.68372

MODEL C-II

Table 5.10

Model C-II
Reduced Form Coefficients Values

	EMP T	EMP S/T
1. EMP T{1}	0.56366	-0.26882
2. EMP T{2}	-0.17991	0.18894
3. EMP T{3}	-0.03787	0.07712
4. EMP T{4}	-0.00083	-0.19688
5. EMP T{5}	0.17423	0.23282
6. EMP T{6}	-0.06583	-0.06184
7. EMP T{7}	0.06925	-0.12330
8. EMP T{8}	-0.08272	0.11338
9. EMP S/T{1}	-0.03852	0.06448
10. EMP S/T{2}	-0.11520	-0.05671
11. EMP S/T{3}	-0.05562	0.02615
12. EMP S/T{4}	-0.02666	0.05314
13. EMP S/T{5}	-0.02559	0.04405
14. EMP S/T{6}	0.04253	0.09759
15. EMP S/T{7}	0.05341	0.11159
16. EMP S/T{8}	-0.09115	0.02262
17. DUM1	-4.64465	1.39361
18. DUM3	0.84187	-10.52298
19. Constant	1.01705	-0.00920

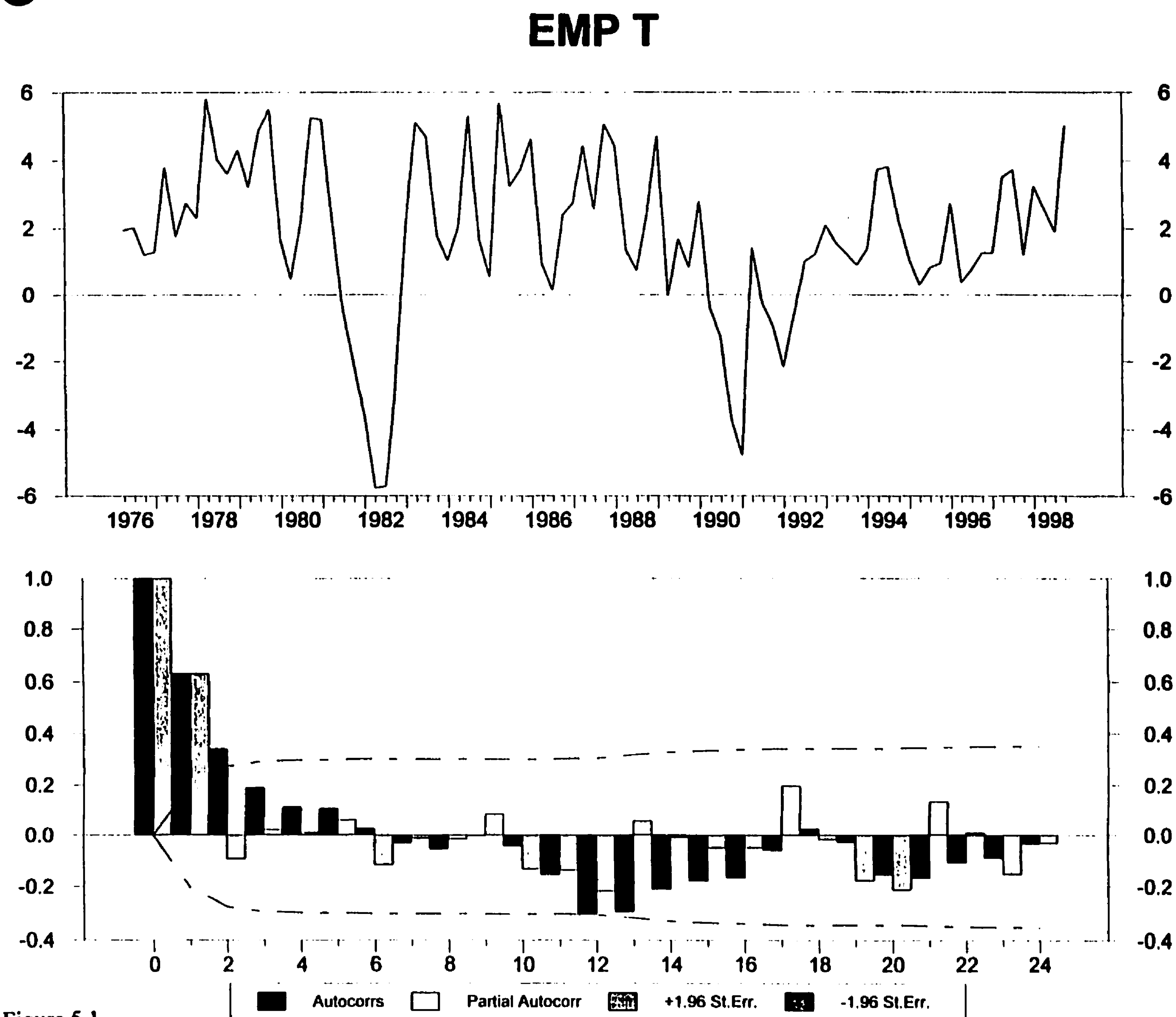

EMP T
6
4
2
0
-2
-4
-6
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
0
2
4
6
8
10
12
14
16
18
20
22
24
Autocorrs
Partial Autocorr
+1.96 St.Err.
-1.96 St.Err.

Figure 5.1

EMP M/T

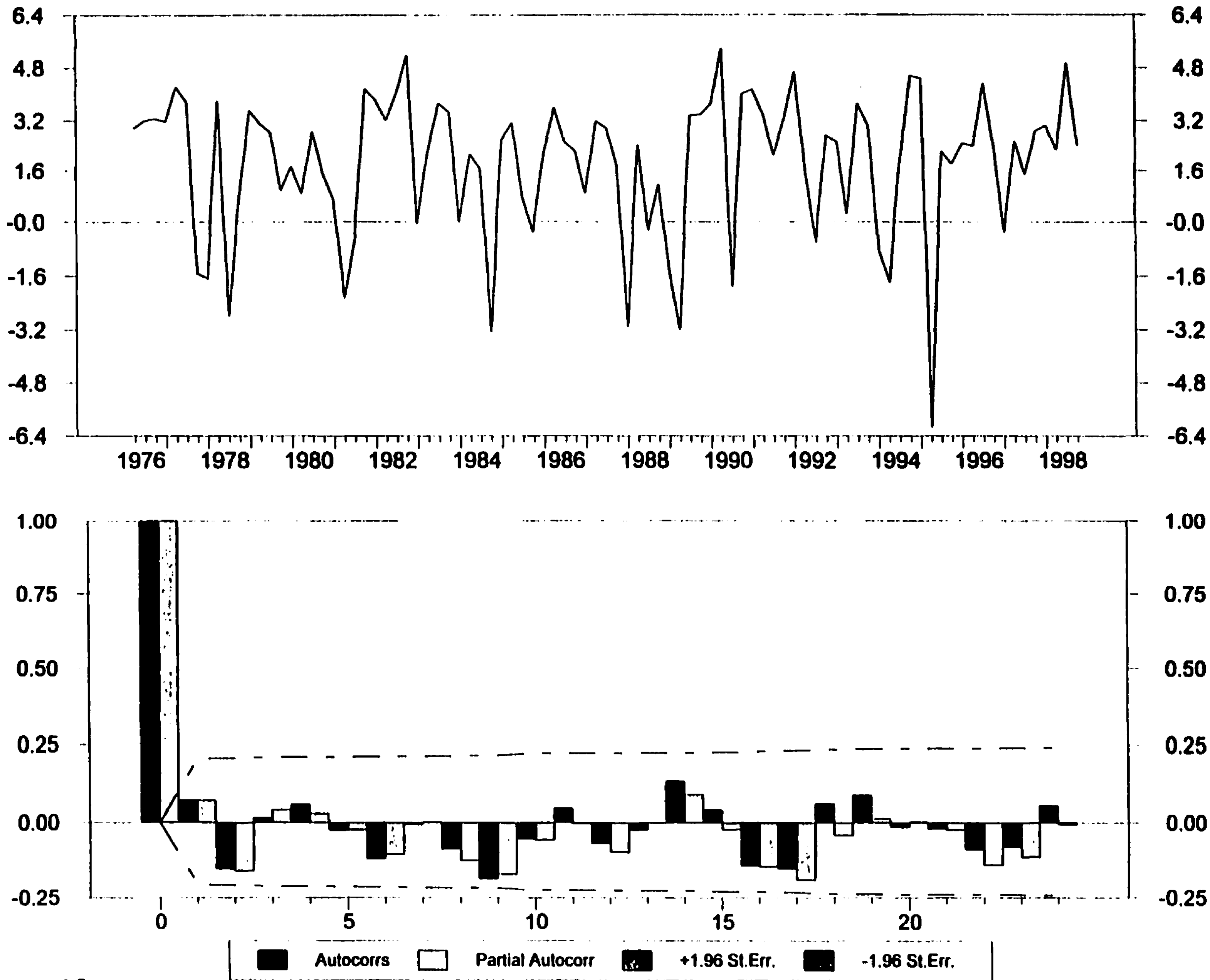


Figure 5.2

EMP S/T

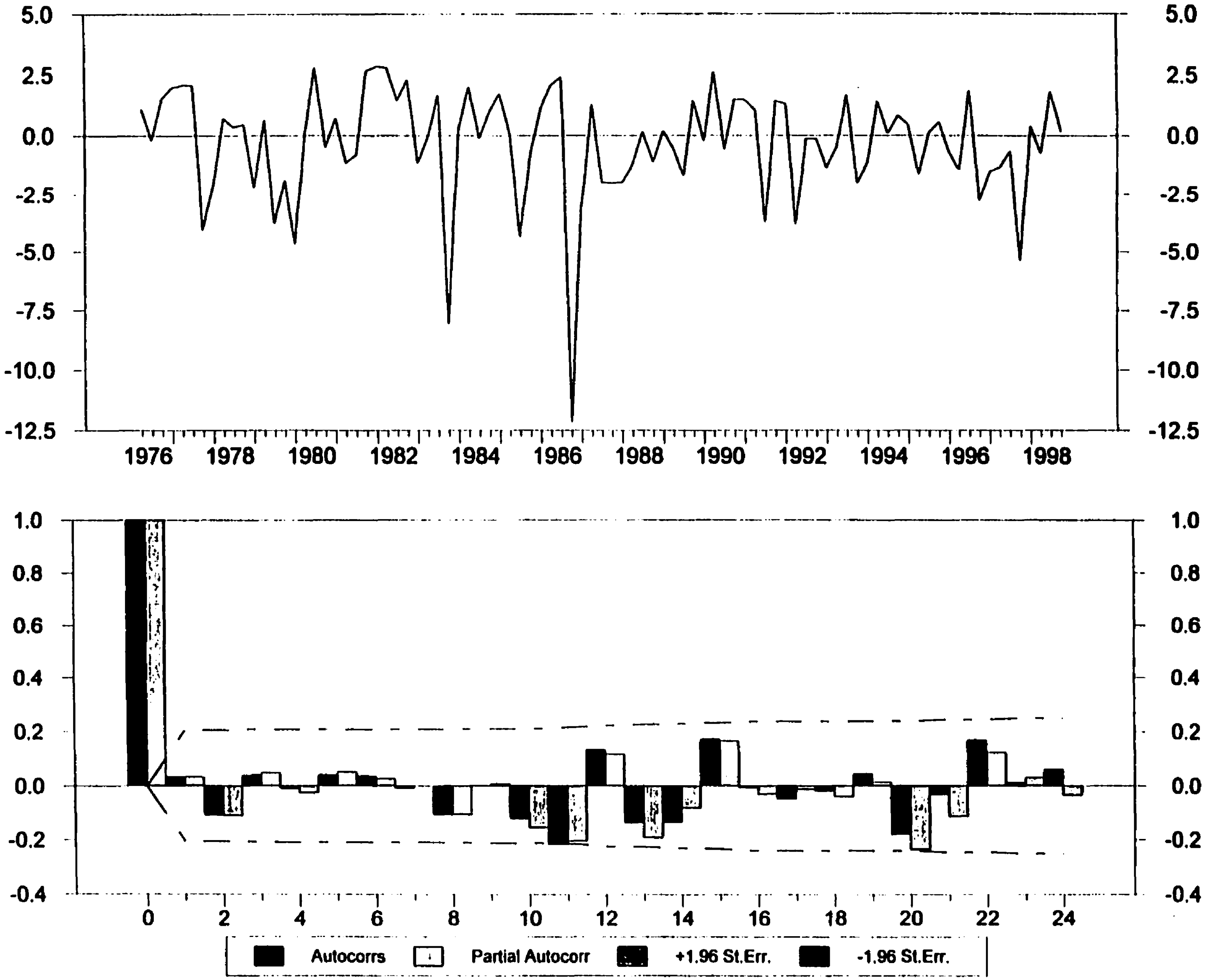


Figure 5.3

Accumulated Effects of a Shock to EMP M/T

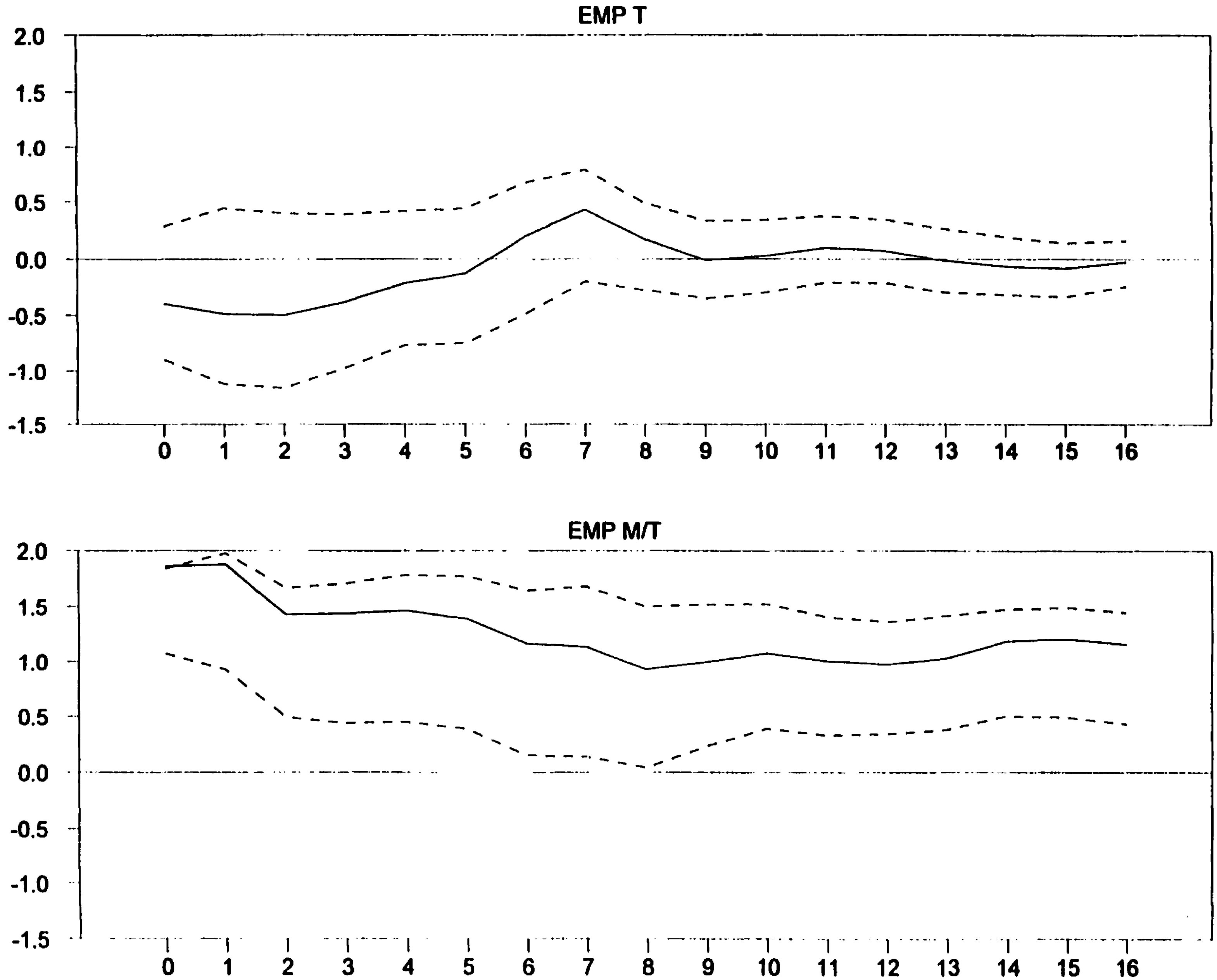


Figure 5.4

Accumulated Effects of a Shock to EMP S/T

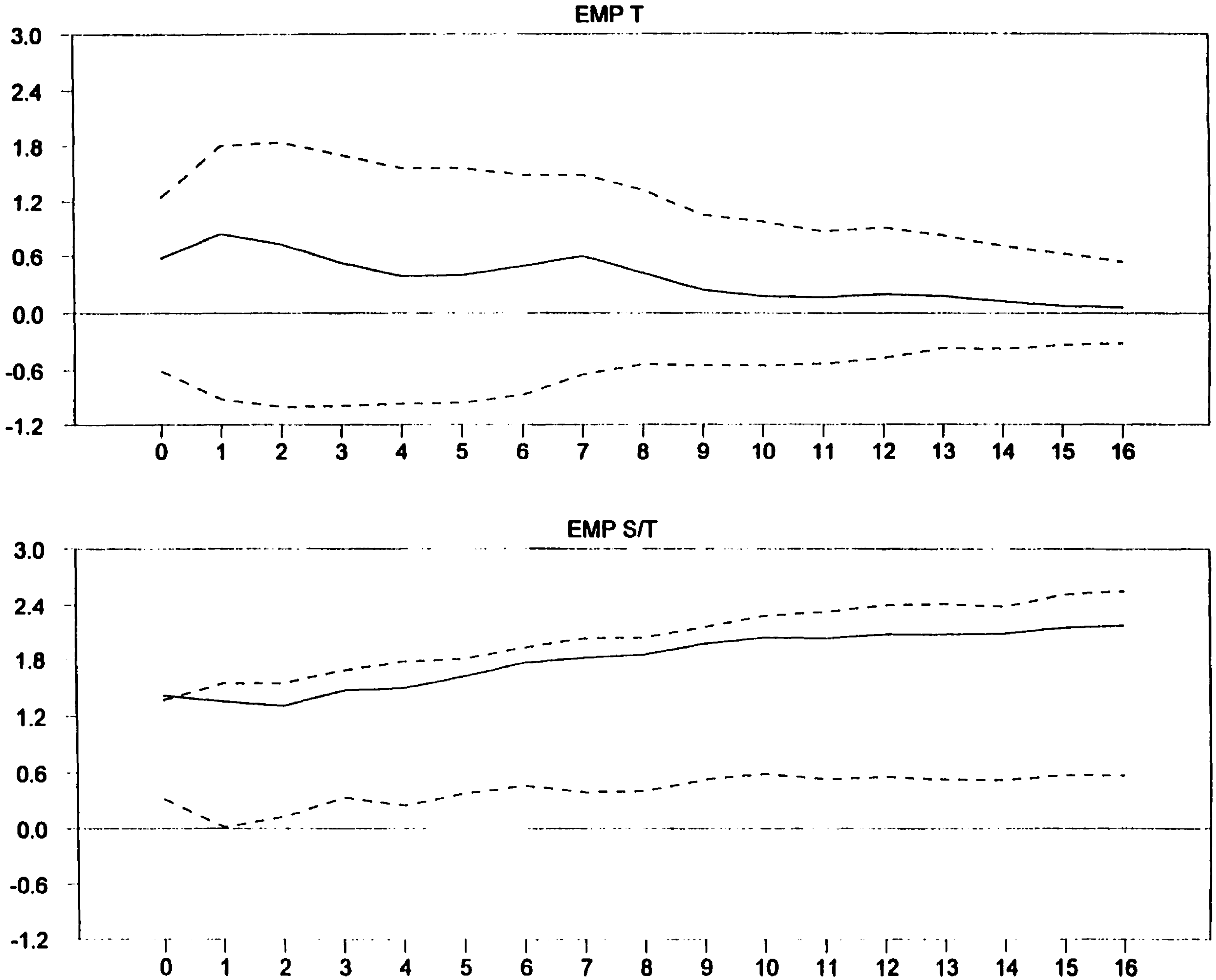


Figure 5.5

Accumulated Effects of a Shock to EMP M/T

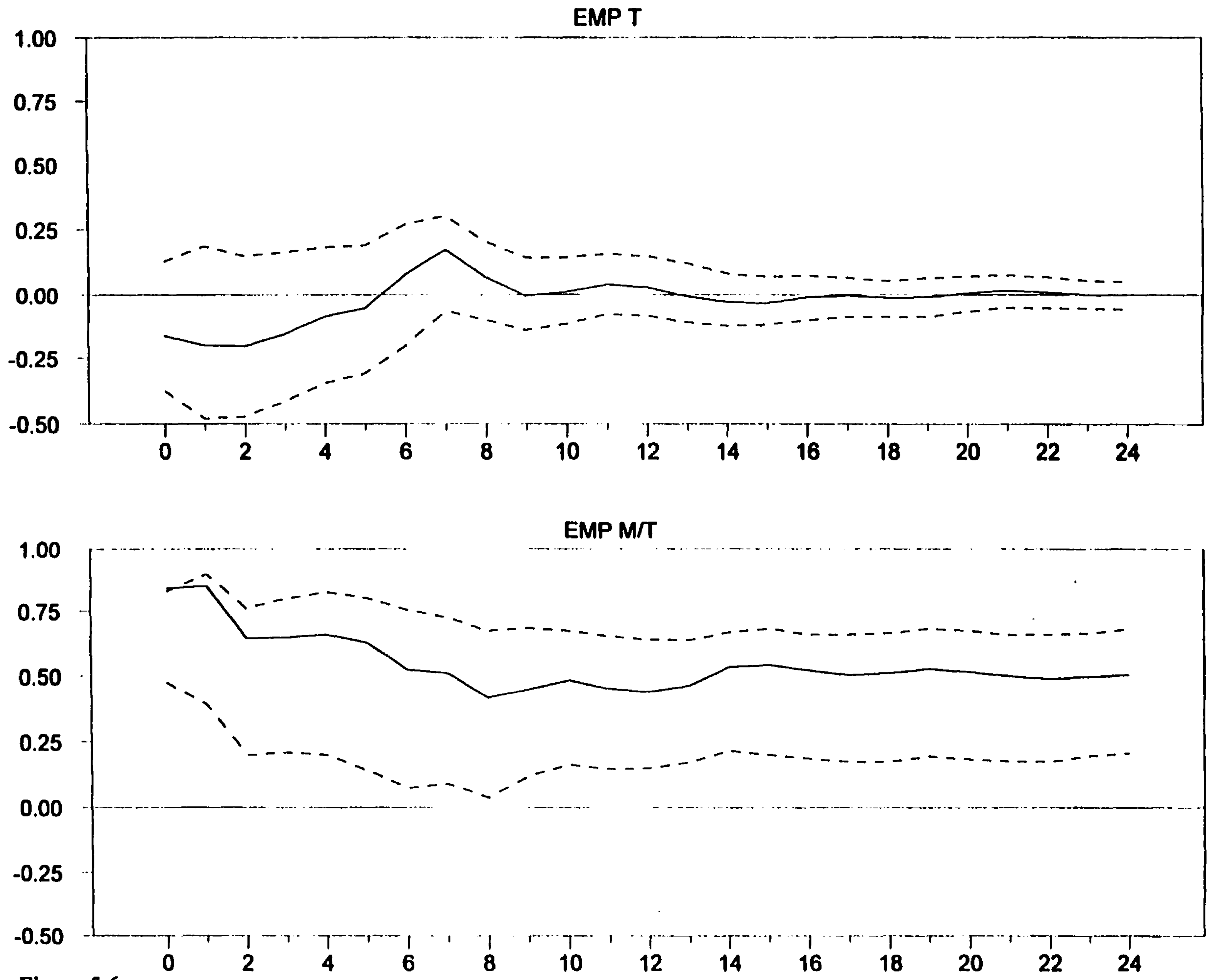


Figure 5.6

Accumulated Effects of a Shock to EMP S/T

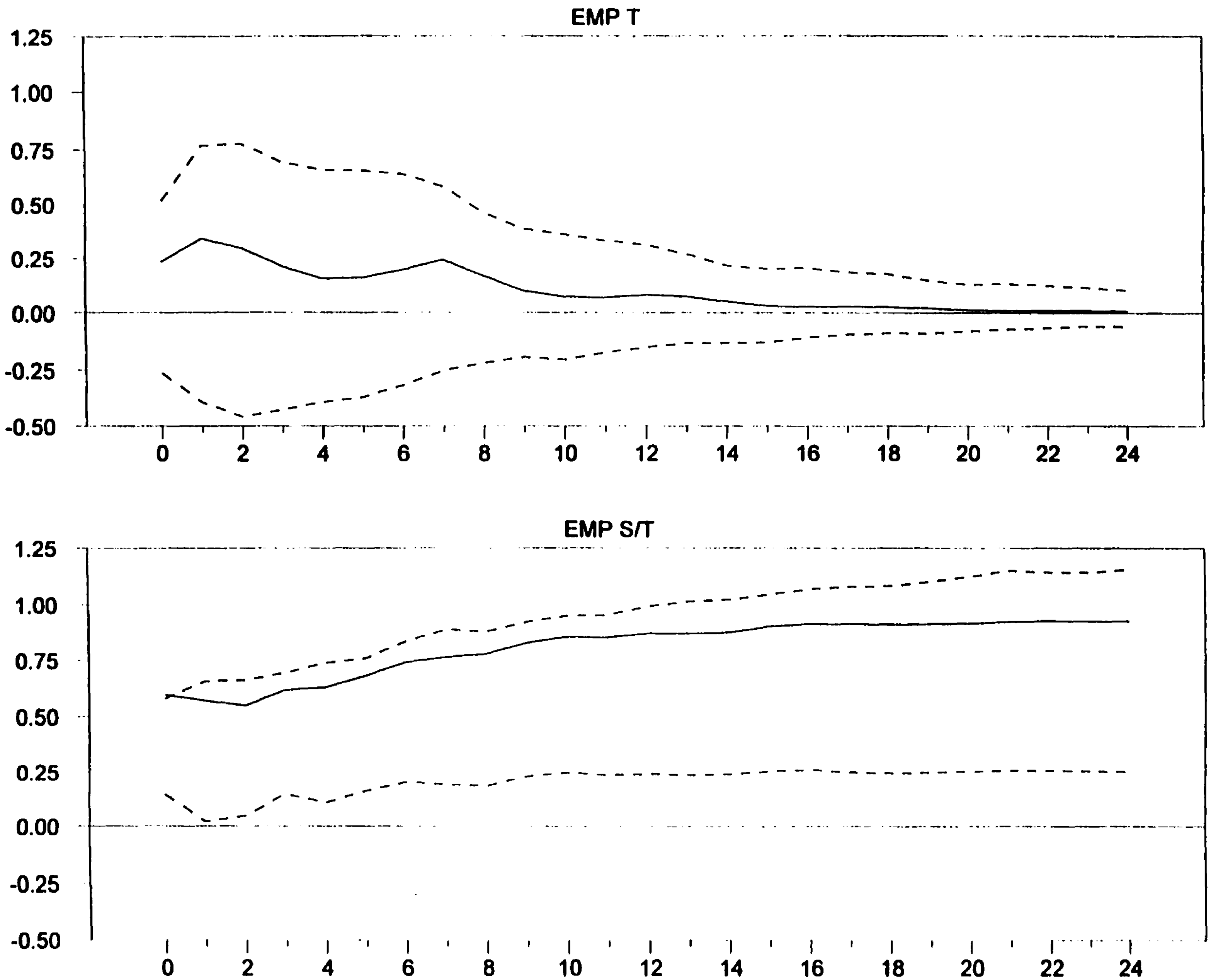


Figure 5.7

5.6.2 Bayesian VAR results

For the Bayesian VAR models, the results are reported, as well as their corresponding impulse response functions and variance decomposition. Three Bayesian VAR models are estimated. Each model is estimated using five different parameter specifications, for a total of 15 sub-models.

The first model (B-I) is a bivariate VAR (≡BVAR) including total employment and manufacturing employment (where total employment is defined as all employment less manufacturing). The second model (B-II) is a bivariate VAR (≡BVAR) including total employment and services employment (where total employment is defined as all employment less services). The third model (T-III) is a trivariate VAR (≡TVAR) including total employment, manufacturing employment and services employment (where total employment is defined as all employment less manufacturing and services). All monthly employment series are in log form. All tabular results are reported, as well as the impulse responses graphs. The different specifications are,

Specification	Tightness (γ)	Weight to off-diagonal (w)
Univariate OLS	2	0.001
Univariate VAR	0.1	0.001
Simple Bayesian VAR	0.1	0.5
Common Bayesian VAR	0.2	0.5
OLS VAR	2	1.0

As the value of w approaches zero, the system approaches a set of univariate autoregressions, i.e., forcing all coefficients on other than own lags toward zero. A smaller value for γ forces the own lag coefficient closer to the prior mean. A higher value for γ erases the Bayesian part from the VAR system and results in a general OLS. For each specification, the impulse responses are graphed, and the variance decomposition and the Theil U statistics are reported. To impose a minimum restrictions on the VAR in levels, all models are identified with the Bernanke-Sims scheme.

The tables for the variance decomposition read as follows. The first column is the standard-error of forecast for the variable in the title of the model. The remaining columns provide the variance decomposition. Each row adds up to 100 percent. For example, if the value of the last column at step 1 is 88.35 percent, then 88.35 percent of the one-step forecast error of the variable in the last column is due to the innovation in the variable title.

The Theil U statistic is a unit free measure. It is computed as the ratio of the root mean square errors of the model relative to the root mean square errors of the naive forecast model. The naive forecast model is computed assuming no change in the dependent variable over time. The Theil U statistic is an in-sample performance measure. The VAR is estimated before the end of data and the Theil U statistic is computed as an in-sample forecast. A value of the Theil U statistic higher (lower) than 1 indicates that the VAR model is worse (better) than the naive one. The changing patterns in the Theil U values are used to discriminate between different specifications. A lower Theil U value indicates a better model. Once selected, the impulse responses are examined and conclusions are drawn regarding persistence.

Table 5.12 defines the employment-level data used in the Bayesian VAR estimation and shows the CANSIM source labels. All series are in log form and cover the monthly period from 1976M1 to 1998M12 for a total of 276 observations. We carried a series of information criteria tests to determine the lag length and we choose 24 lags for the VAR. We included a constant, a trend and two dummy variables in the commonly used BVAR. The dummy variables are set to capture both recessions. For model B-I, employment is the log-level of total employment minus manufacturing employment. For model B-II, employment is computed as the log-level of total employment minus services employment. The following table reports the residuals analysis for both Bivariate models. Note that for the Classical VAR, we used the quarter frequency.

Table 5.11 reports the Jarque-Bera normality test, the Lagrange-multiplier serial autocorrelation test and the Lagrange-multiplier ARCH test for the reduced form VAR residuals. Evidence of deviations from normality appears only for total employment in model B-II, where normality is rejected. For both models, the residuals of the reduced form are serially uncorrelated and no evidence of conditional heteroskedasticity is found.

MODELS B-I and B-II

Table 5.11: Residual Analysis

	Jarque-Bera Normality Test	Ljung-Box Residual Autocorrelation	Lagrange Multiplier Residual ARCH
MODEL B-I			
EMP T	0.4377 [0.8034]	14.9124 [0.7814]	25.4518 [0.3816]
MANUFACTURING	4.9398 [0.0846]	15.2519 [0.7618]	19.1632 [0.7432]
MODEL B-II			
EMP T	7.2552 [0.0266]	10.8087 [0.9510]	17.6403 [0.8201]
SERVICES	1.7720 [0.4123]	12.0973 [0.9127]	20.2782 [0.6809]

[Significance]

Table 5.13 reports - HP filtered[29] - basic descriptive statistics for employment time series across sectors. Service employment is as variable as total employment. The highest employment variability is recorded for the agriculture sector. Table 5.14 presents the correlation matrix between de-trended employment series. Total employment is highly correlated with services employment (0.68), with goods[30] employment (0.77) and with manufacturing employment (0.62). Agricultural employment records the lowest correlation (0.18) with total employment. For these reasons, we focus on the dynamic relation between total employment, services employment and manufacturing employment.

Tables 5.15 to 5.34 present the results for models B-I and B-II. The results include the Theil U statistic for 5 different specifications of each model (Tables 5.15 to 5.24). We also report the variance decomposition for each specification of each model (Tables 5.25 to 5.34). Tables 5.15 to 5.19 report the Theil U statistics for model B-I (bivariate) VAR between total employment and manufacturing employment. The statistics are reported for all the 5 specifications. The Theil U statistic for the step-1 forecast is lowest within the commonly used Bayesian VAR (specification: $\gamma = 0.2$ and $w = 0.5$). It equals 0.78 and 0.88 respectively for total employment and manufacturing employment (step-1 in Table 5.17).

The step-1 forecast is computed using 12 observations (i.e., one year). The higher the forecast steps, the smaller the number of observations used to compute the statistic and the less reliable it becomes. Based on the Theil U statistic, the Bayesian VAR

[29]Since we are using monthly data, the smoothing parameter λ is set to 14400. See section 2.6 for details regarding λ.

[30]Goods employment is classified into manufacturing and non-manufacturing employment.

specification for the dynamic relation between total employment and manufacturing employment best fits the data.

Tables 5.20 to 5.24 present the Theil U statistics for model B-II (bivariate) VAR between total employment and services employment. For all five specifications, the step-1 forecast statistic is lowest within univariate OLS (specification: $\gamma = 2.0$ and $w = 0.001$) for services employment (step-1 in Table 5.20) and equals 0.782. However, to forecast total employment in this univariate OLS specification, the Theil U statistic value is 1.08 (step-1 in Table 5.20). This indicates a poor forecasting specification. Across all models, the commonly used Bayesian VAR (Table 5.23) is the best in terms of forecasting ability for both total and services employment. The statistic equals 0.88 and 0.87 for total and services employment, respectively.

Given that the Bayesian VAR models were conducted with focus on exploring empirical regularities. We treat these results with caution. No economic suggestion is made regarding the behaviour of the statistics. Tables 5.25 to 5.29 report the variance decomposition for model B-I for all parametric specifications. Table 5.25 suggests that an innovation shock in manufacturing employment is responsible for a variance in the rest of employment of 1.76 percent after one month (step-1) and has an effect similar in magnitude up to and including three years (step-36). However, since the Theil U statistic points to a commonly used Bayesian VAR as a better specification (Table 5.18), Table 5.28 is of interest here and we focus on the commonly Bayesian VAR results only to investigate economic persistence from the impulse responses. Table 5.28 suggests that a shock in manufacturing employment is responsible for a high (20 percent) variation in the rest of the employment forecast after one year from the shock (step-12). The effect diminishes to 14.3 percent after three years (step-36). The dynamic relationship between manufacturing employment and the rest of employment is not symmetric. A shock in the rest of employment predicts 19.53 percent variation in manufacturing employment after 3 years (step-36) and 7.47 percent after one year (step-12).

Tables 5.30 to 5.34 report the results for the variance decomposition for model B-II for all parametric specifications. Table 5.33 is the variance decomposition for the commonly used Bayesian VAR between total employment and services employment. A shock of one percent in services employment is responsible for a maximum of 6.12 percent of the variance of total employment after 30 months (step-30). Thereafter, the effect of the shock diminishes. A one percent shock in the rest of employment proves powerful in terms of the effects on services employment. Almost one third of services' employment variation after two years is due to the shock in total employment. The effect peaks at 34.44 percent at two years, then slowly decreases.

Results for model T-III are presented in tables 5.35 to 5.44. Tables 5.35 to 5.39 report the Theil U statistic for the trivariate VAR between total, manufacturing and services employment. In this setup, total employment is defined as all employment minus manufacturing and services. Tables 5.40 to 5.44 report the variance decomposition for model T-III. None of the specifications dominates the others. However, for manufacturing and services employment, the Bayesian Tri-VAR provides the lowest Theil U statistic for their forecast. Table 5.38 points to the usefulness of the Bayesian approach in describing the dynamic relationship. For step-1 forecasts (for the next month), the Tri-VAR is better than the naive model of no change in the dependent variables. The Theil U value is 0.95 and 0.71 for manufacturing and services employment, respectively.

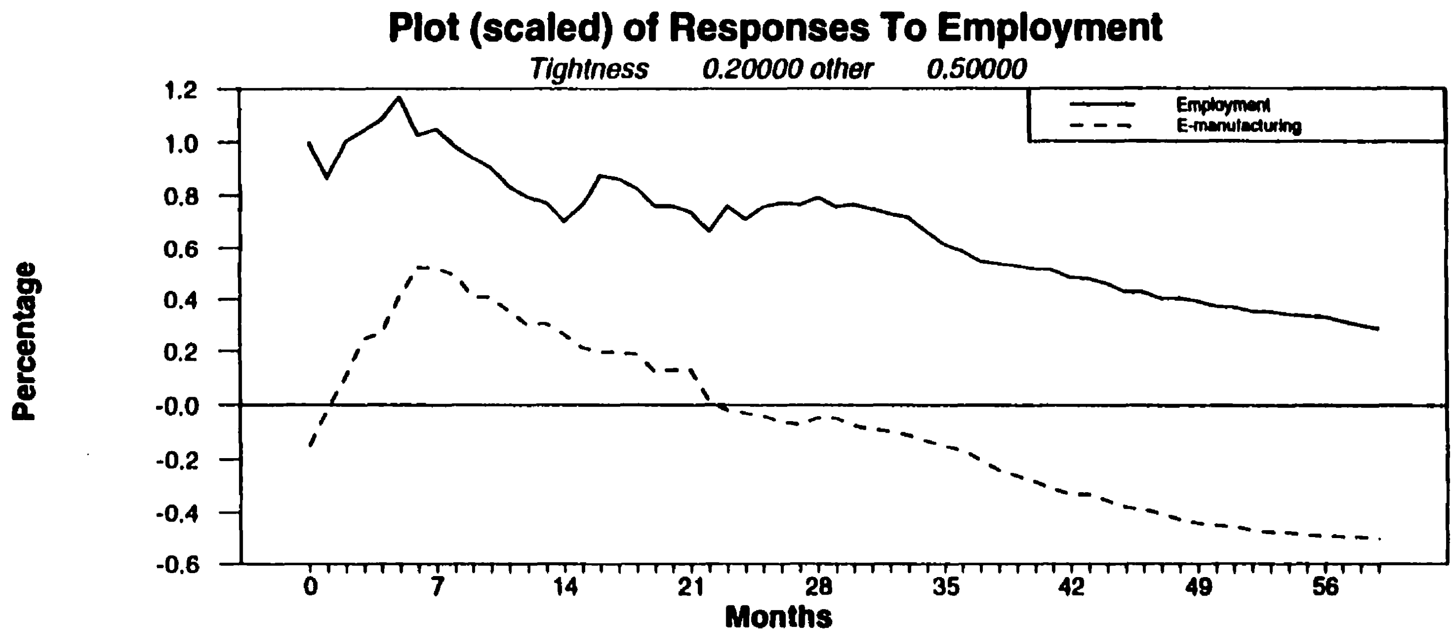
Tables 5.40 to 5.44 present the variance decomposition of the tri-VAR. Specifically, the Bayesian approach (Table 5.43) suggests that a one percent shock in total employment is responsible for 12.24 percent and 51.35 percent variance in manufacturing and services after 28 months, respectively. A one percent shock in manufacturing employment influences service employment the most, 18.71 percent effect after two years (step-24). A one percent shock in service employment influences equally both total employment and manufacturing employment over a period of two years.

Figures 5.8 to 5.22 present the impulse responses of all 15 models. We focus on the commonly Bayesian VAR, i.e., Figures 5.8 and 5.9. Figures 5.10 to 5.14 are the impulse responses of model B-I. Figures 5.15 to 5.17 are the impulse responses of model B-II. Figures 5.18 to 5.22 are the impulse responses of model T-III.

Model B-I, Figure 5.8 (upper graph) shows that a one percent shock to total employment results in a peak influence (0.6 percent) on manufacturing employment after 7 months, then it becomes negligible. The effect of the shock dies after 22 months. In the lower graph, a one percent shock to manufacturing employment results in a peak of 0.58 percent change in total employment. The influence peaks after 24 months and persists for 36 months.

Figure 5.9 presents the impulse response for model B-II. The figure shows the dynamic relation between total employment and services employment. The upper graph shows that a one percent shock to total employment influences services employment by at most 0.32 percent after 15 months. The influence of the shock decreases with time and becomes negligible after 36 months. The lower graph shows a one percent response of total employment to a shock in services employment. The shock reaches a peak effect at 0.75 percent after 10 months but diminishes quickly thereafter.

Figure 5.21 shows the impulse responses of a shock in each employment series and the responses of the other two series. The upper graph shows the symmetry with which a shock to total employment influences both services and manufacturing employment. The effect on both series is similar, reaching a peak of 0.25 percent and disappearing after 8 months. The middle graph shows the responses of a shock to manufacturing employment. The shock mostly affects total employment - reaching 0.4 percent - and, more importantly, the effect persists throughout the time line of 36 months. The lower graph shows the symmetric effect a shock to services employment has on the economy. A shock of one percent increases both total employment and manufacturing employment by the same percentage, reaching a peak after 8 months and then diminishing slowly thereafter.


Plot (scaled) of Responses To Employment
Tightness 0.20000 other 0.50000
Employment
E-manufacturing
Percentage
Months
1.2
1.0
0.8
0.6
0.4
0.2
-0.0
-0.2
-0.4
-0.6
0
7
14
21
28
35
42
49
56

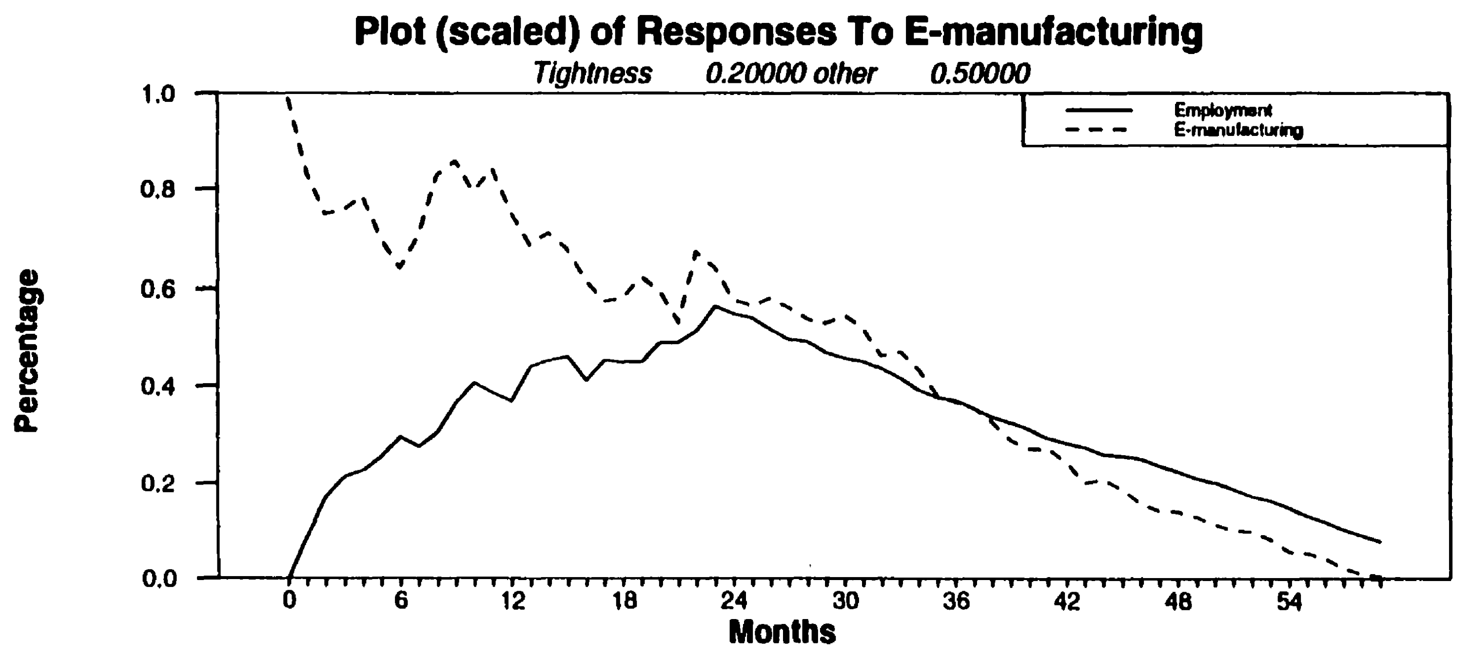
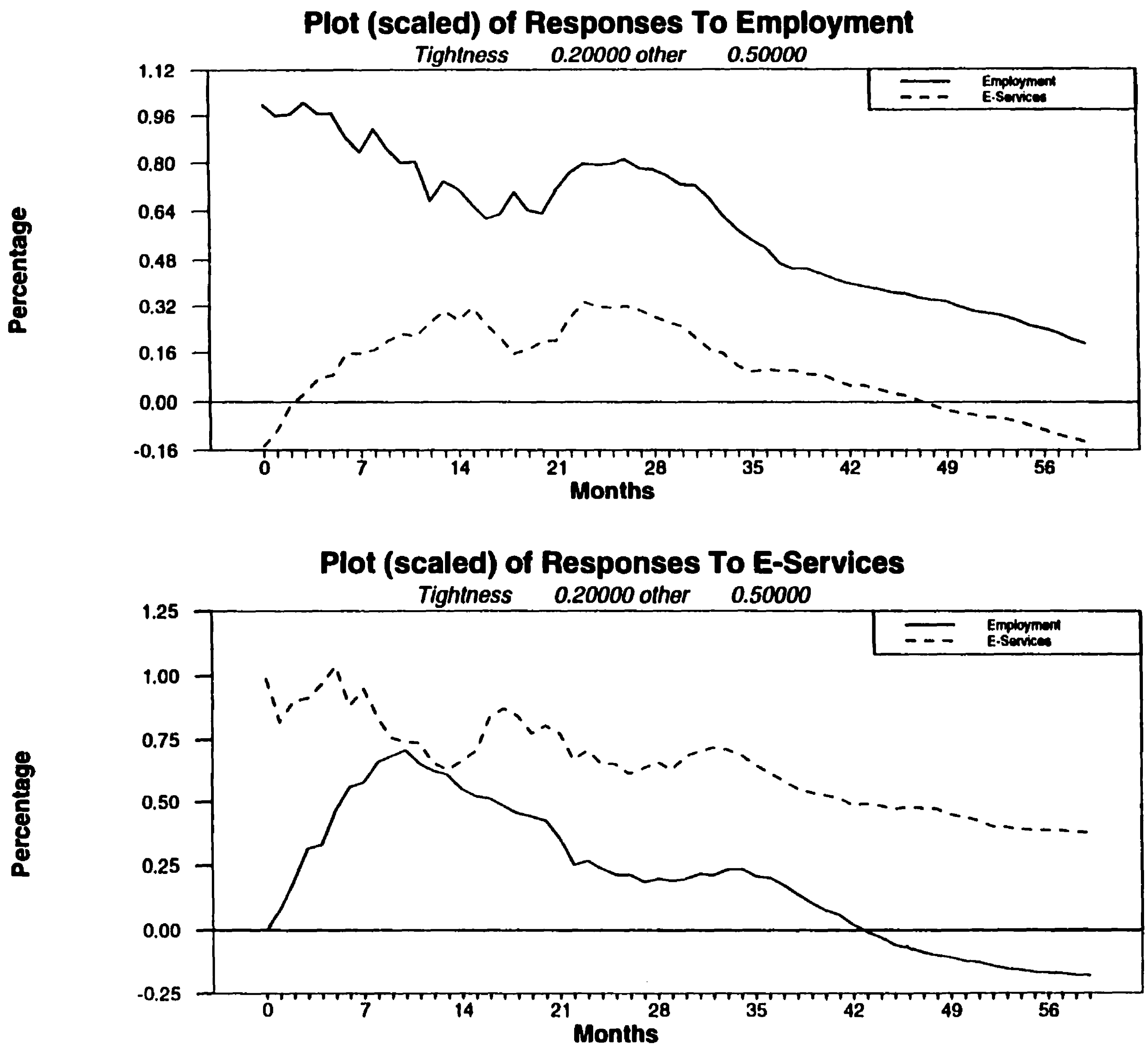

Plot (scaled) of Responses To E-manufacturing
Tightness 0.20000 other 0.50000
Employment
E-manufacturing
Percentage
Months
1.0
0.8
0.6
0.4
0.2
0.0
0
6
12
18
24
30
36
42
48
54

Figure 5.8



Plot (scaled) of Responses To Employment
Tightness 0.20000 other 0.50000
Employment
E-Services
Percentage
1.12
0.96
0.80
0.64
0.48
0.32
0.16
0.00
-0.16
0
7
14
21
28
35
42
49
56
Months
Plot (scaled) of Responses To E-Services
Tightness 0.20000 other 0.50000
Employment
E-Services
Percentage
1.25
1.00
0.75
0.50
0.25
0.00
-0.25
0
7
14
21
28
35
42
49
56
Months

Figure 5.9

5.7 Conclusions

The Lilien (1982) hypothesis argued that 50% of employment variability is due to sectoral reallocation. Under different identifying restrictions, Campbell and Kuttner (1996) found that reallocative shocks are responsible for at least 27% of aggregate employment variation (See Campbell and Kuttner (1996, p. 113) and Swanson (1999b, p. 1)).

Here, using Canadian data over the 1976 to 1998 period, across all considered Bayesian VAR models, the model with a tightness parameter γ (standard deviation of own-lag prior) equal to 0.2 and an off-diagonal tightness parameter w (standard deviation of off-diagonal prior) equal to 0.5, best explained the dynamics between total employment and manufacturing employment. Also, the same specification proved the best in terms of forecasting ability for both total and services employment.

Based only on the Bayesian results, in the short-run, Kaldor's first law holds for Canadian employment data over the period 1976 to 1998. A shock in manufacturing employment of one percent is responsible for at most 20 percent of the variation in the rest of employment after one year. Using the Classical VAR, a reallocation shock of one standard deviation in manufacturing is responsible for 13.87 percent variation in the growth rate of employment after 4 years (Table 5.4).

In terms of variability, the VAR results for the Classical (C-I) and Bayesian (B-I) models are,

	C-I Bernanke-Sims	C-I Blanchard-Quah	B-I
Shock in:	Emp M/T	Emp M/T	Manuf. Emp.
Effect on variance of:	Emp T	Emp T	Rest of Emp.
1 Year	2.17 %	6.95 %	20.00 %
2 Years	10.95 %	12.63 %	16.35 %
3 Years	11.95 %	13.58 %	14.30 %

Source: Tables 5.4 and 5.27.

The VAR results for the Classical C-II and Bayesian B-II models are,

	C-II Bernanke-Sims	C-II Blanchard-Quah	B-II
Shock in:	Emp S/T	Emp S/T	Serv. Emp.
Effect on variance of:	Emp T	Emp T	Rest of Emp.
1 Year	2.70 %	11.48 %	3.29 %
2 Years	3.49 %	12.26 %	5.63 %
3 Years	4.23 %	12.99 %	5.64 %

Source: Tables 5.9 and 5.32.

One should proceed with caution in interpreting the results from the above tables. First, note that the variables are different across the Classical and Bayesian VARs. Second, one cannot easily compare the results across approaches. Third, the results of the Blanchard-Quah identification for model C-II are counter-intuitive for reasons emphasized in the Classical VAR results section.

Using the Blanchard-Quah identification, we assumed that there is no long-run effect on the level of employment following a 'pure' manufacturing shock. A manufacturing reallocation shock is responsible for (at most) 13.87 percent variance in the growth rate of employment after four years. This is much lower than the 27 percent reported for the employment level by Campbell and Kuttner (1996) and definitely narrower than the 50 percent upper bound suggested by Lilien.

After four years, a one standard deviation 'pure' sectoral shock to the square of the growth rate of the fraction of service employment is responsible for at most 13.11 percent variation in the growth rate of employment. Again, this percentage is much lower than the reported 27 percent by Campbell and Kuttner (1996).

In terms of persistence and from the impulse response figures, a 'pure' sectoral shock decreases the employment growth rate by 16.4 percent in the initial period. The effect of a 'pure' sectoral shock on employment growth is negligible after 4 years. From the impulse response and the forecast variance decomposition, one can deduce that employment variability is influenced for at least 10 quarters. Given the transitory nature of the shock, employment returns to its initial pre-shock level after 4 years. Regardless of the source of the reallocation shock, all shocks assert an influence for at least 2 years.

Note that our results are conditional on the model, approach, specification and identification used. Given our goal of sectoral exploration, these results suggest that sectoral shocks are quite significant for aggregate fluctuations. Empirically and in terms of magnitude, sectoral shocks are less influential than reported in the literature.

5.8 Appendix: Distributions and Tests

This appendix reproduces the densities referred to in the Bayesian section. The source is Zellner (1971) and Bauwens et al. (1999). It also reports the tests used in the Classical VAR estimation process.

5.8.1 The Matricvariate Normal Distribution

Let X and $vecX$ denote a $p \times q$ random matrix and its pq-dimensional column expansion respectively. X is said to have a matricvariate normal distribution with parameters $M \in \Re^{p\times q}$, $P \in C_p$, i.e., $X \sim MN_{p\times q}(vecM,\ Q \otimes P)$ if and only if $vecX \sim N_{pq}\{vecM,\ Q \otimes P\}$. As derived in Bauwens et al. (1999, p. 301), its density function is given by,

$$f_{MN}^{p\times q}(X|M, Q\otimes P) = \left\{ \begin{array}{c} C_{MN}^{-1}(P,Q;p,q) \\ \times \exp\left\{-\frac{1}{2}\left[vec(X-M)^T(Q\otimes P)^{-1}vec(X-M)\right]\right\} \end{array} \right\} \tag{5.93}$$

$$= \left\{ \begin{array}{c} C_{MN}^{-1}(P,Q;p,q) \\ \times \exp\left\{-\frac{1}{2}\left[\sum_{i=1}^{q}\sum_{j=1}^{q} q^{ij}(x_i - m_i)^T P^{-1}(x_j - m_j)\right]\right\} \end{array} \right\} \tag{5.94}$$

$$= \left\{ \begin{array}{c} C_{MN}^{-1}(P,Q;p,q) \\ \times \exp\left\{-\frac{1}{2}tr\left[Q^{-1}(X-M)^T P^{-1}(X-M)\right]\right\} \end{array} \right\} \tag{5.95}$$

$$C_{MN}(P,Q;p,q) = \{(2\pi)^{pq} \quad | P |^q \quad | Q |^p\}^{1/2} \tag{5.96}$$

All the properties of the multivariate normal distribution apply to the matricvariate normal distribution through the vec operator. See Bauwens et al. (1999, pp. 301-302) for details.

5.8.2 The Inverted Wishart Distribution

A random matrix $\Sigma \in C_q$ has an inverted Wishart distribution with parameters $S \in C_q$ and $v > q - 1$, i.e., $\Sigma \sim IW_q(S, v)$, if its density function is given by,

$$f_{IW}^{q}(\Sigma|S,v) = C_{IW}^{-1}(S,v;q) \mid \Sigma \mid^{-\frac{(v+q+1)}{2}} \exp\left[-\frac{1}{2} tr\left(\Sigma^{-1}S\right)\right] \quad (5.97)$$

$$C_{IW}^{-1}(S,v;q) = 2^{-\frac{vq}{2}} \pi^{\frac{q(q-1)}{4}} \prod_{i=1}^{p} \Gamma\left(\frac{v+1-i}{2}\right) \mid S \mid^{-\frac{1}{2}v} \quad (5.98)$$

The recursion on the dimension q is the key device for deriving many of this density properties.

5.8.3 The Jarque-Bera Normality Test

Bera and Jarque (1981)[31]

$$BJ = \frac{T}{6}(Skewness)^2 + \frac{T}{24}(Kurtosis - 3)^2 \quad (5.99)$$

Under the null hypothesis of normality, the test statistic is $\sim \chi^2(2)$.

5.8.4 The Ljung-Box Serial Autocorrelation Test

Ljung-Box (1978) devised the following statistic to test for serial autocorrelation,

$$Q(k) = T(T+2)\sum_{m=1}^{k}(T-m)^{-1}\rho^2(m) \quad (5.100)$$

where k denotes the lag of the sample autocorrelation. The null hypothesis of linear independence is tested and the test statistic is $\sim \chi^2(k)$.

[31]Bera, Anil K. and Jarque, Carlos M. (1981) "An efficient large sample test for normality of observations and regressions residuals." *Working Paper in Econometrics* no. 40, Australian National University, Canberra. Also as "Model specification Tests: A simultaneous Approach." *Journal of Econometrics*, vol. 20, pp. 59-82.

5.8.5 The Granger Causality Test

Granger (1969) proposed[32] the following test to answer the following question: how useful are some variables in forecasting others? y is said to Granger-cause x, if x can be forecast better using past x and past y than just past x. One concludes that y *fails to Granger-cause* x if for all $s > 0$ the mean squared error of a forecast of x_{t+s} based on $(x_t, x_{t-1}, ...)$ is the same as the MSE of a forecast of x_{t+s} that uses both $(x_t, x_{t-1}, ...)$ and $(y_t, y_{t-1}, ...)$. Formally, for linear functions,

$$MSE[\widehat{E}(x_{t+s}|x_t, x_{t-1}, ...)] = MSE[\widehat{E}(x_{t+s}|x_t, x_{t-1}, ..., y_t, y_{t-1}, ...)] \tag{5.101}$$

Equivalently, x is exogenous in the time series sense with respect to y. Granger's point of view was; if an event y cause another event x, then the event y should precede the event x. This test of causality is based on the autoregressive representation. For other tests, see Pierce and Haugh (1977) and Geweke, Meese, and Dent (1983) for[33] a survey.

$$x_t = c_1 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + ... + \alpha_p x_{t-p} \tag{5.102}$$

$$+\beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + u_t \tag{5.103}$$

Then, one constructs an F test of the null hypothesis,

$$H_0 : \beta_1 = \beta_2 = ... = \beta_p = 0 \tag{5.104}$$

[32]Granger, Clive W. J. (1969) "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica*, vol. 37, pp. 424-438.
[33]Pierce, David A. and Haugh, Larry D. (1977) "Causality in Temporal Systems: Characterization and a Survey." *Journal of Econometrics*, vol. 5, pp. 265-293.
Geweke, John. Meese, Richard. and Dent, Warren. (1983) "Comparing Alternative Tests of Causality in Temporal Systems: Analytic Results and Experimental Evidence." *Journal of Econometrics*, vol. 21, pp. 161-194.

The test statistic is

$$S \equiv \frac{T(RSS_0 - RSS_1)}{RSS_1} \sim^{asy} \chi^2(p) \tag{5.105}$$

where RSS_1 and RSS_0 refer to the sum of squared residuals of the regression equation (5.102) and of a univariate autoregression of x, respectively. One rejects the null that y does not Granger-cause x if S is greater than the 5 percent critical values for a $\chi^2(p)$ variable.

5.8.6 The ARCH Test

This test is based on the notion that the nonlinearity in the residuals is of the multiplicative type.

$$LM = TR^2 \tag{5.106}$$

where R^2 is the coefficient of determination of the following regression

$$e_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + v_t \tag{5.107}$$

Under the null hypothesis of no ARCH effect, the statistic LM is $\chi^2(p)$. Weiss (1984)[34] concluded that ignoring the ARCH effect will result in identifying ARMA models containing too many parameters, i.e., overparametrized. This leads to a downward bias in the standard errors associated with the parameters of the model.

[34] Weiss, Andrew A. (1984) "ARMA models with ARCH errors." *Journal of Time Series Analysis*, vol. 5, pp. 129-143.

Table 5.12

CANSIM SOURCE	
MONTHLY DATA FROM 1976:1 To 1998:12	
TOTAL EMPLOYMENT	D980595
EMPLOYMENT - GOODS	D980626
EMPLOYMENT - PRIMARY	D980627
EMPLOYMENT - AGRICULTURE	D980628
EMPLOYMENT - MANUFACTURING	D980634
EMPLOYMENT - SERVICES	D980638

Label	: D980595
Title	: CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT AGE 15+ SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1976 - March 2000
Frequency	: monthly

Label	: D968117 (WAS D980626 from 1976 to 1998)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT GOODS-PRODUCING SECTOR SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: PERSONS
Source	: SDDS 3701 STC (71-001)
Update	: 11 April, 2000
Period	: January 1987 - March 2000
Frequency	: monthly

Label	: D989542 (WAS D980627 from 1976 to 1998)
Title	: CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT PRIMARY OCC SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF

WORKER; HOURS OF WORK BY INDUSTRY.

Factor : THOUSAND
Unit : PERSONS
Source : SDDS 3701 STC (71-001)
Update : 11 April, 2000
Period : January 1987 - March 2000
Frequency : monthly

Label : D968118 (WAS D980628 from 1976 to 1998)
Title : CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT AGRICULTURE SA CDA
Subtitle : CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor : THOUSAND
Unit : PERSONS
Source : SDDS 3701 STC (71-001)
Update : 11 April, 2000
Period : January 1987 - March 2000
Frequency : monthly

Label : D968122 (WAS D980634 from 1976 to 1998)
Title : CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT MANUFACTURING SA CDA
Subtitle : CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor : THOUSAND
Unit : PERSONS
Source : SDDS 3701 STC (71-001)
Update : 11 April, 2000
Period : January 1987 - March 2000
Frequency : monthly

Label : D968123 (WAS D980638 from 1976 to 1998)
Title : CDA LF CHARACTERISTICS MONTHLY SA / EMPLOYMENT SERVICES-PRODUCING SECTOR SA CDA
Subtitle : CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor : THOUSAND
Unit : PERSONS
Source : SDDS 3701 STC (71-001)
Update : 11 April, 2000
Period : January 1987 - March 2000
Frequency : monthly

Table 5.13

DESCRIPTIVE STATISTICS FOR CANADIAN EMPLOYMENT BY INDUSTRY

Series	Obs	Mean	St-Dev	MIN	MAX	CV
TOTAL EMP	276	12160.40	1291.73	9694.20	14563.40	0.10622
GOODS EMP	276	3644.39	160.85	3358.20	3957.60	0.04414
PRIMARY EMP	276	749.39	34.77	675.30	845.20	0.04639
AGRI EMP	276	463.44	25.96	411.10	511.00	0.05601
MANUF EMP	276	2069.20	113.66	1844.50	2299.10	0.05493
NON-DURABLE MANUF	276	1051.38	50.03	935.60	1164.60	0.04758
DURABLE MANUF EMP	276	1017.81	70.38	876.10	1157.70	0.06915
SERV EMP	276	8515.85	1226.24	6258.60	10659.80	0.14399
HP-FILTERED						
	Obs	Mean	St-Dev	MIN	MAX	
TOTAL EMP	276	0.000	0.0047	-0.0175	0.0129	
GOODS EMP	276	0.000	0.0112	-0.0336	0.0336	
PRIMARY EMP	276	0.000	0.0183	-0.0586	0.0508	
AGRI EMP	276	0.000	0.0232	-0.0550	0.0813	
MANUF EMP	276	0.000	0.0131	-0.0452	0.0358	
NON-DURABLE EMP	276	0.000	0.0186	-0.0612	0.0414	
DURABLE MANUF EMP	276	0.000	0.0169	-0.0535	0.0391	
SERV EMP	276	0.000	0.0043	-0.0118	0.0118	

Table 5.14

CORRELATION MATRIX for CANADIAN EMPLOYMENT by INDUSTRY
HP-FILTERED MONTHLY DATA

	T	G	P	A	M	ND-M	D-M	S
TOTAL EMP (T)	1.000							
GOODS EMP (G)	0.770	1.000						
PRIMARY EMP (P)	0.404	0.568	1.000					
AGRI EMP (A)	0.189	0.349	0.782	1.000				
MANUF EMP (M)	0.627	0.864	0.324	0.180	1.000			
NON-DUR MANUF EMP (ND-M)	0.331	0.570	0.141	0.105	0.779	1.000		
DURABLE MANUF EMP (D-M)	0.616	0.722	0.353	0.163	0.701	0.099	1.000	
SERV EMP (S)	0.680	0.065	-0.021	-0.110	-0.002	-0.118	0.129	1.000

Table 5.15

UNIVARIATE OLS
TIGHTNESS = 2.0 AND OTHER = 0.001
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0016727	0.0027867	0.0034271	0.7521584	12
2	0.0034727	0.0043482	0.0056645	0.7195202	11
3	0.0057194	0.0057821	0.0081841	0.7322284	10
4	0.0086669	0.0090463	0.0109629	0.7495283	9
5	0.0109197	0.0109197	0.0133081	0.7800742	8
6	0.0130572	0.0130572	0.0151628	0.773552	7
7	0.0150176	0.0150176	0.0157095	0.7289284	6
8	0.0178576	0.0178576	0.0181958	0.7363538	5
9	0.0214799	0.0214799	0.0216058	0.7496881	4
10	0.0228395	0.0228395	0.0228655	0.7406318	3
11	0.0259076	0.0259076	0.0259079	0.7566061	2
12	0.0279762	0.0279762	0.0279762	0.7728518	1

FORECAST STATS FOR MANUF EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0021936	0.0096066	0.0117538	0.9760758	12
2	0.0038035	0.0146427	0.0176497	0.9659807	11
3	0.0036875	0.0182561	0.0224189	0.9852402	10
4	-0.000368	0.0181366	0.0205055	0.8712569	9
5	-0.001927	0.0186495	0.0211061	0.842223	8
6	-0.003673	0.0171415	0.020618	0.8114458	7
7	-0.004157	0.0131815	0.0147045	0.7331044	6
8	-0.002429	0.0072416	0.0086208	0.6170038	5
9	0.0012839	0.0074125	0.0079519	0.5962764	4
10	0.0156558	0.0156558	0.0160054	2.8414892	3
11	0.0246708	0.0246708	0.0246998	3.2210737	2
12	0.0294555	0.0294555	0.0294555	4.2811652	1

Table 5.16

Univariate VAR
TIGHTNESS = 0.1 AND OTHER = 0.001
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.001607	0.0028211	0.0035296	0.7746607	12
2	0.0034605	0.0045158	0.0057629	0.7320109	11
3	0.0055028	0.005915	0.0081977	0.7334428	10
4	0.0083015	0.0088376	0.0107862	0.7374477	9
5	0.01018	0.0102134	0.0127451	0.7470742	8
6	0.0120432	0.0120432	0.014414	0.7353499	7
7	0.0138203	0.0138203	0.01458	0.6765171	6
8	0.0164486	0.0164486	0.0168481	0.6818151	5
9	0.0201716	0.0201716	0.0202898	0.7040228	4
10	0.0213819	0.0213819	0.0214256	0.6939935	3
11	0.0243668	0.0243668	0.024368	0.7116349	2
12	0.0259546	0.0259546	0.0259546	0.7170036	1

FORECAST STATS FOR MANUF EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0014465	0.0093345	0.0116346	0.9661758	12
2	0.0026764	0.0142987	0.0175363	0.9597773	11
3	0.0021034	0.0179809	0.0220548	0.9692395	10
4	-0.00251	0.0178888	0.020811	0.8842361	9
5	-0.004689	0.0185088	0.0214261	0.8549953	8
6	-0.007084	0.0184439	0.0213083	0.8386143	7
7	-0.008093	0.0143181	0.016126	0.8039745	6
8	-0.006933	0.0092213	0.0101478	0.726294	5
9	-0.00431	0.0084418	0.00987	0.7401038	4
10	0.0090406	0.0090406	0.0100797	1.7894769	3
11	0.0170499	0.0170499	0.0171459	2.2359736	2
12	0.0187721	0.0187721	0.0187721	2.7284029	1

Table 5.17

SIMPLE BAYESIAN VAR
TIGHTNESS = 0.1 AND OTHER = 0.5
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0014734	0.0029452	0.003641	0.7991053	12
2	0.0031935	0.0045192	0.006067	0.7706402	11
3	0.0050239	0.0063723	0.0085601	0.7658645	10
4	0.0073253	0.0084532	0.0109347	0.7475985	9
5	0.0087536	0.0094848	0.0124638	0.730584	8
6	0.0100925	0.0106216	0.0133546	0.6813034	7
7	0.0116339	0.0116339	0.0127906	0.5934882	6
8	0.0139913	0.0139913	0.014497	0.5866693	5
9	0.0173461	0.0173461	0.0174547	0.6056499	4
10	0.0188784	0.0188784	0.0189428	0.613573	3
11	0.0221716	0.0221716	0.0221807	0.6477577	2
12	0.0237108	0.0237108	0.0237108	0.6550197	1

FORECAST STATS FOR MANUF EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0002889	0.0084766	0.0108582	0.9017032	12
2	0.0010762	0.0131693	0.0155608	0.8516569	11
3	0.0008308	0.0162474	0.0193382	0.8498545	10
4	-0.002135	0.0169377	0.020666	0.8780768	9
5	-0.003054	0.0182353	0.0223201	0.8906689	8
6	-0.004941	0.0185658	0.0216222	0.850967	7
7	-0.007116	0.0160408	0.0170961	0.8523379	6
8	-0.005787	0.0103302	0.0105196	0.7529046	5
9	-0.001436	0.0072493	0.0079955	0.5995482	4
10	0.0123675	0.0123675	0.0136687	2.4266484	3
11	0.0225094	0.0225094	0.0225129	2.9358746	2
12	0.0258313	0.0258313	0.0258313	3.7544124	1

Table 5.18

COMMONLY USED BAYESIAN VAR
TIGHTNESS = 0.2 AND OTHER = 0.5
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0014247	0.002927	0.0035977	0.7896079	12
2	0.0030361	0.0043657	0.0060657	0.7704837	11
3	0.0048892	0.0064376	0.008631	0.7722129	10
4	0.007093	0.0084017	0.0110526	0.7556573	9
5	0.0085861	0.0097792	0.0127028	0.7445893	8
6	0.0097783	0.0104359	0.0133346	0.6802867	7
7	0.0112327	0.0112327	0.0126077	0.5850022	6
8	0.0134269	0.0134269	0.0139966	0.5664195	5
9	0.0163692	0.0163692	0.0165052	0.5727046	4
10	0.017941	0.017941	0.017985	0.5825481	3
11	0.0213031	0.0213031	0.0213079	0.6222693	2
12	0.0232047	0.0232047	0.0232047	0.6410378	1

FORECAST STATS FOR MANUF EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.000244	0.0082155	0.0106981	0.8884065	12
2	5.714E-05	0.0126666	0.0149493	0.8181887	11
3	-0.000471	0.0157365	0.0186111	0.8178999	10
4	-0.003377	0.0166761	0.0203388	0.8641724	9
5	-0.004369	0.0179516	0.0220638	0.8804412	8
6	-0.006731	0.0186372	0.0216912	0.8536818	7
7	-0.009697	0.016346	0.0181336	0.9040657	6
8	-0.008788	0.0124489	0.0127213	0.9104865	5
9	-0.004843	0.0075531	0.0084194	0.6313353	4
10	0.0087291	0.0087291	0.0102686	1.8230225	3
11	0.0189701	0.0189701	0.0189739	2.4743666	2
12	0.0237665	0.0237665	0.0237665	3.4543131	1

Table 5.19

OLS VAR
TIGHTNESS = 2.0 AND OTHER = 1.0
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0013945	0.002789	0.0035537	0.779956	12
2	0.0029152	0.0043989	0.0060105	0.7634691	11
3	0.0048093	0.0063726	0.0086569	0.7745296	10
4	0.0069448	0.0084638	0.011119	0.7601956	9
5	0.0085488	0.0100119	0.0129049	0.7564394	8
6	0.0096205	0.0103992	0.0133969	0.6834625	7
7	0.0110386	0.0110386	0.0126754	0.5881439	6
8	0.0131067	0.0131067	0.0138264	0.5595299	5
9	0.0156254	0.0156254	0.0158073	0.548487	4
10	0.0172525	0.0172525	0.0172827	0.5598009	3
11	0.0205095	0.0205095	0.020518	0.5992021	2
12	0.0226438	0.0226438	0.0226438	0.6255418	1

FORECAST STATS FOR MANUF EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.000633	0.0079918	0.0107059	0.8890559	12
2	-0.000625	0.0125939	0.0146735	0.8030947	11
3	-0.001346	0.0156326	0.0183083	0.8045911	10
4	-0.004207	0.016696	0.0203486	0.8645897	9
5	-0.005298	0.0182794	0.021737	0.867401	8
6	-0.008175	0.0182987	0.0215338	0.8474892	7
7	-0.011523	0.0161183	0.0187691	0.9357499	6
8	-0.010678	0.013399	0.0140802	1.0077465	5
9	-0.007554	0.0084313	0.0099451	0.745736	4
10	0.0058173	0.0062679	0.0076346	1.3553969	3
11	0.0161602	0.0161602	0.0161624	2.1077203	2
12	0.021264	0.021264	0.021264	3.090584	1

Table 5.20

UNIVARIATE OLS
TIGHTNESS = 2.0 AND OTHER = 0.001
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0022544	0.006215	0.0079894	1.08573	12
2	0.0039435	0.0094213	0.0114939	1.0452384	11
3	0.0053808	0.0131603	0.0157363	1.1113262	10
4	0.0034572	0.013256	0.014545	1.0206347	9
5	0.003035	0.0128292	0.0143061	0.9830675	8
6	0.0022756	0.0113019	0.0131741	0.9805946	7
7	0.0026777	0.0063859	0.0080823	0.7877344	6
8	0.0053137	0.0076964	0.0091971	1.23429	5
9	0.0089196	0.0089196	0.0108846	2.2092925	4
10	0.0194563	0.0194563	0.0197185	1.7377428	3
11	0.0236425	0.0236425	0.023649	1.4594222	2
12	0.0299192	0.0299192	0.0299192	1.4615068	1

FORECAST STATS FOR SERV EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0014984	0.0030992	0.0038371	0.7822123	12
2	0.00325	0.004319	0.0062066	0.7569028	11
3	0.0051046	0.0065186	0.0089595	0.7515565	10
4	0.0075765	0.0088094	0.0114716	0.7371194	9
5	0.0090112	0.0101042	0.0130369	0.7280364	8
6	0.0101661	0.010872	0.013759	0.6693107	7
7	0.0117187	0.0117187	0.0135685	0.600136	6
8	0.0141362	0.0141362	0.0152338	0.5915024	5
9	0.0171646	0.0171646	0.0173703	0.5808457	4
10	0.0177315	0.0177315	0.0178535	0.5615521	3
11	0.0205521	0.0205521	0.020583	0.5839924	2
12	0.0205594	0.0205594	0.0205594	0.5753333	1

Table 5.21

Univariate VAR
TIGHTNESS = 0.1 AND OTHER = 0.001
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0025675	0.0062123	0.0078056	1.0607534	12
2	0.0046412	0.0094955	0.0117152	1.0653588	11
3	0.0061531	0.0127713	0.0156481	1.1050982	10
4	0.0046721	0.0129759	0.0145654	1.0220662	9
5	0.00477	0.0130995	0.0145906	1.0026157	8
6	0.0044332	0.0114203	0.013446	1.0008341	7
7	0.0052897	0.0079833	0.0097977	0.954931	6
8	0.0082957	0.0087357	0.0108347	1.4540661	5
9	0.0119032	0.0119032	0.0130251	2.6437387	4
10	0.0224183	0.0224183	0.0225531	1.9875541	3
11	0.02793	0.02793	0.0279341	1.7238647	2
12	0.034134	0.034134	0.034134	1.6673953	1

FORECAST STATS FOR SERV EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0014069	0.0031677	0.0038944	0.7938901	12
2	0.0031652	0.0041939	0.0061714	0.7526119	11
3	0.0048817	0.0066515	0.0089152	0.7478414	10
4	0.0072798	0.0085402	0.0113315	0.7281166	9
5	0.0084473	0.0096962	0.0125981	0.7035334	8
6	0.0096438	0.0105643	0.013465	0.6550066	7
7	0.0110512	0.0110512	0.0129624	0.5733264	6
8	0.0131516	0.0131516	0.0142864	0.554718	5
9	0.0163764	0.0163764	0.0165757	0.5542744	4
10	0.0168571	0.0168571	0.0170086	0.5349769	3
11	0.0195003	0.0195003	0.0195367	0.5543044	2
12	0.0191512	0.0191512	0.0191512	0.5359258	1

Table 5.22

SIMPLE BAYESIAN VAR
TIGHTNESS = 0.1 AND OTHER = 0.5

FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0008871	0.0049808	0.0066245	0.9002462	12
2	0.0017751	0.0074065	0.0090329	0.8214364	11
3	0.0025544	0.0106205	0.0121801	0.8601832	10
4	0.0009716	0.0115657	0.0128471	0.9014971	9
5	0.000362	0.0120282	0.0138162	0.9493989	8
6	-0.00134	0.0102889	0.0126695	0.9430391	7
7	-0.002762	0.0078267	0.0090253	0.879651	6
8	-0.00176	0.005061	0.0061032	0.8190721	5
9	0.0008909	0.0038443	0.0042118	0.8548826	4
10	0.0091922	0.0091922	0.0093436	0.8234249	3
11	0.0153169	0.0153169	0.0153301	0.9460501	2
12	0.0196141	0.0196141	0.0196141	0.9581181	1

FORECAST STATS FOR SERV EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0015976	0.003482	0.0041914	0.854447	12
2	0.0034307	0.0051116	0.0068889	0.8401142	11
3	0.0050329	0.0076129	0.0097513	0.8179782	10
4	0.0070229	0.0090984	0.0121117	0.7782487	9
5	0.007884	0.0098428	0.0130334	0.727842	8
6	0.0087428	0.0099882	0.0131848	0.6413749	7
7	0.0101321	0.0102729	0.0122825	0.543256	6
8	0.0124438	0.0124438	0.0134958	0.5240183	5
9	0.0159074	0.0159074	0.0160491	0.536667	4
10	0.0173756	0.0173756	0.0174783	0.5497519	3
11	0.0203652	0.0203652	0.0203818	0.5782841	2
12	0.0211998	0.0211998	0.0211998	0.593255	1

Table 5.23

COMMONLY USED BAYESIAN VAR
TIGHTNESS = 0.2 AND OTHER = 0.5
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0003136	0.004683	0.0064767	0.8801573	12
2	0.0008338	0.0067347	0.0082878	0.7536775	11
3	0.0015321	0.010158	0.0114708	0.810086	10
4	-0.000209	0.0114397	0.0127437	0.8942406	9
5	-0.001139	0.0118865	0.0139067	0.9556224	8
6	-0.00352	0.0103964	0.0130293	0.9698145	7
7	-0.005678	0.0076778	0.0100154	0.9761471	6
8	-0.005231	0.0068466	0.0078569	1.0544348	5
9	-0.003215	0.00377	0.0054939	1.1151225	4
10	0.004657	0.004657	0.0049277	0.4342664	3
11	0.0101671	0.0101671	0.0101807	0.6282695	2
12	0.0140976	0.0140976	0.0140976	0.6886477	1

FORECAST STATS FOR SERV EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0016337	0.0035023	0.0042685	0.870168	12
2	0.0033753	0.0055531	0.0071047	0.8664335	11
3	0.004881	0.0077728	0.0099633	0.8357621	10
4	0.0066828	0.0093209	0.0123242	0.7919034	9
5	0.0074666	0.0100226	0.0132847	0.7418739	8
6	0.0079436	0.0100981	0.0129289	0.6289262	7
7	0.0091676	0.0096404	0.0116932	0.5171924	6
8	0.0114542	0.0114542	0.0126532	0.4913003	5
9	0.0146708	0.0146708	0.0148677	0.4971613	4
10	0.0162189	0.0162189	0.0163171	0.5132285	3
11	0.0193309	0.0193309	0.0193509	0.5490334	2
12	0.0205606	0.0205606	0.0205606	0.5753655	1

Table 5.24

OLS VAR
TIGHTNESS = 2.0 AND OTHER = 1.0
FORECAST STATS FOR TOTAL EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.000158	0.0046158	0.0065313	0.8875797	12
2	0.000183	0.0065725	0.0078669	0.7153994	11
3	0.0009088	0.0097087	0.0109709	0.7747844	10
4	-0.000837	0.0116674	0.0128942	0.9048026	9
5	-0.001812	0.0118818	0.0138718	0.9532247	8
6	-0.004699	0.0099652	0.0130117	0.9685034	7
7	-0.007131	0.0076243	0.0105862	1.0317799	6
8	-0.006883	0.0070865	0.0087874	1.1793065	5
9	-0.005573	0.0055731	0.0080058	1.6249721	4
10	0.002304	0.0030482	0.0034999	0.3084353	3
11	0.0073337	0.0073337	0.0074242	0.4581614	2
12	0.0093857	0.0093857	0.0093857	0.4584763	1

FORECAST STATS FOR SERV EMP

Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.0016936	0.003534	0.0044221	0.9014775	12
2	0.0034031	0.0058834	0.0072778	0.8875389	11
3	0.0048144	0.0078039	0.0100496	0.8430036	10
4	0.0065504	0.0093539	0.0124746	0.8015685	9
5	0.0073844	0.0102634	0.0135414	0.7562108	8
6	0.0075562	0.0101217	0.0127863	0.6219898	7
7	0.0087522	0.0094342	0.0114973	0.5085281	6
8	0.0111219	0.0111219	0.0124576	0.4837083	5
9	0.0140872	0.0140872	0.0143378	0.4794428	4
10	0.0157015	0.0157015	0.0158098	0.4972701	3
11	0.0189535	0.0189535	0.0189936	0.5388957	2
12	0.0204172	0.0204172	0.0204172	0.5713535	1

Table 5.25

UNIVARIATE OLS				TIGHTNESS = 2.0 AND OTHER = 0.001			
TOTAL EMP				MANUFACTURING EMP			
Step	St-Dev	TOT	MANUF	Step	St-Dev	TOT	MANUF
1	0.00306	100	0	1	0.00909	1.76798	98.232
2	0.00417	100	0.00001	2	0.01257	1.76153	98.2385
3	0.00545	100	0.00002	3	0.01538	1.75266	98.2473
4	0.00666	99.9999	0.00006	4	0.01808	1.74144	98.2586
5	0.00787	99.9999	0.00011	5	0.02080	1.72931	98.2707
6	0.00916	99.9998	0.00019	6	0.02298	1.71663	98.2834
7	0.01014	99.9997	0.00031	7	0.02468	1.70377	98.2962
8	0.01120	99.9996	0.00045	8	0.02645	1.6912	98.3088
9	0.01216	99.9994	0.00062	9	0.02860	1.67981	98.3202
10	0.01308	99.9992	0.00081	10	0.03075	1.67039	98.3296
11	0.01393	99.999	0.00102	11	0.03259	1.66246	98.3375
12	0.01469	99.9988	0.00124	12	0.03455	1.65658	98.3434
13	0.01540	99.9986	0.00145	13	0.03621	1.65216	98.3478
14	0.01607	99.9984	0.00164	14	0.03754	1.64888	98.3511
15	0.01667	99.9982	0.00179	15	0.03887	1.64735	98.3527
16	0.01732	99.9981	0.00187	16	0.04000	1.64709	98.3529
17	0.01807	99.9982	0.00185	17	0.04096	1.64795	98.3521
18	0.01878	99.9982	0.00178	18	0.04175	1.64963	98.3504
19	0.01946	99.9983	0.00167	19	0.04247	1.65244	98.3476
20	0.02005	99.9984	0.00158	20	0.04326	1.65698	98.343
21	0.02064	99.9985	0.00153	21	0.04394	1.66239	98.3376
22	0.02120	99.9984	0.00163	22	0.04448	1.66808	98.3319
23	0.02168	99.998	0.00198	23	0.04522	1.67689	98.3231
24	0.02223	99.9973	0.00272	24	0.04587	1.68623	98.3138
25	0.02272	99.996	0.00405	25	0.04637	1.69528	98.3047
26	0.02323	99.9939	0.00608	26	0.04679	1.7045	98.2955
27	0.02372	99.991	0.00902	27	0.04717	1.71421	98.2858
28	0.02419	99.987	0.01301	28	0.04749	1.72396	98.276
29	0.02467	99.9818	0.01816	29	0.04773	1.73328	98.2667
30	0.02512	99.9754	0.02464	30	0.04793	1.74261	98.2574
31	0.02557	99.9675	0.03248	31	0.04814	1.75295	98.2471
32	0.02603	99.9583	0.04175	32	0.04831	1.76313	98.2369
33	0.02650	99.9475	0.05247	33	0.04842	1.77205	98.228
34	0.02697	99.9353	0.06469	34	0.04851	1.78123	98.2188
35	0.02741	99.9215	0.07853	35	0.04857	1.78946	98.2105
36	0.02783	99.906	0.09398	36	0.04859	1.79579	98.2042

Table 5.26

UNIVARIATE VAR				TIGHTNESS = 0.1 AND OTHER = 0.001			
TOTAL EMP				MANUFACTURING EMP			
Step	St-Dev	TOT	MANUF	Step	St-Dev	TOT	MANUF
1	0.00312	100	0	1	0.00920	1.6931	98.3069
2	0.00438	100	0	2	0.01282	1.69311	98.3069
3	0.00562	100	0	3	0.01566	1.69314	98.3069
4	0.00682	100	0	4	0.01832	1.69319	98.3068
5	0.00800	100	0	5	0.02090	1.69326	98.3067
6	0.00922	100	0	6	0.02310	1.69335	98.3067
7	0.01026	100	0	7	0.02495	1.69346	98.3065
8	0.01129	100	0	8	0.02683	1.69361	98.3064
9	0.01227	100	0	9	0.02895	1.6938	98.3062
10	0.01319	100	0	10	0.03103	1.69403	98.306
11	0.01405	100	0	11	0.03292	1.69428	98.3057
12	0.01483	100	0	12	0.03482	1.69456	98.3054
13	0.01557	100	0	13	0.03649	1.69488	98.3051
14	0.01628	100	0	14	0.03788	1.69522	98.3048
15	0.01694	100	0	15	0.03918	1.6956	98.3044
16	0.01763	100	0	16	0.04033	1.696	98.304
17	0.01838	100	0	17	0.04131	1.69643	98.3036
18	0.01910	100	0	18	0.04212	1.69688	98.3031
19	0.01979	100	0	19	0.04287	1.69737	98.3026
20	0.02042	100	0	20	0.04364	1.6979	98.3021
21	0.02102	100	0	21	0.04433	1.69846	98.3015
22	0.02160	100	0	22	0.04491	1.69904	98.301
23	0.02213	100	0	23	0.04561	1.69971	98.3003
24	0.02268	100	0	24	0.04624	1.7004	98.2996
25	0.02320	100	0	25	0.04675	1.70108	98.2989
26	0.02370	100	0	26	0.04718	1.70176	98.2982
27	0.02419	100	0	27	0.04755	1.70245	98.2976
28	0.02465	100	0	28	0.04786	1.70313	98.2969
29	0.02512	100	0	29	0.04811	1.70379	98.2962
30	0.02556	100	0	30	0.04832	1.70444	98.2956
31	0.02600	100	0	31	0.04852	1.7051	98.2949
32	0.02644	100	0	32	0.04867	1.70573	98.2943
33	0.02688	100	0	33	0.04878	1.7063	98.2937
34	0.02730	100	0	34	0.04886	1.70682	98.2932
35	0.02772	100	0	35	0.04892	1.70727	98.2927
36	0.02811	100	0	36	0.04894	1.7076	98.2924

Table 5.27

SIMPLE BAYESIAN VAR				TIGHTNESS = 0.1 AND OTHER = 0.5			
TOTAL EMP				MANUFACTURING EMP			
Step	St-Dev	TOT	MANUF	Step	St-Dev	TOT	MANUF
1	0.00300	100	0	1	0.00856	1.52918	98.4708
2	0.00416	99.8779	0.12206	2	0.01156	0.88343	99.1166
3	0.00527	99.5711	0.42888	3	0.01373	0.9091	99.0909
4	0.00632	99.2352	0.76476	4	0.01575	2.01315	97.9869
5	0.00732	98.9119	1.08808	5	0.01774	3.61352	96.3865
6	0.00831	98.5381	1.46194	6	0.01954	6.25117	93.7488
7	0.00914	97.9995	2.00049	7	0.02122	9.58097	90.419
8	0.00993	97.5188	2.48116	8	0.02300	12.2254	87.7746
9	0.01065	96.9538	3.04623	9	0.02499	13.7543	86.2457
10	0.01131	96.2012	3.79884	10	0.02694	14.4861	85.5139
11	0.01191	95.2985	4.70152	11	0.02875	15.0242	84.9758
12	0.01243	94.4068	5.59325	12	0.03055	15.1239	84.8762
13	0.01291	93.5509	6.44914	13	0.03212	15.1118	84.8882
14	0.01336	92.5398	7.46025	14	0.03345	15.1634	84.8366
15	0.01378	91.508	8.49203	15	0.03469	15.0282	84.9718
16	0.01422	90.5706	9.42944	16	0.03578	14.8073	85.1927
17	0.01469	89.8773	10.1227	17	0.03671	14.6027	85.3973
18	0.01514	89.1723	10.8277	18	0.03754	14.4332	85.5668
19	0.01557	88.4959	11.5041	19	0.03832	14.2162	85.7838
20	0.01595	87.8147	12.1853	20	0.03914	13.8698	86.1302
21	0.01631	87.0908	12.9092	21	0.03989	13.5232	86.4768
22	0.01665	86.4048	13.5952	22	0.04055	13.1965	86.8035
23	0.01696	85.7108	14.2892	23	0.04131	12.7378	87.2623
24	0.01728	85.0631	14.9369	24	0.04200	12.3289	87.6712
25	0.01758	84.4782	15.5218	25	0.04254	12.0222	87.9778
26	0.01787	83.9759	16.0241	26	0.04300	11.7728	88.2272
27	0.01814	83.5622	16.4378	27	0.04340	11.5559	88.4441
28	0.01839	83.2184	16.7816	28	0.04375	11.3745	88.6255
29	0.01864	82.9396	17.0604	29	0.04404	11.2272	88.7728
30	0.01887	82.7155	17.2845	30	0.04429	11.0989	88.9011
31	0.01909	82.5573	17.4428	31	0.04453	10.9823	89.0177
32	0.01930	82.4504	17.5496	32	0.04473	10.892	89.108
33	0.01950	82.3917	17.6083	33	0.04488	10.8315	89.1685
34	0.01969	82.3765	17.6235	34	0.04499	10.7902	89.2098
35	0.01986	82.3912	17.6088	35	0.04507	10.7711	89.2289
36	0.02002	82.4245	17.5755	36	0.04511	10.7727	89.2274

Table 5.28

COMMONLY USED BVAR				TIGHTNESS = 0.2 AND OTHER = 0.5			
TOTAL EMP				MANUFACTURING EMP			
Step	St-Dev	TOT	MANUF	Step	St-Dev	TOT	MANUF
1	0.0028	100.000	0.0000	1	0.0081	2.1460	97.8540
2	0.0038	99.7630	0.2370	2	0.0107	1.2699	98.7301
3	0.0048	99.2973	0.7027	3	0.0124	1.4299	98.5701
4	0.0057	98.9139	1.0861	4	0.0141	3.2931	96.7069
5	0.0066	98.6708	1.3292	5	0.0157	4.8288	95.1713
6	0.0074	98.4119	1.5881	6	0.0171	8.0467	91.9533
7	0.0080	97.9316	2.0684	7	0.0184	12.5517	87.4483
8	0.0086	97.6312	2.3689	8	0.0197	15.7595	84.2405
9	0.0091	97.1771	2.8229	9	0.0212	17.2861	82.7139
10	0.0096	96.4561	3.5439	10	0.0225	17.5731	82.4269
11	0.0100	95.5750	4.4250	11	0.0237	18.0482	81.9518
12	0.0103	94.8409	5.1591	12	0.0248	17.9681	82.0319
13	0.0106	94.2691	5.7309	13	0.0258	17.7784	82.2216
14	0.0109	93.3148	6.6852	14	0.0265	17.8114	82.1886
15	0.0111	92.3079	7.6921	15	0.0272	17.5790	82.4210
16	0.0114	91.3378	8.6622	16	0.0278	17.2717	82.7283
17	0.0118	90.7729	9.2271	17	0.0282	17.0073	82.9928
18	0.0121	90.0304	9.9696	18	0.0286	16.8342	83.1658
19	0.0124	89.3295	10.6706	19	0.0290	16.6577	83.3423
20	0.0127	88.6339	11.3661	20	0.0295	16.2740	83.7260
21	0.0129	87.8118	12.1882	21	0.0300	15.9353	84.0647
22	0.0132	87.0573	12.9427	22	0.0303	15.6633	84.3368
23	0.0134	86.2280	13.7720	23	0.0309	15.1151	84.8849
24	0.0136	85.3214	14.6786	24	0.0313	14.6607	85.3393
25	0.0139	84.4497	15.5503	25	0.0317	14.3315	85.6685
26	0.0141	83.6845	16.3155	26	0.0320	14.0376	85.9624
27	0.0143	83.0409	16.9591	27	0.0324	13.7540	86.2460
28	0.0146	82.4566	17.5435	28	0.0327	13.5044	86.4956
29	0.0148	81.9138	18.0862	29	0.0330	13.2805	86.7195
30	0.0150	81.3996	18.6004	30	0.0332	13.0721	86.9280
31	0.0152	80.9426	19.0574	31	0.0335	12.8600	87.1400
32	0.0153	80.4893	19.5107	32	0.0338	12.6891	87.3109
33	0.0155	80.0715	19.9285	33	0.0340	12.5735	87.4265
34	0.0157	79.6956	20.3044	34	0.0342	12.4632	87.5368
35	0.0158	79.3353	20.6647	35	0.0344	12.3939	87.6061
36	0.0160	78.9717	21.0283	36	0.0345	12.3733	87.6267

Table 5.29

OLS VAR				TIGHTNESS = 2.0 AND OTHER = 1.0			
TOTAL EMP				MANUFACTURING EMP			
Step	St-Dev	TOT	MANUF	Step	St-Dev	TOT	MANUF
1	0.00286	100	0	1	0.00821	1.98871	98.0113
2	0.00389	99.4243	0.57573	2	0.01090	1.15269	98.8473
3	0.00510	98.3329	1.66714	3	0.01305	2.05359	97.9464
4	0.00622	97.4406	2.55942	4	0.01537	5.89861	94.1014
5	0.00729	96.9274	3.07264	5	0.01753	7.60773	92.3923
6	0.00840	96.4345	3.56553	6	0.01953	11.5699	88.4301
7	0.00925	95.5956	4.40441	7	0.02163	17.1615	82.8386
8	0.01010	95.1525	4.84746	8	0.02375	20.7732	79.2268
9	0.01088	94.3465	5.6535	9	0.02612	22.2453	77.7547
10	0.01163	93.2384	6.76165	10	0.02834	22.1783	77.8217
11	0.01232	91.9482	8.0518	11	0.03041	22.667	77.333
12	0.01290	90.8925	9.10748	12	0.03255	22.6004	77.3997
13	0.01341	90.2404	9.75957	13	0.03424	22.3352	77.6648
14	0.01392	88.9896	11.0105	14	0.03570	22.4032	77.5968
15	0.01436	87.8443	12.1557	15	0.03713	22.22	77.78
16	0.01483	86.7185	13.2815	16	0.03827	21.8997	78.1004
17	0.01535	86.3077	13.6923	17	0.03922	21.5337	78.4663
18	0.01587	85.6087	14.3913	18	0.04010	21.3125	78.6875
19	0.01633	84.9768	15.0232	19	0.04092	21.0765	78.9235
20	0.01673	84.3702	15.6299	20	0.04178	20.5645	79.4355
21	0.01713	83.655	16.345	21	0.04260	20.1318	79.8682
22	0.01749	83.1006	16.8994	22	0.04328	19.8116	80.1885
23	0.01779	82.5043	17.4957	23	0.04410	19.147	80.853
24	0.01814	81.8145	18.1855	24	0.04478	18.5974	81.4026
25	0.01845	81.1584	18.8416	25	0.04526	18.2129	81.7871
26	0.01877	80.6309	19.3691	26	0.04570	17.8774	82.1226
27	0.01907	80.221	19.779	27	0.04611	17.5628	82.4372
28	0.01934	79.8549	20.1451	28	0.04645	17.3038	82.6962
29	0.01962	79.5346	20.4654	29	0.04676	17.0791	82.9209
30	0.01986	79.2746	20.7254	30	0.04704	16.8839	83.1161
31	0.02011	79.0924	20.9076	31	0.04733	16.6806	83.3194
32	0.02035	78.9315	21.0685	32	0.04757	16.5165	83.4835
33	0.02057	78.831	21.169	33	0.04772	16.4252	83.5748
34	0.02080	78.7992	21.2008	34	0.04786	16.3392	83.6608
35	0.02099	78.786	21.214	35	0.04795	16.2884	83.7116
36	0.02115	78.7852	21.2148	36	0.04800	16.2791	83.7209

Table 5.30

UNIVARIATE OLS				TIGHTNESS = 2.0 AND OTHER = 0.001			
TOTAL EMP				SERVICES EMP			
Step	St-Dev	TOT	SERV	Step	St-Dev	TOT	SERV
1	0.00685	100	0	1	0.00307	1.9059	98.094
2	0.00984	100	2E-05	2	0.00413	1.9022	98.098
3	0.01248	100	8E-05	3	0.00527	1.8962	98.104
4	0.01511	100	0.0002	4	0.00627	1.8893	98.111
5	0.01736	100	0.0005	5	0.00726	1.8817	98.118
6	0.01957	99.999	0.0009	6	0.00833	1.874	98.126
7	0.02132	99.998	0.0015	7	0.00906	1.8664	98.134
8	0.02293	99.998	0.0024	8	0.00991	1.8593	98.141
9	0.02467	99.997	0.0035	9	0.01060	1.8532	98.147
10	0.02617	99.995	0.0048	10	0.01121	1.8484	98.152
11	0.02753	99.994	0.0064	11	0.01180	1.8452	98.155
12	0.02887	99.992	0.0081	12	0.01239	1.8443	98.156
13	0.02982	99.99	0.0102	13	0.01289	1.8455	98.155
14	0.03077	99.988	0.0125	14	0.01335	1.8493	98.151
15	0.03161	99.985	0.0149	15	0.01383	1.8569	98.143
16	0.03223	99.982	0.0177	16	0.01432	1.8686	98.131
17	0.03272	99.979	0.0208	17	0.01495	1.8868	98.113
18	0.03316	99.976	0.0241	18	0.01561	1.9102	98.09
19	0.03365	99.973	0.0274	19	0.01626	1.9384	98.062
20	0.03400	99.969	0.0311	20	0.01682	1.9695	98.031
21	0.03428	99.965	0.035	21	0.01740	2.0062	97.994
22	0.03460	99.961	0.039	22	0.01797	2.0478	97.952
23	0.03492	99.957	0.043	23	0.01844	2.0919	97.908
24	0.03524	99.953	0.0471	24	0.01892	2.1426	97.857
25	0.03552	99.949	0.0514	25	0.01935	2.1979	97.802
26	0.03577	99.944	0.0559	26	0.01979	2.2595	97.741
27	0.03601	99.94	0.0605	27	0.02017	2.3252	97.675
28	0.03619	99.935	0.0653	28	0.02057	2.3971	97.603
29	0.03633	99.93	0.0704	29	0.02096	2.4748	97.525
30	0.03644	99.924	0.0756	30	0.02130	2.5556	97.444
31	0.03652	99.919	0.0811	31	0.02167	2.6426	97.357
32	0.03658	99.913	0.0866	32	0.02205	2.7345	97.265
33	0.03662	99.908	0.0923	33	0.02244	2.8313	97.169
34	0.03663	99.902	0.0981	34	0.02283	2.9313	97.069
35	0.03664	99.896	0.104	35	0.02323	3.0345	96.965
36	0.03664	99.89	0.1099	36	0.02360	3.1395	96.861

Table 5.31

UNIVARIATE VAR				TIGHTNESS = 0.1 AND OTHER = 0.001			
TOTAL EMP				SERVICES EMP			
Step	St-Dev	TOT	SERV	Step	St-Dev	TOT	SERV
1	0.00693	100	0	1	0.00315	1.9733	98.027
2	0.00994	100	0	2	0.00435	1.9733	98.027
3	0.01252	100	0	3	0.00546	1.9733	98.027
4	0.01502	100	0	4	0.00649	1.9733	98.027
5	0.01725	100	0	5	0.00748	1.9733	98.027
6	0.01937	100	0	6	0.00849	1.9733	98.027
7	0.02118	100	0	7	0.00931	1.9733	98.027
8	0.02285	100	0	8	0.01014	1.9733	98.027
9	0.02454	100	0	9	0.01086	1.9733	98.027
10	0.02606	100	0	10	0.01151	1.9733	98.027
11	0.02746	100	0	11	0.01213	1.9733	98.027
12	0.02875	100	0	12	0.01273	1.9734	98.027
13	0.02978	100	0	13	0.01327	1.9734	98.027
14	0.03075	100	0	14	0.01378	1.9734	98.027
15	0.03159	100	0	15	0.01431	1.9735	98.027
16	0.03225	100	1E-05	16	0.01486	1.9736	98.026
17	0.03279	100	1E-05	17	0.01551	1.9737	98.026
18	0.03329	100	1E-05	18	0.01618	1.9738	98.026
19	0.03378	100	1E-05	19	0.01685	1.9739	98.026
20	0.03418	100	2E-05	20	0.01745	1.9741	98.026
21	0.03452	100	2E-05	21	0.01805	1.9742	98.026
22	0.03487	100	2E-05	22	0.01862	1.9744	98.026
23	0.03523	100	3E-05	23	0.01912	1.9746	98.025
24	0.03559	100	3E-05	24	0.01961	1.9748	98.025
25	0.03589	100	4E-05	25	0.02006	1.975	98.025
26	0.03617	100	5E-05	26	0.02050	1.9752	98.025
27	0.03641	100	6E-05	27	0.02091	1.9754	98.025
28	0.03661	100	7E-05	28	0.02130	1.9756	98.024
29	0.03677	100	8E-05	29	0.02169	1.9759	98.024
30	0.03689	100	9E-05	30	0.02206	1.9761	98.024
31	0.03698	100	0.0001	31	0.02243	1.9764	98.024
32	0.03705	100	0.0001	32	0.02281	1.9767	98.023
33	0.03710	100	0.0001	33	0.02320	1.9769	98.023
34	0.03712	100	0.0002	34	0.02358	1.9772	98.023
35	0.03713	100	0.0002	35	0.02397	1.9775	98.023
36	0.03713	100	0.0002	36	0.02433	1.9778	98.022

Table 5.32

SIMPLE BAYESIAN VAR				TIGHTNESS = 0.1 AND OTHER = 0.5			
TOTAL EMP				SERVICES EMP			
Step	St-Dev	TOT	SERV	Step	St-Dev	TOT	SERV
1	0.00660	100	0	1	0.00302	1.639	98.361
2	0.00926	99.701	0.299	2	0.00410	1.2714	98.729
3	0.01143	98.726	1.2736	3	0.00507	0.8667	99.133
4	0.01351	96.891	3.1094	4	0.00594	0.6317	99.368
5	0.01535	94.819	5.1811	5	0.00676	0.5405	99.459
6	0.01713	92.093	7.9066	6	0.00757	0.5507	99.449
7	0.01873	88.84	11.16	7	0.00820	0.7747	99.225
8	0.02023	85.773	14.227	8	0.00883	1.0509	98.949
9	0.02182	82.89	17.11	9	0.00935	1.4509	98.549
10	0.02330	80.238	19.762	10	0.00980	1.937	98.063
11	0.02470	77.894	22.106	11	0.01023	2.4578	97.542
12	0.02600	76.083	23.917	12	0.01062	2.9358	97.064
13	0.02709	74.441	25.559	13	0.01097	3.479	96.521
14	0.02811	73.221	26.779	14	0.01130	4.0622	95.938
15	0.02900	72.32	27.68	15	0.01164	4.5148	95.485
16	0.02974	71.508	28.492	16	0.01199	4.9468	95.053
17	0.03036	70.774	29.226	17	0.01242	5.0976	94.902
18	0.03094	70.207	29.794	18	0.01286	5.0744	94.926
19	0.03150	69.858	30.142	19	0.01328	4.9668	95.033
20	0.03198	69.5	30.5	20	0.01365	4.8893	95.111
21	0.03241	69.228	30.772	21	0.01400	4.8222	95.178
22	0.03283	69.189	30.811	22	0.01433	4.7688	95.231
23	0.03324	69.358	30.642	23	0.01461	4.818	95.182
24	0.03363	69.561	30.439	24	0.01488	4.8972	95.103
25	0.03397	69.726	30.274	25	0.01512	4.9699	95.03
26	0.03427	69.875	30.125	26	0.01534	5.0278	94.972
27	0.03454	69.994	30.006	27	0.01553	5.0748	94.925
28	0.03476	70.078	29.922	28	0.01572	5.0943	94.906
29	0.03494	70.129	29.871	29	0.01590	5.084	94.916
30	0.03509	70.16	29.84	30	0.01606	5.056	94.944
31	0.03521	70.174	29.826	31	0.01623	5.0025	94.998
32	0.03530	70.182	29.818	32	0.01639	4.9259	95.074
33	0.03537	70.175	29.825	33	0.01657	4.8326	95.167
34	0.03541	70.148	29.852	34	0.01673	4.7369	95.263
35	0.03543	70.116	29.884	35	0.01690	4.6483	95.352
36	0.03544	70.09	29.91	36	0.01704	4.5771	95.423

Table 5.33

COMMONLY USED BVAR				TIGHTNESS = 0.2 AND OTHER = 0.5			
TOTAL EMP				SERVICES EMP			
Step	St-Dev	TOT	SERV	Step	St-Dev	TOT	SERV
1	0.0063	100.000	0.0000	1	0.0029	2.1806	97.8194
2	0.0087	99.5256	0.4744	2	0.0038	1.8814	98.1186
3	0.0107	98.1124	1.8876	3	0.0047	1.3194	98.6806
4	0.0127	95.5623	4.4377	4	0.0055	0.9996	99.0004
5	0.0142	93.6958	6.3042	5	0.0062	0.7862	99.2138
6	0.0157	90.8001	9.1999	6	0.0069	0.6335	99.3665
7	0.0170	87.2325	12.7675	7	0.0074	0.6650	99.3350
8	0.0182	84.3003	15.6998	8	0.0079	0.6972	99.3028
9	0.0195	81.2932	18.7068	9	0.0083	0.8243	99.1757
10	0.0206	78.5454	21.4546	10	0.0087	1.0397	98.9604
11	0.0217	75.9642	24.0358	11	0.0090	1.3037	98.6964
12	0.0227	74.2135	25.7865	12	0.0093	1.4967	98.5034
13	0.0234	72.5563	27.4437	13	0.0095	1.7957	98.2043
14	0.0242	71.3934	28.6066	14	0.0098	2.2656	97.7344
15	0.0248	70.6765	29.3235	15	0.0100	2.5956	97.4044
16	0.0253	70.0087	29.9913	16	0.0103	3.1496	96.8504
17	0.0258	69.4097	30.5904	17	0.0107	3.3970	96.6031
18	0.0262	69.0059	30.9941	18	0.0110	3.4610	96.5390
19	0.0267	68.9218	31.0782	19	0.0114	3.4154	96.5846
20	0.0272	68.7449	31.2552	20	0.0117	3.4323	96.5677
21	0.0276	68.6241	31.3759	21	0.0120	3.4968	96.5032
22	0.0280	68.8796	31.1204	22	0.0122	3.5671	96.4329
23	0.0285	69.4722	30.5278	23	0.0125	3.8490	96.1510
24	0.0290	70.0437	29.9563	24	0.0127	4.2670	95.7330
25	0.0294	70.6060	29.3940	25	0.0129	4.7166	95.2835
26	0.0299	71.1654	28.8346	26	0.0131	5.1527	94.8473
27	0.0304	71.6731	28.3269	27	0.0133	5.6355	94.3645
28	0.0308	72.1436	27.8564	28	0.0135	6.0733	93.9267
29	0.0312	72.5429	27.4571	29	0.0137	6.4649	93.5351
30	0.0315	72.9114	27.0886	30	0.0139	6.8697	93.1303
31	0.0319	73.2354	26.7646	31	0.0141	7.2429	92.7571
32	0.0322	73.5450	26.4550	32	0.0142	7.5561	92.4439
33	0.0325	73.8215	26.1785	33	0.0144	7.7797	92.2203
34	0.0328	74.0056	25.9945	34	0.0146	7.9819	92.0181
35	0.0330	74.1511	25.8489	35	0.0148	8.1094	91.8906
36	0.0332	74.3006	25.6994	36	0.0150	8.2250	91.7750

Table 5.34

OLS VAR				TIGHTNESS = 2.0 AND OTHER = 1.0			
TOTAL EMP				SERVICES EMP			
Step	St-Dev	TOT	SERV	Step	St-Dev	TOT	SERV
1	0.00629	100	0	1	0.00290	1.9646	98.035
2	0.00892	99.106	0.894	2	0.00384	1.5991	98.401
3	0.01123	96.365	3.6351	3	0.00483	1.0082	98.992
4	0.01361	91.877	8.1228	4	0.00569	0.7403	99.26
5	0.01546	89.879	10.121	5	0.00654	0.7603	99.24
6	0.01749	86.061	13.939	6	0.00745	0.7005	99.3
7	0.01932	81.393	18.607	7	0.00807	1.0833	98.917
8	0.02087	78.282	21.718	8	0.00878	1.3394	98.661
9	0.02273	74.928	25.072	9	0.00934	1.7566	98.243
10	0.02442	72.018	27.982	10	0.00983	2.3283	97.672
11	0.02603	69.338	30.662	11	0.01030	2.9601	97.04
12	0.02755	67.589	32.411	12	0.01073	3.3585	96.642
13	0.02873	65.949	34.051	13	0.01110	3.861	96.139
14	0.02992	64.887	35.113	14	0.01144	4.6807	95.319
15	0.03091	64.256	35.744	15	0.01176	5.0461	94.954
16	0.03170	63.632	36.368	16	0.01214	5.795	94.205
17	0.03239	63.067	36.933	17	0.01260	6.0317	93.968
18	0.03302	62.636	37.364	18	0.01306	6.0356	93.964
19	0.03364	62.586	37.414	19	0.01349	5.8529	94.147
20	0.03419	62.371	37.629	20	0.01383	5.752	94.248
21	0.03467	62.106	37.894	21	0.01417	5.6874	94.313
22	0.03514	62.219	37.781	22	0.01450	5.5747	94.425
23	0.03555	62.65	37.35	23	0.01474	5.634	94.366
24	0.03595	63.001	36.999	24	0.01501	5.7911	94.209
25	0.03630	63.367	36.633	25	0.01523	5.9689	94.031
26	0.03662	63.699	36.301	26	0.01546	6.0845	93.916
27	0.03691	63.969	36.031	27	0.01564	6.2528	93.747
28	0.03714	64.228	35.772	28	0.01582	6.3482	93.652
29	0.03735	64.393	35.607	29	0.01600	6.3841	93.616
30	0.03750	64.551	35.449	30	0.01614	6.4215	93.579
31	0.03763	64.671	35.329	31	0.01630	6.4194	93.581
32	0.03774	64.771	35.229	32	0.01646	6.3728	93.627
33	0.03782	64.86	35.14	33	0.01663	6.2715	93.729
34	0.03787	64.875	35.125	34	0.01680	6.1669	93.833
35	0.03790	64.868	35.132	35	0.01695	6.0563	93.944
36	0.03792	64.869	35.131	36	0.01709	5.9671	94.033

Table 5.35

UNIVARIATE OLS			TIGHTNESS = 2.0 AND OTHER = 0.001		
FORECAST STATS FOR TOTAL EMP					
Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.00213593	0.00766815	0.00985663	1.1182676	12
2	0.00231306	0.00767823	0.00984517	0.9767387	11
3	0.00360493	0.0087236	0.01012651	1.002243	10
4	0.00450827	0.00863514	0.00997602	0.9226643	9
5	0.00559027	0.01075743	0.01339741	0.8765388	8
6	0.00565128	0.00955499	0.0127967	0.7918073	7
7	0.00683713	0.00683713	0.00762872	0.466616	6
8	0.008963	0.00929232	0.01076544	0.5343405	5
9	0.00974681	0.01049567	0.01171587	0.5133011	4
10	0.01168661	0.01168661	0.0134108	0.5118952	3
11	0.01370781	0.01370781	0.01412413	0.5023511	2
12	0.02377091	0.02377091	0.02377091	0.6066029	1
FORECAST STATS FOR MANUF EMP					
1	0.00202395	0.00955618	0.01172775	0.9739156	12
2	0.00347008	0.0145096	0.0175955	0.9630171	11
3	0.0031805	0.01819255	0.02236879	0.9830375	10
4	-0.0010766	0.01808897	0.02058463	0.8746193	9
5	-0.0028562	0.0187116	0.02128898	0.8495219	8
6	-0.0048177	0.01773282	0.02094106	0.8241593	7
7	-0.0055038	0.01373605	0.01521843	0.7587275	6
8	-0.0039955	0.00823719	0.00920944	0.6591352	5
9	-0.0005201	0.00742491	0.00787809	0.5907429	4
10	0.01361525	0.01361525	0.01404171	2.4928676	3
11	0.02244999	0.02244999	0.02248486	2.9322215	2
12	0.02688495	0.02688495	0.02688495	3.9075556	1
FORECAST STATS FOR SERVICE EMP					
1	0.00144974	0.0030893	0.00381628	0.7779735	12
2	0.00315801	0.00429013	0.00615604	0.7507389	11
3	0.0049626	0.00648489	0.00887489	0.7444624	10
4	0.00738234	0.00865886	0.01133881	0.7285849	9
5	0.00876036	0.00997386	0.01285754	0.7180193	8
6	0.00985093	0.01063963	0.01351912	0.6576398	7
7	0.01134597	0.01134597	0.01323818	0.5855263	6
8	0.01370118	0.01370118	0.01482771	0.5757343	5
9	0.01667637	0.01667637	0.01688686	0.5646797	4
10	0.01719089	0.01719089	0.0173199	0.5447694	3
11	0.01998612	0.01998612	0.02001968	0.5680085	2
12	0.01990209	0.01990209	0.01990209	0.5569386	1

Table 5.36

Univariate VAR		TIGHTNESS = 0.1 AND OTHER = 0.001			
FORECAST STATS FOR TOTAL EMP					
Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	0.00371441	0.00818204	0.0096298	1.0925327	12
2	0.00564265	0.00866718	0.01086901	1.0783138	11
3	0.00837129	0.010312	0.01192161	1.179909	10
4	0.01075046	0.01090604	0.01319744	1.2206079	9
5	0.0132374	0.01595912	0.01752909	1.1468581	8
6	0.01479811	0.01479811	0.01841301	1.1393218	7
7	0.01733114	0.01733114	0.01773557	1.0848094	6
8	0.0206073	0.0206073	0.02137033	1.060712	5
9	0.02275361	0.02275361	0.02370819	1.0387139	4
10	0.02599669	0.02599669	0.02689344	1.0265324	3
11	0.02923634	0.02923634	0.02930935	1.0424413	2
12	0.03958974	0.03958974	0.03958974	1.0102791	1
FORECAST STATS FOR MANUF EMP					
1	0.00145589	0.00933667	0.01163708	0.9663856	12
2	0.00269519	0.01430642	0.01754333	0.9601618	11
3	0.00213132	0.01799241	0.02206541	0.9697048	10
4	-0.0024749	0.01790141	0.02081583	0.8844427	9
5	-0.004645	0.01852037	0.02142798	0.8550685	8
6	-0.00703	0.01843458	0.02130407	0.8384458	7
7	-0.0080269	0.01431185	0.01610338	0.8028473	6
8	-0.0068512	0.00918154	0.01009647	0.7226213	5
9	-0.0042113	0.00844866	0.00983015	0.7371186	4
10	0.00916494	0.00916494	0.01019437	1.8098386	3
11	0.01719855	0.01719855	0.01729361	2.2552367	2
12	0.01893742	0.01893742	0.01893742	2.7524319	1
FORECAST STATS FOR SERVICE EMP					
1	0.00140678	0.00316763	0.00389431	0.7938804	12
2	0.00316498	0.00419374	0.00617127	0.7525965	11
3	0.00488133	0.00665143	0.00891497	0.7478246	10
4	0.00727928	0.00853982	0.01133121	0.7280963	9
5	0.00844674	0.00969602	0.01259772	0.7035096	8
6	0.00964303	0.01056377	0.01346443	0.6549792	7
7	0.01105031	0.01105031	0.01296155	0.5732906	6
8	0.01315053	0.01315053	0.01428545	0.5546794	5
9	0.01637515	0.01637515	0.0165745	0.5542346	4
10	0.01685574	0.01685574	0.01700726	0.5349357	3
11	0.01949895	0.01949895	0.01953529	0.5542651	2
12	0.01914955	0.01914955	0.01914955	0.5358796	1

Table 5.37

SIMPLE BAYESIAN VAR			TIGHTNESS = 0.1 AND OTHER = 0.5		
FORECAST STATS FOR TOTAL EMP					
Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.0029427	0.00777809	0.00997986	1.132249	12
2	-0.0072347	0.01276924	0.01483073	1.4713555	11
3	-0.0104649	0.01494538	0.01837827	1.8189385	10
4	-0.0148704	0.01951879	0.0222703	2.0597401	9
5	-0.0188584	0.02490553	0.02694343	1.7628013	8
6	-0.0237229	0.02802896	0.02963885	1.8339305	7
7	-0.0263741	0.02637413	0.02792276	1.7079164	6
8	-0.0263605	0.02636049	0.0267845	1.3294433	5
9	-0.0258647	0.02586471	0.02630351	1.1524209	4
10	-0.0235081	0.0235081	0.02391353	0.9127883	3
11	-0.0179233	0.01792329	0.01866567	0.6638792	2
12	-0.0146323	0.01463231	0.01463231	0.3733978	1
FORECAST STATS FOR MANUF EMP					
1	-0.0010832	0.00863978	0.01154125	0.9584278	12
2	-0.0021382	0.01415406	0.01751324	0.9585148	11
3	-0.0049543	0.01937973	0.02338364	1.0276369	10
4	-0.0116915	0.02369432	0.0276955	1.1767525	9
5	-0.0169195	0.02845157	0.0319305	1.2741642	8
6	-0.0239182	0.03095348	0.03524498	1.3871066	7
7	-0.0305342	0.0310902	0.03620599	1.8050797	6
8	-0.0329746	0.03297461	0.03520612	2.5197613	5
9	-0.0320933	0.03209334	0.03345899	2.5089394	4
10	-0.0205082	0.02050817	0.02198002	3.9021805	3
11	-0.0114971	0.01149713	0.01166962	1.5218201	2
12	-0.0117095	0.01170949	0.01170949	1.7018993	1
FORECAST STATS FOR SERVICE EMP					
1	0.00071521	0.00308996	0.00362631	0.7392477	12
2	0.00175087	0.0041499	0.0055466	0.6764163	11
3	0.00244925	0.00635021	0.00788419	0.6613587	10
4	0.00354379	0.00789872	0.00951953	0.6116856	9
5	0.00337112	0.00818945	0.00993716	0.554933	8
6	0.00307455	0.00823132	0.00959186	0.4665978	7
7	0.00299473	0.00580185	0.00660582	0.292176	6
8	0.00385324	0.00558443	0.00602987	0.2341293	5
9	0.00629593	0.00629593	0.00654035	0.2187029	4
10	0.00680805	0.00680805	0.0072328	0.2274959	3
11	0.00958773	0.00958773	0.00969817	0.2751613	2
12	0.00891029	0.00891029	0.00891029	0.2493448	1

Table 5.38

COMMONLY BAYESIAN VAR			TIGHTNESS = 0.2 AND OTHER = 0.5		
FORECAST STATS FOR TOTAL EMP					
Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.0037939	0.00859013	0.01101828	1.250061	12
2	-0.0086067	0.01474901	0.0169089	1.6775308	11
3	-0.011953	0.01763599	0.02124403	2.102569	10
4	-0.0169944	0.02283759	0.02589836	2.3952931	9
5	-0.0211227	0.02830015	0.0304685	1.9934325	8
6	-0.0267419	0.0309159	0.03287846	2.0343845	7
7	-0.0298855	0.02988555	0.03147735	1.9253353	6
8	-0.0295842	0.02958424	0.0299528	1.486701	5
9	-0.0293973	0.02939729	0.02968445	1.3005482	4
10	-0.026542	0.02654198	0.02683835	1.0244297	3
11	-0.0210406	0.02104059	0.02173307	0.7729772	2
12	-0.0185039	0.01850388	0.01850388	0.4721951	1
FORECAST STATS FOR MANUF EMP					
1	-0.001275	0.00831019	0.01146731	0.9522878	12
2	-0.0026016	0.01396936	0.01714247	0.9382221	11
3	-0.0056408	0.01994736	0.02361376	1.0377498	10
4	-0.0125739	0.02457293	0.0288025	1.2237878	9
5	-0.0180915	0.02935786	0.03326188	1.3272921	8
6	-0.0265778	0.03262643	0.03724566	1.4658455	7
7	-0.0346123	0.03461227	0.03961549	1.975063	6
8	-0.0370813	0.0370813	0.03930792	2.8133346	5
9	-0.0362187	0.0362187	0.03740613	2.8049176	4
10	-0.0243214	0.02432139	0.02539216	4.5079491	3
11	-0.0147242	0.01472417	0.01503454	1.9606345	2
12	-0.0137459	0.01374594	0.01374594	1.9978844	1
FORECAST STATS FOR SERVICE EMP					
1	0.00077534	0.00310408	0.00348727	0.7109027	12
2	0.00184889	0.00431182	0.0055192	0.6730759	11
3	0.00251463	0.00650677	0.00799588	0.6707272	10
4	0.00348308	0.0079908	0.00975229	0.6266416	9
5	0.00332827	0.00848324	0.01041135	0.5814136	8
6	0.0027571	0.00830604	0.00986294	0.4797842	7
7	0.00248429	0.00564843	0.00665551	0.294374	6
8	0.0031724	0.00519398	0.00572954	0.2224681	5
9	0.00544073	0.00544073	0.00586525	0.1961281	4
10	0.00625372	0.00625372	0.00678551	0.213427	3
11	0.0093558	0.0093558	0.00952013	0.27011	2
12	0.00888693	0.00888693	0.00888693	0.2486911	1

Table 5.39

OLS VAR				TIGHTNESS = 2.0 AND OTHER = 1.0	
FORECAST STATS FOR TOTAL EMP					
Step	Mean Error	M-Abs-E	RMS Error	Theil U	N.Obs
1	-0.0041069	0.00890336	0.01198808	1.3600873	12
2	-0.0089658	0.0154523	0.01774121	1.7601047	11
3	-0.01183	0.0184435	0.02191065	2.1685459	10
4	-0.0170851	0.02399354	0.02700188	2.4973558	9
5	-0.0205841	0.02918211	0.03110608	2.0351464	8
6	-0.0266179	0.03037613	0.03271111	2.0240294	7
7	-0.0302117	0.03021165	0.03169123	1.9384178	6
8	-0.0300237	0.03002373	0.03030571	1.5042177	5
9	-0.0303193	0.03031925	0.03080254	1.3495346	4
10	-0.0267597	0.02675975	0.02726563	1.0407388	3
11	-0.0226567	0.02265672	0.02371529	0.8434784	2
12	-0.0231799	0.02317991	0.02317991	0.5915215	1
FORECAST STATS FOR MANUF EMP					
1	-0.0013872	0.00791102	0.0119692	0.9939668	12
2	-0.0030572	0.01393323	0.01702278	0.9316716	11
3	-0.006283	0.02060027	0.02409163	1.0587508	10
4	-0.013143	0.02533134	0.03006983	1.2776352	9
5	-0.0182505	0.02972916	0.03425421	1.3668903	8
6	-0.0282491	0.03363506	0.03810348	1.4996059	7
7	-0.0370859	0.03708588	0.0412123	2.0546734	6
8	-0.0384132	0.03841316	0.04043938	2.8943148	5
9	-0.0378309	0.03783091	0.038849	2.9131123	4
10	-0.0260617	0.0260617	0.02687598	4.7713767	3
11	-0.0160889	0.0160889	0.0172416	2.2484545	2
12	-0.0152622	0.01526221	0.01526221	2.2182646	1
FORECAST STATS FOR SERVICE EMP					
1	0.00084831	0.00334132	0.00354037	0.7217278	12
2	0.00211743	0.00431881	0.00545395	0.6651182	11
3	0.00277993	0.00683291	0.00813817	0.6826631	10
4	0.00376076	0.00790912	0.00993862	0.6386141	9
5	0.00382188	0.00862903	0.0109501	0.6114996	8
6	0.00320415	0.00848818	0.01040112	0.5059643	7
7	0.00299222	0.00589862	0.00732108	0.3238122	6
8	0.00359726	0.00579051	0.00646442	0.2510021	5
9	0.00579477	0.00579477	0.00660758	0.220951	4
10	0.00683171	0.00683171	0.00768101	0.2415938	3
11	0.01020556	0.01020556	0.01056112	0.2996454	2
12	0.00923306	0.00923306	0.00923306	0.2583773	1

Table 5.40

UNIVARIATE OLS					TIGHTNESS = 2.0 AND OTHER = 0.001					VARIANCE DECOMPOSITION				
TOTAL EMPLOYMENT					MANUFACTURING EMPLOYMENT					SERVICES EMPLOYMENT				
Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV
1	0.010154	100	0	0	1	0.009081	0.09064	99.90936	0	1	0.003071	0.00274	2.91764	97.07962
2	0.013948	99.99997	0.00001	0.00002	2	0.012545	0.09059	99.9094	0.00001	2	0.004127	0.00272	2.91117	97.08612
3	0.016573	99.99984	0.00005	0.00011	3	0.015339	0.09043	99.9095	0.00006	3	0.005259	0.00266	2.90049	97.09685
4	0.019322	99.99951	0.00014	0.00035	4	0.018018	0.09005	99.90979	0.00017	4	0.006254	0.00253	2.88708	97.11039
5	0.021522	99.99885	0.00028	0.00086	5	0.020724	0.08921	99.91046	0.00033	5	0.007233	0.00236	2.87118	97.12646
6	0.02337	99.99766	0.00052	0.00181	6	0.022878	0.08799	99.91143	0.00058	6	0.008288	0.00212	2.85296	97.14492
7	0.024695	99.99566	0.00089	0.00345	7	0.024557	0.08633	99.91274	0.00093	7	0.009013	0.00188	2.83319	97.16494
8	0.025582	99.99253	0.00139	0.00608	8	0.026306	0.08399	99.91468	0.00133	8	0.009854	0.0016	2.81091	97.18749
9	0.026621	99.98832	0.00198	0.0097	9	0.028433	0.08088	99.91742	0.00169	9	0.010526	0.00141	2.78769	97.2109
10	0.0274	99.98257	0.00274	0.01468	10	0.030553	0.07725	99.9207	0.00205	10	0.011127	0.00137	2.76312	97.23551
11	0.028177	99.97542	0.00366	0.02092	11	0.032373	0.07345	99.92414	0.00242	11	0.011704	0.00156	2.73715	97.26129
12	0.028864	99.96673	0.00475	0.02851	12	0.034305	0.06926	99.92801	0.00273	12	0.012279	0.00206	2.7103	97.28764
13	0.029348	99.95602	0.0061	0.03788	13	0.035946	0.06518	99.93177	0.00305	13	0.012761	0.00308	2.68382	97.3131
14	0.029779	99.94353	0.00771	0.04875	14	0.037262	0.06146	99.93516	0.00338	14	0.013207	0.00471	2.6574	97.33789
15	0.030092	99.92905	0.00965	0.0613	15	0.038569	0.05776	99.93858	0.00366	15	0.013675	0.00697	2.63099	97.36204
16	0.030309	99.91249	0.01192	0.07559	16	0.039689	0.05458	99.94149	0.00393	16	0.014152	0.00992	2.60544	97.38464
17	0.030486	99.89411	0.01451	0.09137	17	0.040637	0.05212	99.94369	0.00419	17	0.01476	0.01323	2.58131	97.40546
18	0.030651	99.8741	0.01742	0.10848	18	0.041416	0.05066	99.9449	0.00444	18	0.015399	0.01719	2.55979	97.42303
19	0.030937	99.85378	0.02043	0.1258	19	0.042134	0.04997	99.94536	0.00468	19	0.016032	0.02193	2.54111	97.43695
20	0.031155	99.83154	0.02372	0.14474	20	0.042913	0.04955	99.94558	0.00487	20	0.016573	0.02793	2.52467	97.4474
21	0.031325	99.80736	0.02736	0.16528	21	0.043599	0.05029	99.94468	0.00504	21	0.017136	0.03466	2.51128	97.45406
22	0.031591	99.78302	0.03107	0.18591	22	0.044133	0.05275	99.94206	0.0052	22	0.017683	0.04234	2.50088	97.45678
23	0.031897	99.75801	0.03486	0.20713	23	0.044887	0.05431	99.94043	0.00526	23	0.018128	0.0517	2.4924	97.4559
24	0.03227	99.73281	0.03871	0.22848	24	0.045546	0.05721	99.9375	0.00529	24	0.01859	0.06194	2.48754	97.45052
25	0.032543	99.70457	0.04304	0.25239	25	0.046056	0.06203	99.93265	0.00533	25	0.019001	0.0738	2.48534	97.44085
26	0.032746	99.67353	0.04777	0.2787	26	0.046486	0.06832	99.92635	0.00534	26	0.019412	0.08676	2.48657	97.42667
27	0.032955	99.64098	0.05265	0.30637	27	0.046881	0.07569	99.91899	0.00532	27	0.019778	0.10141	2.48996	97.40863
28	0.033086	99.60515	0.05796	0.33689	28	0.047214	0.08451	99.91019	0.00529	28	0.020148	0.1171	2.49672	97.38619

Table 5.41

UNIVARIATE VAR					TIGHTNESS = 0.1 AND OTHER = 0.001					VARIANCE DECOMPOSITION				
TOTAL EMPLOYMENT					MANUFACTURING EMPLOYMENT					SERVICES EMPLOYMENT				
Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV
1	0.010298	100	0	0	1	0.009195	0.19962	99.80038	0	1	0.003154	0.00584	2.47734	97.51682
2	0.014289	100	0	0	2	0.012819	0.19962	99.80038	0	2	0.004348	0.00584	2.47732	97.51684
3	0.017232	100	0	0	3	0.015657	0.19962	99.80038	0	3	0.005457	0.00584	2.4773	97.51686
4	0.020003	100	0	0	4	0.018315	0.19962	99.80038	0	4	0.006487	0.00584	2.47727	97.51688
5	0.022347	100	0	0	5	0.020902	0.19961	99.80039	0	5	0.007485	0.00584	2.47724	97.51692
6	0.024352	100	0	0	6	0.023099	0.1996	99.8004	0	6	0.008487	0.00584	2.4772	97.51695
7	0.025885	100	0	0	7	0.024946	0.19959	99.80041	0	7	0.009307	0.00585	2.47717	97.51699
8	0.027065	100	0	0	8	0.026829	0.19958	99.80042	0	8	0.010142	0.00585	2.47712	97.51703
9	0.028251	100	0	0	9	0.028945	0.19956	99.80044	0	9	0.01086	0.00585	2.47708	97.51707
10	0.02926	100	0	0	10	0.031031	0.19954	99.80046	0	10	0.011512	0.00586	2.47703	97.51711
11	0.03022	99.99999	0	0.00001	11	0.032917	0.19952	99.80048	0	11	0.012132	0.00586	2.47699	97.51715
12	0.031067	99.99999	0	0.00001	12	0.03482	0.19949	99.80051	0	12	0.012732	0.00586	2.47694	97.5172
13	0.03174	99.99999	0	0.00001	13	0.036487	0.19946	99.80054	0	13	0.013271	0.00587	2.47689	97.51724
14	0.032339	99.99998	0	0.00002	14	0.037875	0.19943	99.80057	0	14	0.013784	0.00587	2.47685	97.51727
15	0.032816	99.99998	0	0.00002	15	0.039177	0.1994	99.8006	0	15	0.014313	0.00588	2.47681	97.5173
16	0.033197	99.99997	0	0.00003	16	0.04033	0.19936	99.80063	0	16	0.014863	0.00589	2.47678	97.51733
17	0.033526	99.99996	0	0.00004	17	0.041305	0.19933	99.80067	0	17	0.015506	0.0059	2.47676	97.51734
18	0.033849	99.99995	0	0.00005	18	0.042116	0.19929	99.80071	0	18	0.016179	0.0059	2.47675	97.51735
19	0.034265	99.99993	0	0.00007	19	0.04287	0.19925	99.80074	0	19	0.016846	0.00591	2.47674	97.51734
20	0.034646	99.99992	0	0.00008	20	0.043638	0.19921	99.80078	0.00001	20	0.017448	0.00592	2.47675	97.51733
21	0.035002	99.9999	0	0.0001	21	0.04432	0.19917	99.80082	0.00001	21	0.018047	0.00593	2.47676	97.51731
22	0.035436	99.99988	0	0.00012	22	0.044906	0.19913	99.80086	0.00001	22	0.01862	0.00594	2.47679	97.51727
23	0.035925	99.99985	0	0.00014	23	0.0456	0.19908	99.80091	0.00001	23	0.019117	0.00595	2.47682	97.51723
24	0.036465	99.99983	0	0.00017	24	0.046235	0.19904	99.80095	0.00002	24	0.019609	0.00595	2.47687	97.51718
25	0.036918	99.9998	0	0.0002	25	0.046743	0.19899	99.80099	0.00002	25	0.020063	0.00596	2.47692	97.51711
26	0.037307	99.99976	0	0.00024	26	0.047169	0.19895	99.80103	0.00002	26	0.020497	0.00597	2.47699	97.51704
27	0.037664	99.99972	0.00001	0.00028	27	0.047544	0.19891	99.80107	0.00003	27	0.020905	0.00598	2.47706	97.51695
28	0.037956	99.99967	0.00001	0.00032	28	0.047859	0.19886	99.8011	0.00003	28	0.0213	0.00599	2.47715	97.51686

Table 5.42

SIMPLE BAYESIAN VAR					TIGHTNESS = 0.1 AND OTHER = 0.5					VARIANCE DECOMPOSITION				
TOTAL EMPLOYMENT					MANUFACTURING EMPLOYMENT					SERVICES EMPLOYMENT				
Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV
1	0.009219	100	0	0	1	0.008264	0.31711	99.68289	0	1	0.002943	0.00035	3.81168	96.18797
2	0.012333	99.66425	0.25667	0.07908	2	0.011135	0.58098	99.1509	0.26811	2	0.003959	0.04231	3.68173	96.27596
3	0.014352	98.43065	0.96665	0.6027	3	0.013202	1.18266	97.78994	1.0274	3	0.004841	0.20583	3.42612	96.36805
4	0.016094	96.33787	1.72123	1.94091	4	0.015064	2.09856	95.41019	2.49126	4	0.005605	0.28508	3.14678	96.56814
5	0.017434	93.57159	2.5177	3.9107	5	0.016817	2.8925	93.01351	4.09398	5	0.00631	0.41411	2.90534	96.68054
6	0.018622	89.67951	3.42839	6.89209	6	0.018317	3.88216	89.91053	6.20731	6	0.006999	0.5081	2.67907	96.81283
7	0.019604	85.0671	4.26532	10.66758	7	0.019652	4.7217	86.48892	8.78938	7	0.00752	0.55556	2.41056	97.03388
8	0.020475	80.01463	4.87733	15.10804	8	0.021028	5.15679	83.89582	10.94739	8	0.008034	0.55394	2.15983	97.28623
9	0.021483	74.57619	5.08695	20.33686	9	0.022571	5.17126	82.37602	12.45271	9	0.008441	0.51106	1.95645	97.5325
10	0.022505	69.22063	5.31025	25.46911	10	0.024086	4.7954	81.65633	13.54827	10	0.008797	0.47705	1.84479	97.67816
11	0.023517	64.53535	5.47407	29.99058	11	0.025469	4.38996	81.11398	14.49606	11	0.009134	0.52796	1.87972	97.59233
12	0.024402	60.77939	5.53396	33.68665	12	0.026862	3.97617	80.98325	15.04057	12	0.009465	0.71853	2.0412	97.24026
13	0.025194	57.47441	5.49577	37.02982	13	0.028051	3.64672	80.98255	15.37074	13	0.009759	0.95914	2.35501	96.68585
14	0.025914	54.71008	5.58384	39.70608	14	0.029014	3.40897	80.98179	15.60924	14	0.010051	1.26468	2.83546	95.89986
15	0.026494	52.54045	5.71293	41.74662	15	0.029921	3.22712	81.12244	15.65044	15	0.010366	1.69303	3.35712	94.94985
16	0.026985	50.72987	5.82231	43.44782	16	0.030735	3.17723	81.21725	15.60552	16	0.010688	2.0107	3.83094	94.15836
17	0.027401	49.25789	5.90571	44.83639	17	0.031431	3.23856	81.23161	15.52983	17	0.011067	2.33445	4.03613	93.62942
18	0.027759	48.08066	6.06823	45.85111	18	0.032038	3.3784	81.17756	15.44404	18	0.011468	2.83686	4.1887	92.97445
19	0.028082	47.24152	6.25471	46.50378	19	0.032627	3.59039	81.12618	15.28343	19	0.011853	3.49339	4.31381	92.19281
20	0.028353	46.52861	6.4294	47.04199	20	0.033296	4.01494	80.98463	15.00042	20	0.012179	4.19054	4.49717	91.31229
21	0.028593	45.90692	6.75101	47.34207	21	0.03394	4.58408	80.73916	14.67677	21	0.012486	4.83965	4.68234	90.47801
22	0.028842	45.44768	7.16233	47.38999	22	0.034493	5.05915	80.62627	14.31459	22	0.012759	5.44835	4.85693	89.69472
23	0.029081	45.12521	7.56892	47.30588	23	0.035162	5.53053	80.67733	13.79214	23	0.012975	5.97301	5.14789	88.8791
24	0.029367	44.71463	8.18246	47.10291	24	0.035793	6.07635	80.61295	13.3107	24	0.013171	6.36292	5.43234	88.20474
25	0.029642	44.06245	9.00479	46.93276	25	0.0363	6.55985	80.49196	12.94819	25	0.013336	6.7461	5.75114	87.50276
26	0.029918	43.30157	9.89457	46.80386	26	0.036741	6.97236	80.35454	12.6731	26	0.013486	7.12009	6.09353	86.78639
27	0.030196	42.52168	10.74108	46.73724	27	0.037164	7.35777	80.17913	12.4631	27	0.013622	7.53087	6.45837	86.01075
28	0.030466	41.77219	11.56716	46.66064	28	0.037573	7.76271	79.91308	12.32421	28	0.013757	8.00245	6.81676	85.18079

Table 5.43

COMMONLY USED BAYESIAN VAR					TIGHTNESS = 0.2 AND OTHER = 0.5					VARIANCE DECOMPOSITION				
TOTAL EMPLOYMENT					MANUFACTURING EMPLOYMENT					SERVICES EMPLOYMENT				
Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV
1	0.008741	100	0	0	1	0.007845	0.25564	99.74436	0	1	0.002805	0.00006	4.1875	95.81244
2	0.011574	99.08795	0.81144	0.10061	2	0.01044	0.66456	98.74226	0.59317	2	0.003697	0.09073	4.20597	95.7033
3	0.013471	96.31765	2.54272	1.13963	3	0.012462	1.55466	96.52147	1.92387	3	0.004574	0.49072	3.99636	95.51292
4	0.015309	92.57678	3.8756	3.54762	4	0.014386	2.9357	92.52679	4.53751	4	0.005304	0.5447	3.67639	95.77891
5	0.016687	88.52072	5.0948	6.38448	5	0.016217	3.76863	89.53807	6.6933	5	0.005997	0.74438	3.4243	95.83132
6	0.018029	83.13912	6.30588	10.555	6	0.017776	5.18757	85.27042	9.54201	6	0.006725	0.83659	3.21935	95.94406
7	0.019123	77.77599	7.18679	15.03721	7	0.019223	6.40332	80.45602	13.14066	7	0.007227	0.88966	2.90762	96.20272
8	0.020049	72.33886	7.78122	19.87992	8	0.020719	6.95434	77.08006	15.96559	8	0.007773	0.89822	2.64102	96.46076
9	0.021239	66.3484	7.64904	26.00256	9	0.022385	6.99739	75.26505	17.73756	9	0.008181	0.83475	2.38912	96.77612
10	0.022455	60.62566	7.68354	31.6908	10	0.023992	6.37289	74.7407	18.88641	10	0.008541	0.76594	2.20795	97.02611
11	0.023634	55.97625	7.64573	36.37802	11	0.025445	5.82795	74.05338	20.11867	11	0.008886	0.77525	2.15944	97.06531
12	0.024581	52.72496	7.54681	39.72823	12	0.026925	5.29322	73.86455	20.84223	12	0.009223	0.96326	2.20157	96.83517
13	0.02544	49.73158	7.26225	43.00617	13	0.028117	4.86616	73.91162	21.22222	13	0.009506	1.12872	2.38508	96.4862
14	0.026246	47.21079	7.22487	45.56434	14	0.029037	4.59706	73.91716	21.48578	14	0.009785	1.33491	2.78532	95.87976
15	0.026834	45.4042	7.27003	47.32577	15	0.029924	4.33271	74.17354	21.49375	15	0.010088	1.74721	3.24097	95.01182
16	0.027343	43.82641	7.29341	48.88018	16	0.030696	4.1691	74.38124	21.44966	16	0.010384	1.87383	3.6659	94.46027
17	0.027777	42.54989	7.24141	50.2087	17	0.031329	4.09955	74.57828	21.32217	17	0.010749	1.95812	3.72384	94.31804
18	0.028158	41.52582	7.32091	51.15326	18	0.031869	4.07316	74.73145	21.19539	18	0.011139	2.28958	3.77937	93.93105
19	0.0285	40.88871	7.43498	51.67631	19	0.032371	4.06748	74.91204	21.02048	19	0.011504	2.85365	3.79148	93.35487
20	0.028782	40.30311	7.508	52.18888	20	0.032976	4.29674	75.01562	20.68764	20	0.01179	3.43452	3.87878	92.6867
21	0.029027	39.77011	7.78941	52.44048	21	0.033562	4.69883	74.97185	20.32932	21	0.012069	3.96316	3.96708	92.06976
22	0.029284	39.43341	8.17249	52.39409	22	0.033995	4.89796	75.1484	19.95364	22	0.012311	4.4797	4.00832	91.51198
23	0.029502	39.28402	8.46805	52.24793	23	0.034581	5.1367	75.56549	19.29781	23	0.01249	4.92142	4.20671	90.87186
24	0.029808	38.98807	9.07015	51.94177	24	0.035119	5.5622	75.72629	18.71151	24	0.012654	5.17275	4.40204	90.42521
25	0.030097	38.41671	9.90908	51.67421	25	0.03552	5.89529	75.79768	18.30703	25	0.012786	5.43623	4.65622	89.90755
26	0.030385	37.7377	10.75609	51.50621	26	0.035869	6.14844	75.84139	18.01018	26	0.012909	5.6729	4.94649	89.38062
27	0.03068	37.0433	11.48679	51.46991	27	0.03622	6.38511	75.84965	17.76524	27	0.013014	5.9548	5.27508	88.77012
28	0.03095	36.40102	12.24269	51.35629	28	0.036563	6.65556	75.73583	17.60861	28	0.013121	6.31736	5.58392	88.09872

Table 5.44

OLS VAR					TIGHTNESS = 2.0 AND OTHER = 1.0					VARIANCE DECOMPOSITION				
TOTAL EMPLOYMENT					MANUFACTURING EMPLOYMENT					SERVICES EMPLOYMENT				
Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV	Step	St-Dev	TOT	MANUF	SERV
1	0.00842	100	0	0	1	0.007597	0.27964	99.72036	0	1	0.002721	0.00248	4.09435	95.90317
2	0.011309	98.2825	1.70712	0.01039	2	0.010165	1.12076	98.03515	0.84409	2	0.003579	0.12653	4.27064	95.60283
3	0.013395	93.59731	4.53411	1.86859	3	0.012401	2.16035	95.32194	2.51771	3	0.004532	0.96975	4.20766	94.82259
4	0.015564	88.32757	6.34984	5.32259	4	0.014576	4.10911	89.37915	6.51175	4	0.005251	0.86018	3.87262	95.2672
5	0.017073	83.83807	7.87593	8.28599	5	0.016552	4.74015	86.60907	8.65078	5	0.005955	1.18141	3.56956	95.24903
6	0.018722	77.48253	9.27292	13.24455	6	0.018215	6.48398	81.9855	11.53052	6	0.006739	1.16577	3.42592	95.40832
7	0.019898	72.63667	9.74715	17.61618	7	0.01984	8.06184	76.64625	15.29191	7	0.00725	1.22054	3.08543	95.69403
8	0.020767	68.11825	10.24968	21.63207	8	0.021539	8.71135	72.75667	18.53198	8	0.007844	1.225	2.85239	95.9226
9	0.02212	61.91474	9.82879	28.25647	9	0.023336	8.95201	70.64996	20.39803	9	0.008263	1.13769	2.58007	96.28224
10	0.023543	56.10925	9.69388	34.19687	10	0.025008	8.06136	70.56211	21.37653	10	0.008646	1.0703	2.36009	96.56961
11	0.024853	51.70522	9.41157	38.88321	11	0.026586	7.42042	69.77242	22.80716	11	0.009016	1.02381	2.26235	96.71384
12	0.025829	48.97249	9.23807	41.78944	12	0.028222	6.7834	69.34235	23.87426	12	0.009356	1.18683	2.19917	96.61399
13	0.026725	46.33231	8.72594	44.94175	13	0.029445	6.25632	69.42867	24.31502	13	0.009641	1.25736	2.27244	96.4702
14	0.027649	43.83686	8.60877	47.55438	14	0.030362	5.99785	69.44783	24.55432	14	0.00992	1.33067	2.59926	96.07007
15	0.02823	42.32877	8.54217	49.12906	15	0.031292	5.72474	69.68629	24.58896	15	0.010221	1.80493	2.96055	95.23451
16	0.028768	40.87385	8.53307	50.59308	16	0.032093	5.46262	69.87211	24.66527	16	0.01051	1.80748	3.38215	94.81038
17	0.029229	39.69949	8.36804	51.93247	17	0.032716	5.31281	70.17818	24.50901	17	0.010871	1.74235	3.34529	94.91236
18	0.029665	38.69236	8.38566	52.92198	18	0.033231	5.19651	70.4403	24.36319	18	0.011267	1.92744	3.38958	94.68299
19	0.030024	38.18102	8.44377	53.37521	19	0.033706	5.07878	70.72838	24.19285	19	0.011633	2.41601	3.31445	94.26954
20	0.030321	37.69899	8.4554	53.84561	20	0.034296	5.18167	70.94852	23.86982	20	0.011896	2.86073	3.32865	93.81062
21	0.030585	37.20737	8.68424	54.10839	21	0.034887	5.47441	70.97422	23.55136	21	0.012165	3.29036	3.38471	93.32493
22	0.030873	36.93554	9.05328	54.01118	22	0.035297	5.48886	71.31417	23.19697	22	0.012395	3.73663	3.32472	92.93865
23	0.03106	36.91162	9.23702	53.85135	23	0.035857	5.55025	71.94389	22.50586	23	0.012552	4.16418	3.4224	92.41341
24	0.031392	36.66243	9.84037	53.4972	24	0.036368	5.89429	72.22357	21.88215	24	0.012696	4.34348	3.5354	92.12112
25	0.031687	36.20078	10.57429	53.22494	25	0.036732	6.15644	72.35778	21.48578	25	0.012815	4.52276	3.72949	91.74774
26	0.031995	35.60308	11.28827	53.10865	26	0.037057	6.35817	72.44131	21.20053	26	0.012935	4.63794	3.95136	91.41069
27	0.032313	34.95755	11.8524	53.19005	27	0.037394	6.52097	72.56462	20.91441	27	0.01302	4.80304	4.22941	90.96754
28	0.032573	34.41188	12.5332	53.05492	28	0.0377	6.68757	72.5406	20.77183	28	0.01311	5.09164	4.45394	90.45442

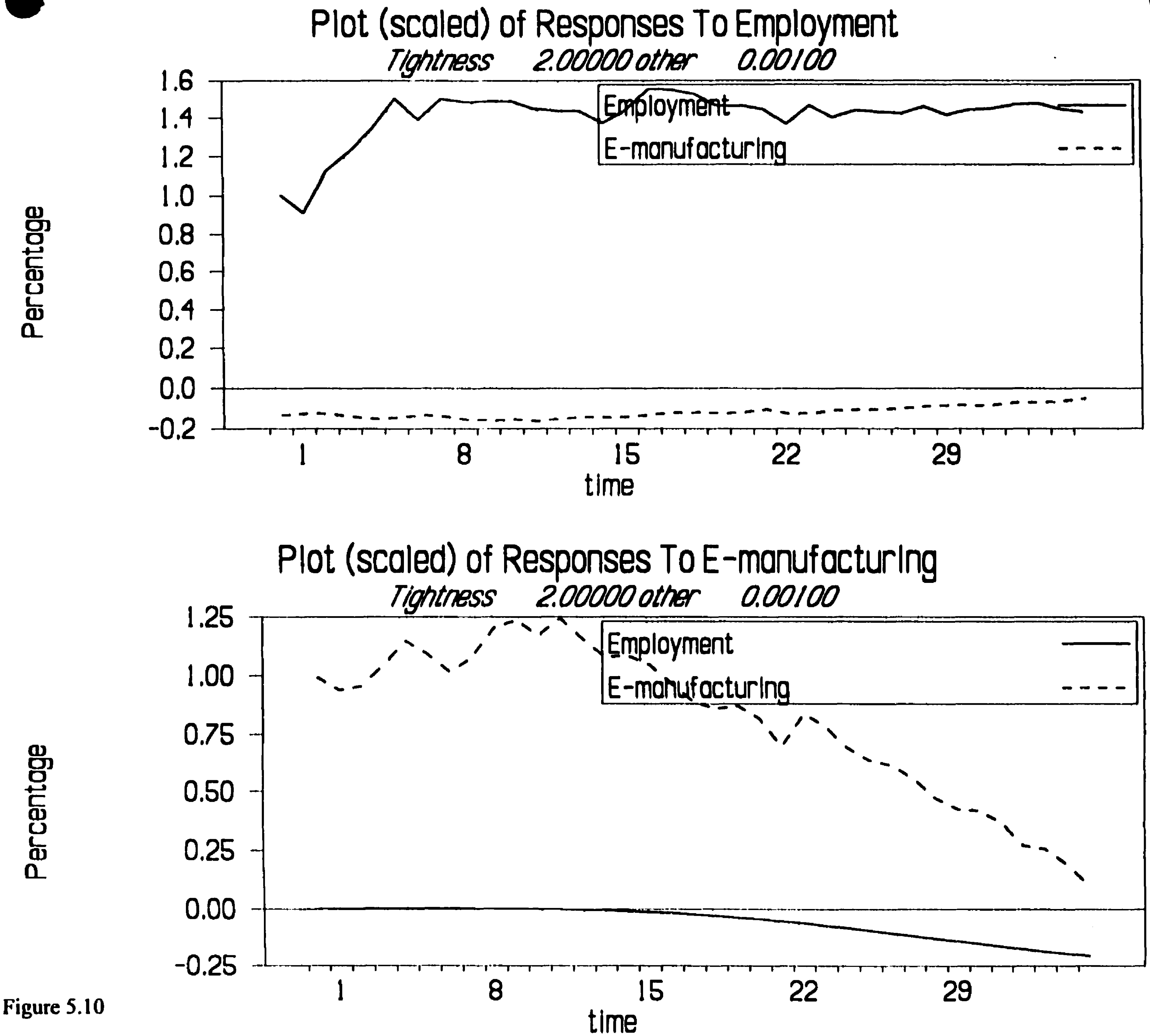
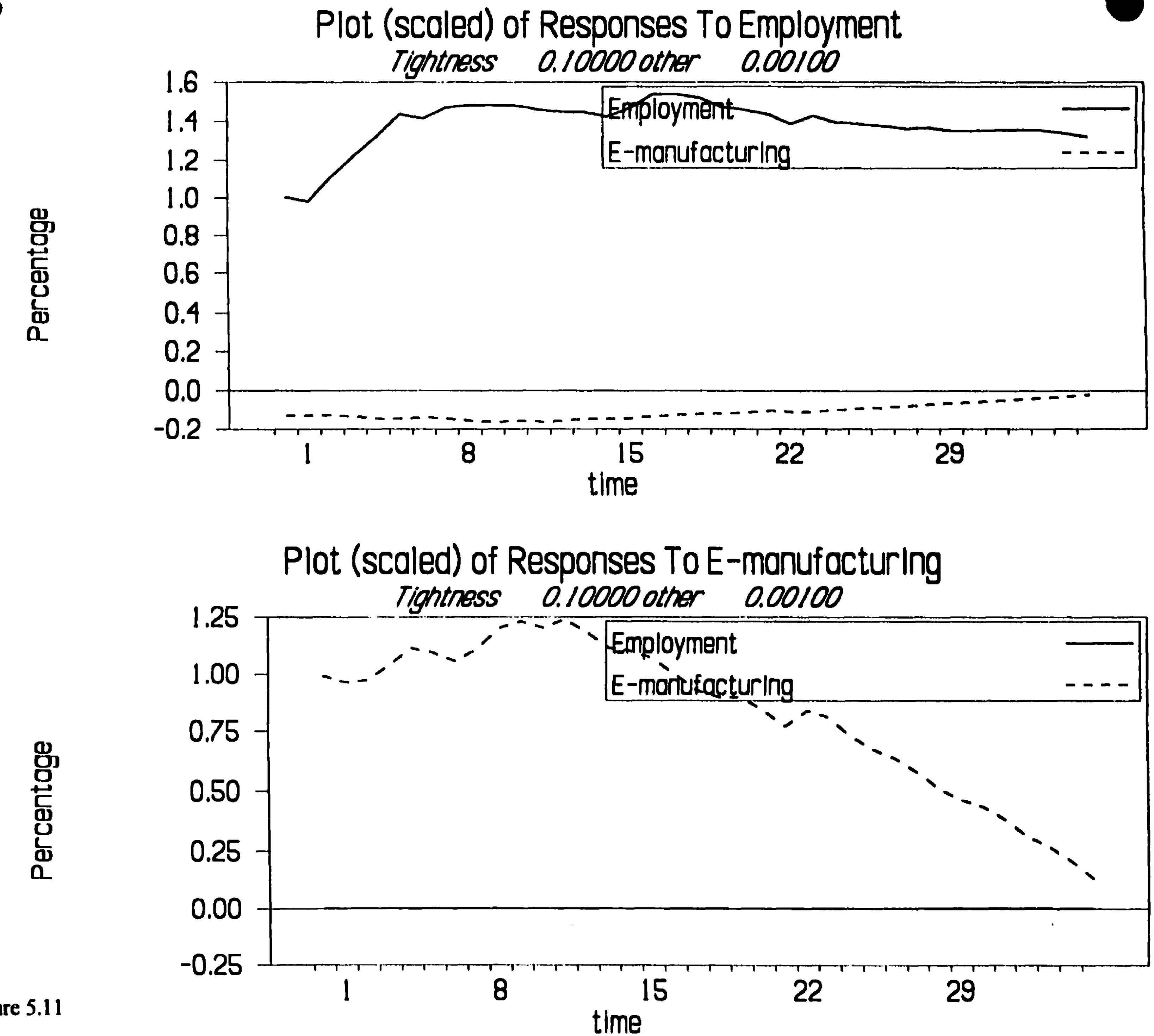


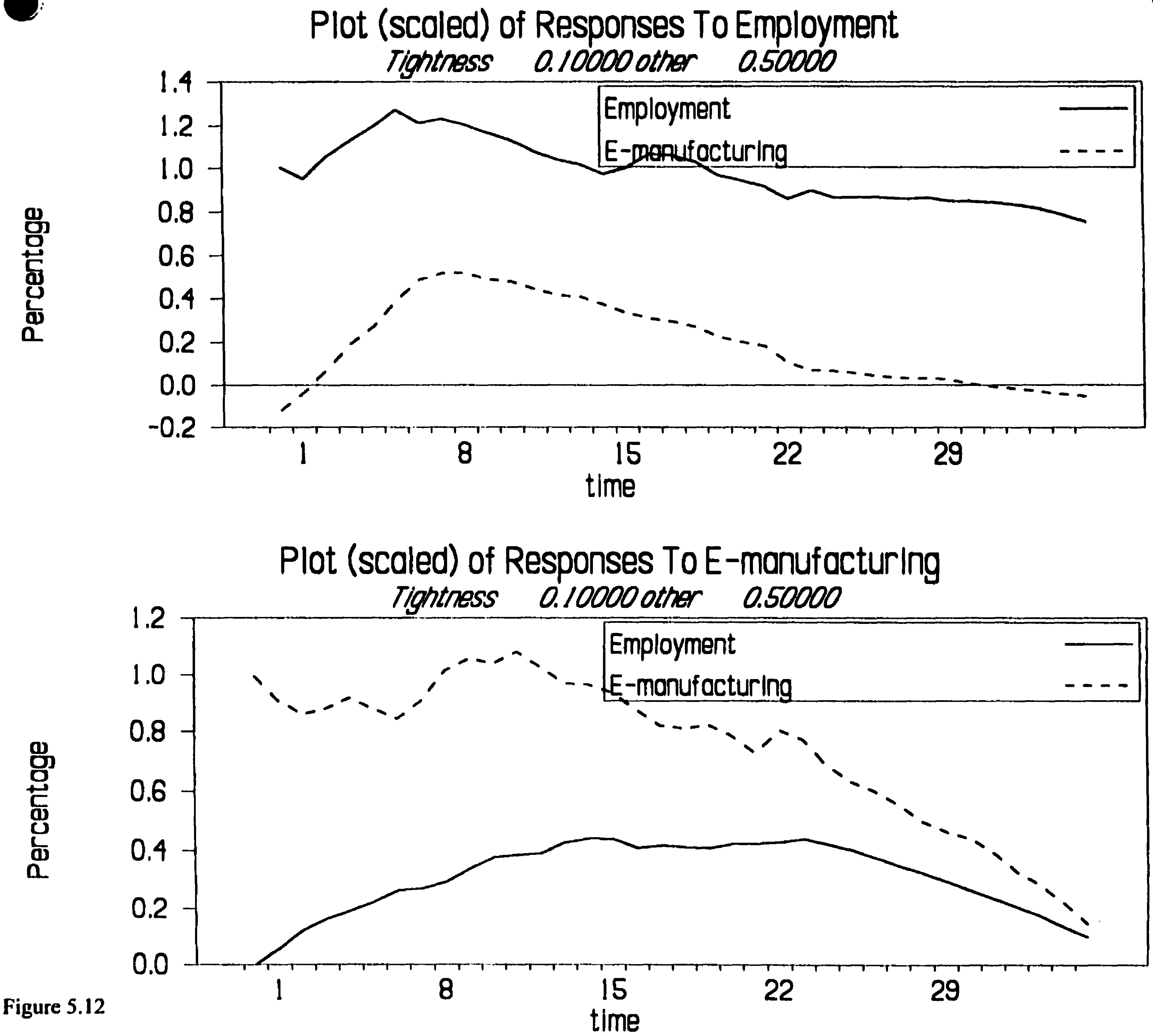
Figure 5.10

5.8



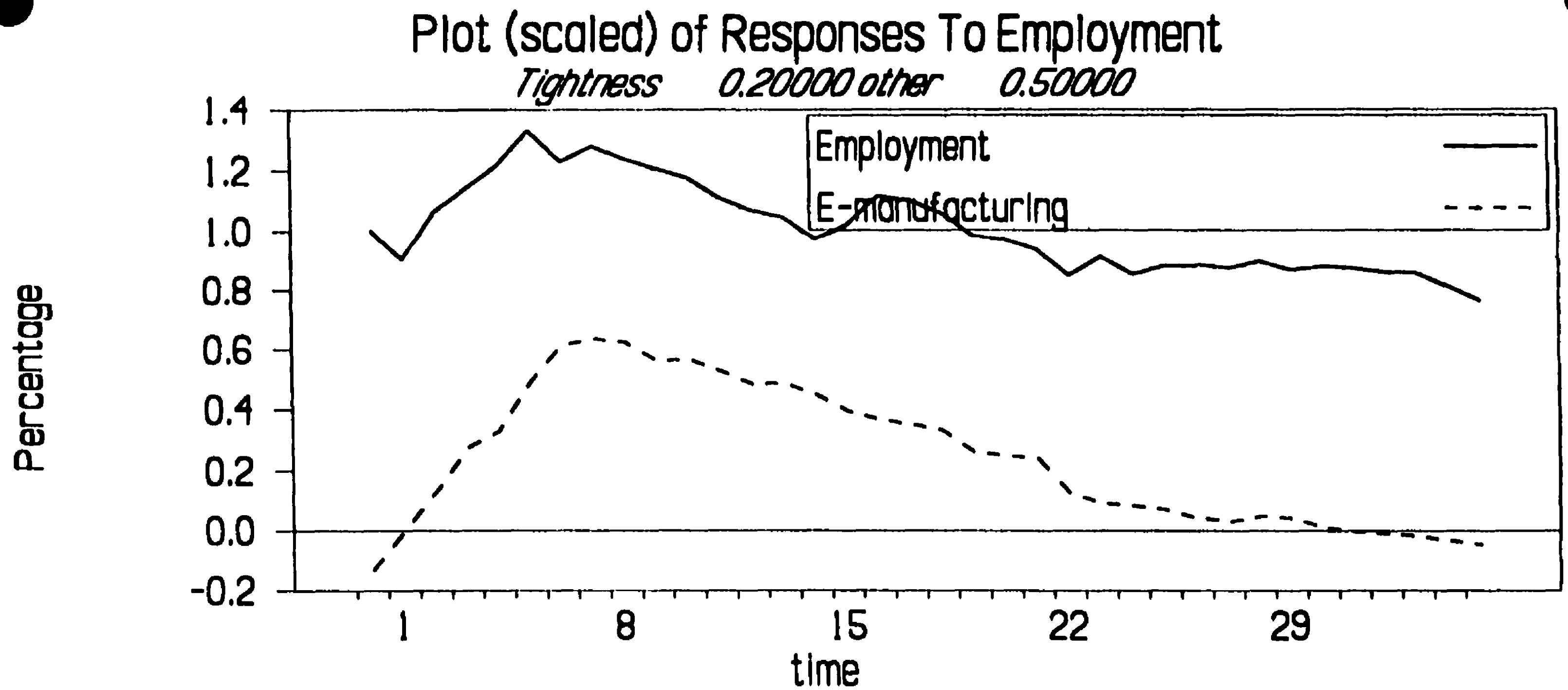
Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.00100
Percentage
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
Employment
E-manufacturing
1
8
15
22
29
time
Plot (scaled) of Responses To E-manufacturing
Tightness 0.10000 other 0.00100
Percentage
1.25
1.00
0.75
0.50
0.25
0.00
-0.25
Employment
E-manufacturing
1
8
15
22
29
time

Figure 5.11



Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.50000
Employment
E-manufacturing
Percentage
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
time
Plot (scaled) of Responses To E-manufacturing
Tightness 0.10000 other 0.50000
Employment
E-manufacturing
Percentage
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
8
15
22
29
time

Figure 5.12



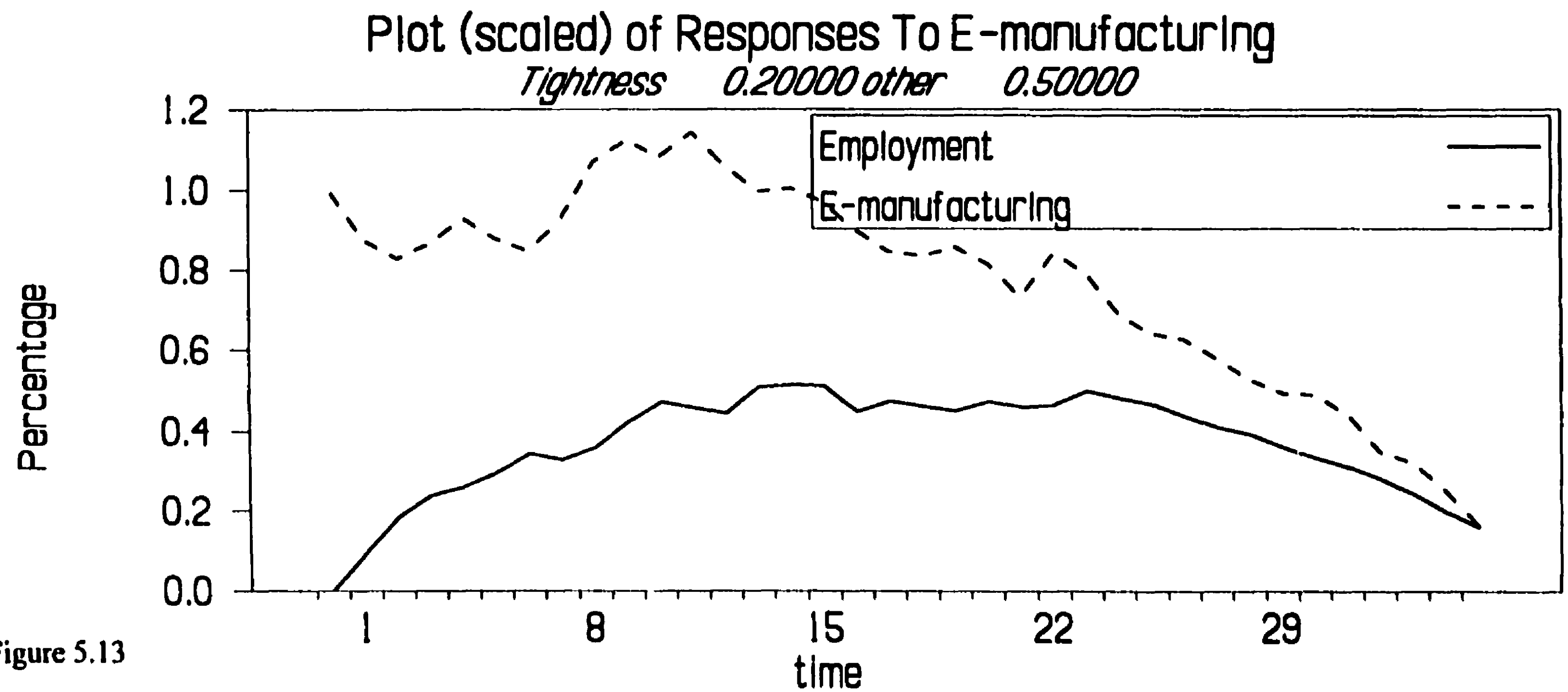
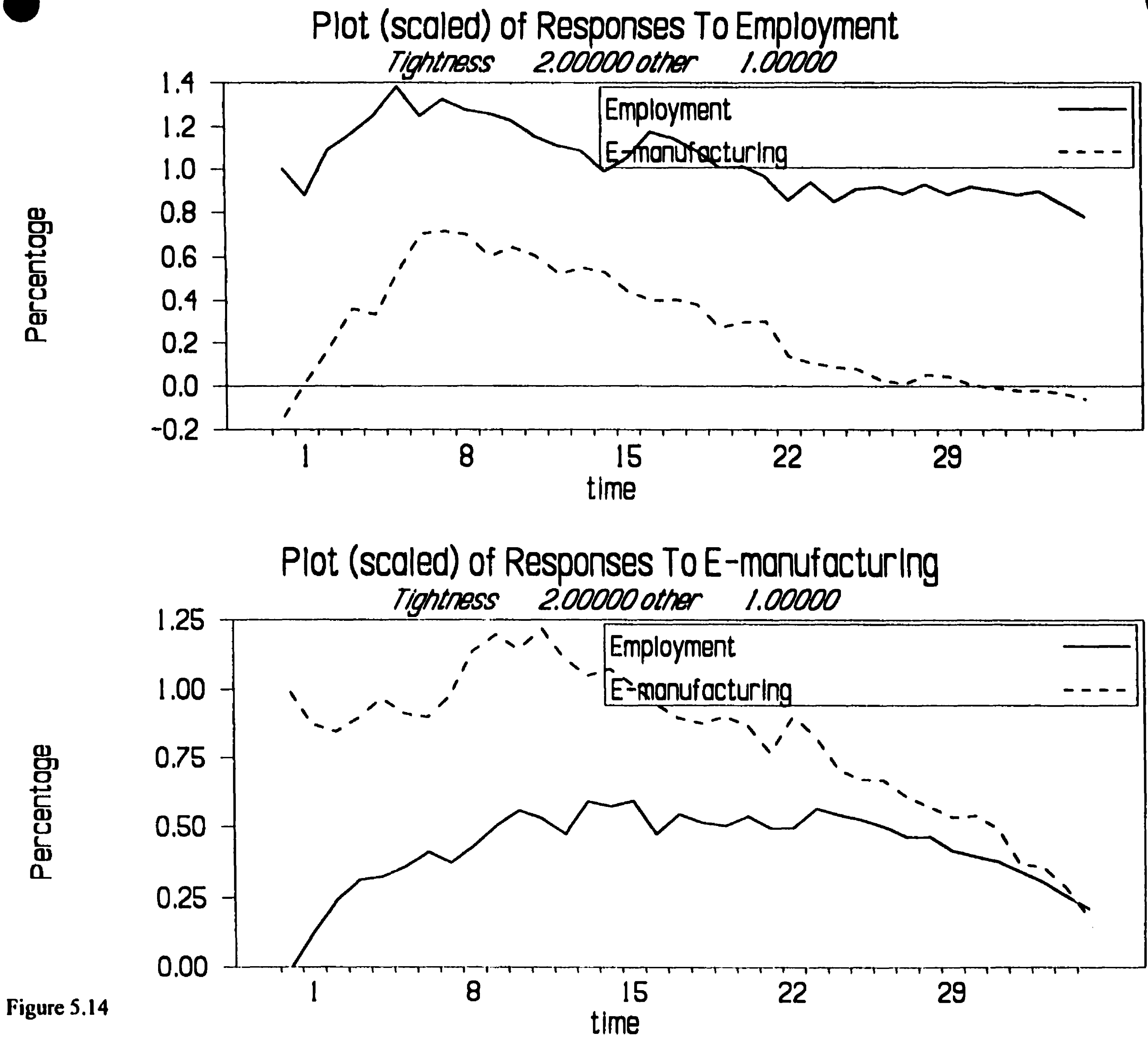


Figure 5.13

5.8



Plot (scaled) of Responses To Employment
Tightness 2.00000 other 1.00000
Employment
E-manufacturing
Percentage
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
time
Plot (scaled) of Responses To E-manufacturing
Tightness 2.00000 other 1.00000
Employment
E-manufacturing
Percentage
1.25
1.00
0.75
0.50
0.25
0.00
1
8
15
22
29
time

Figure 5.14

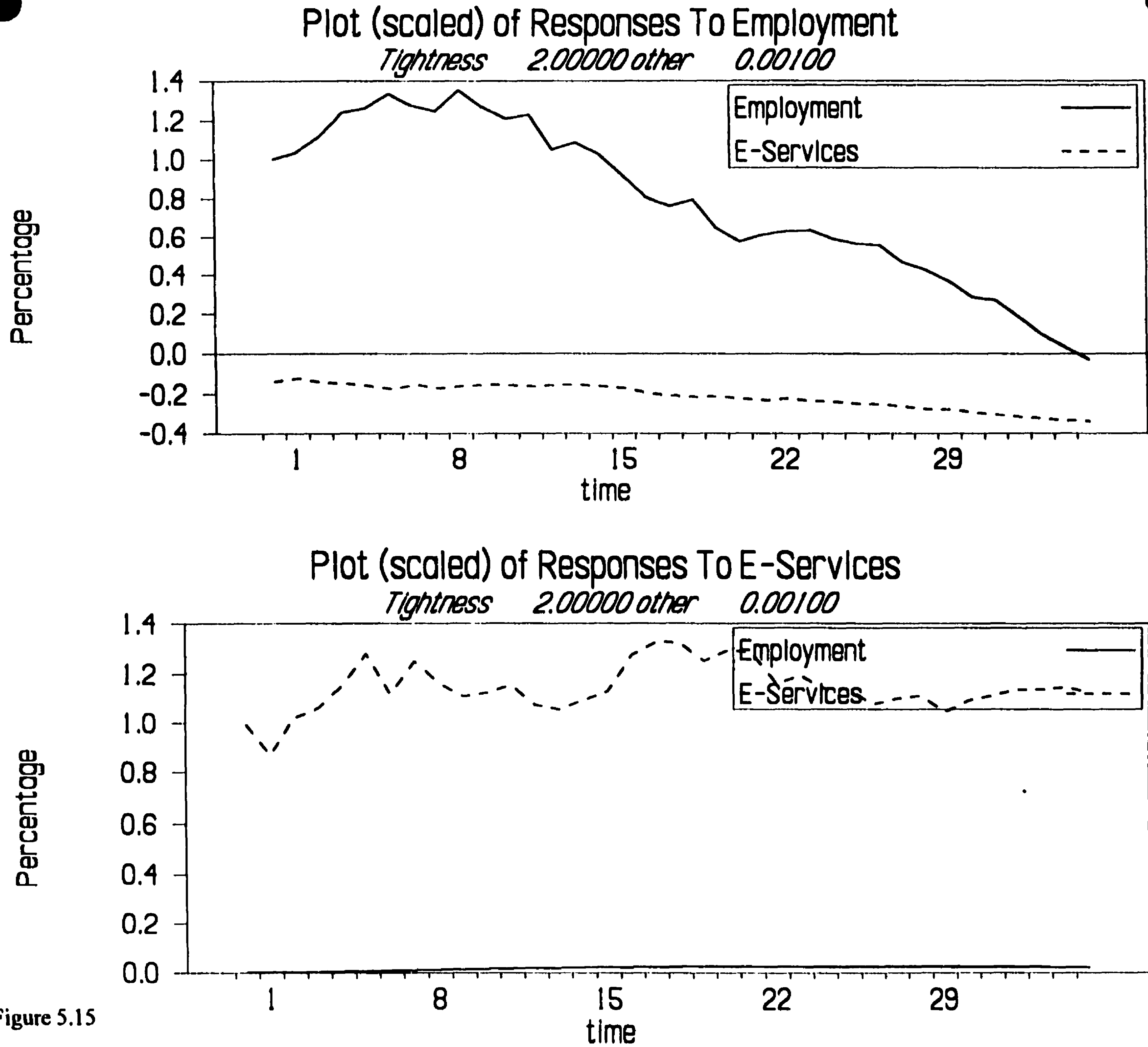
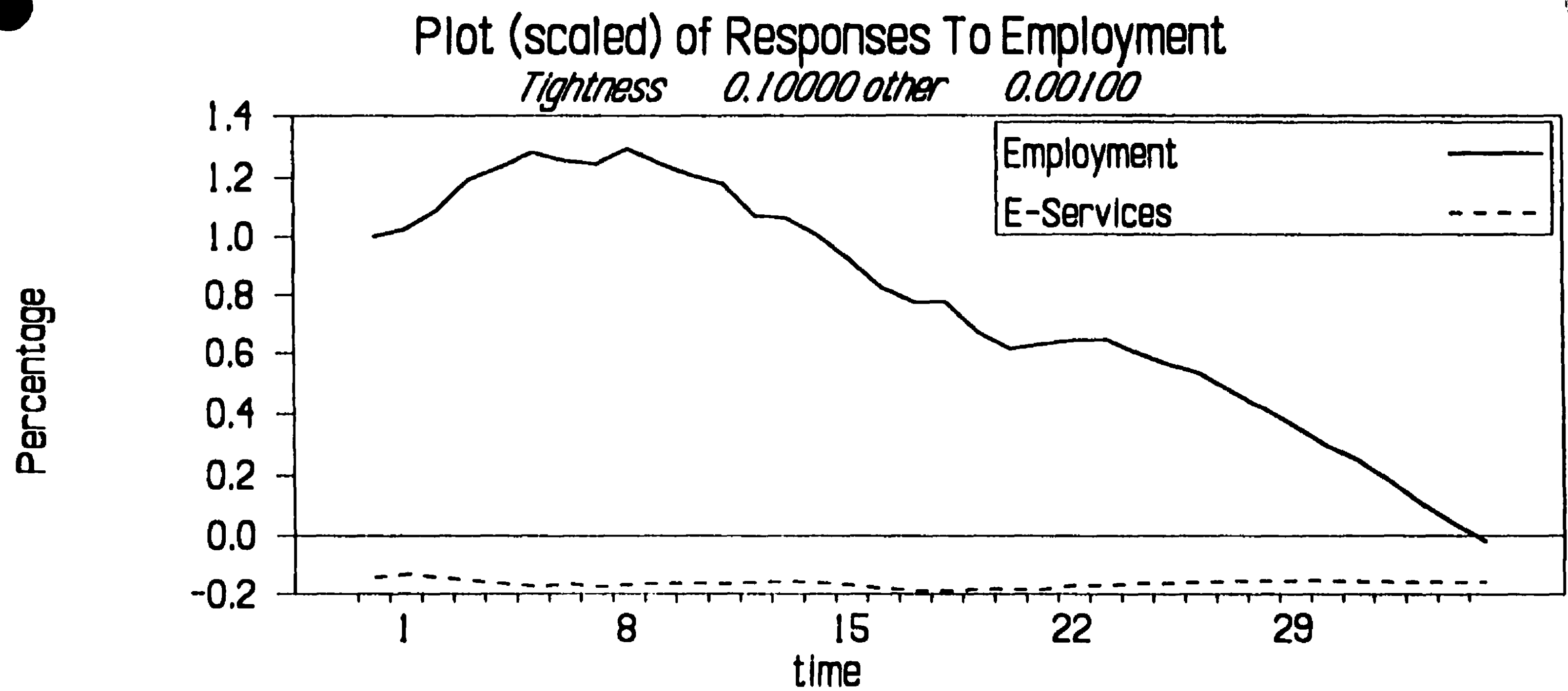
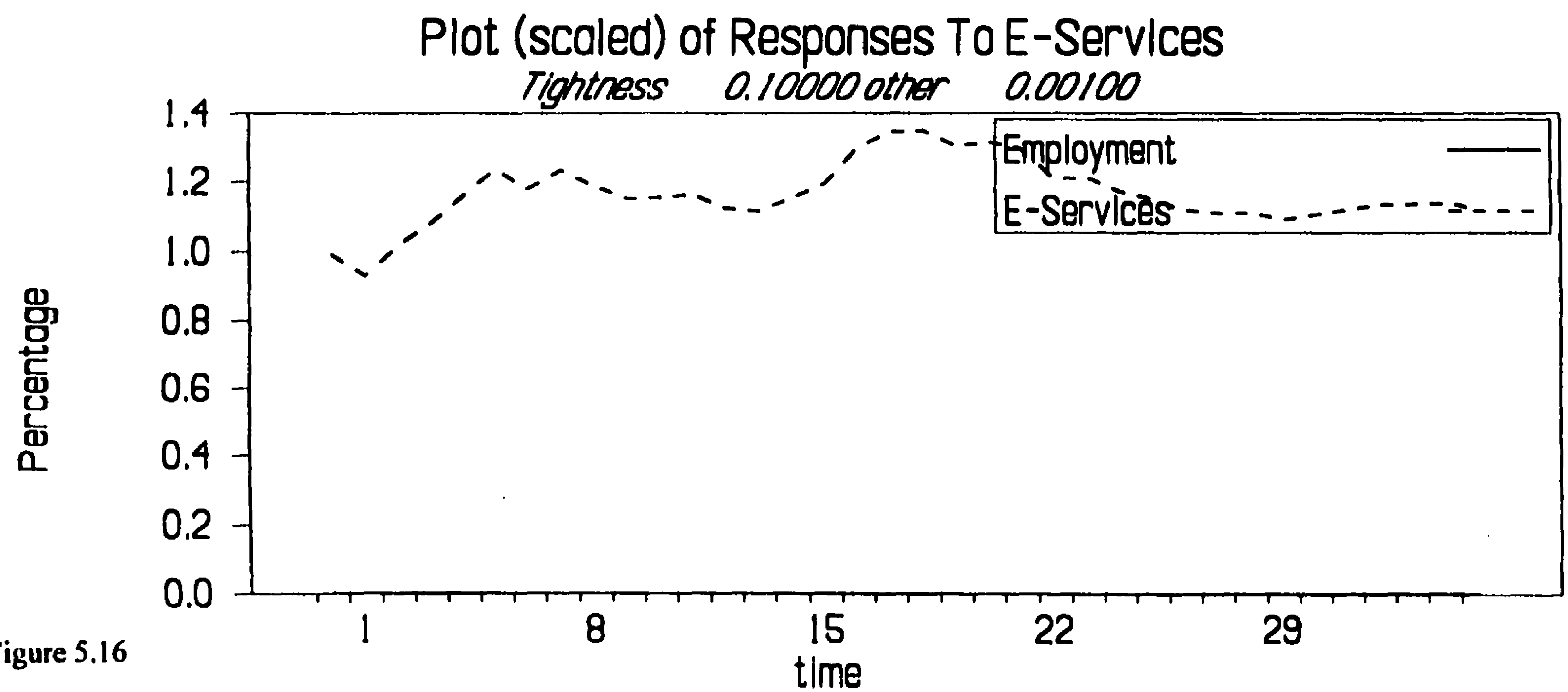


Figure 5.15

5.13

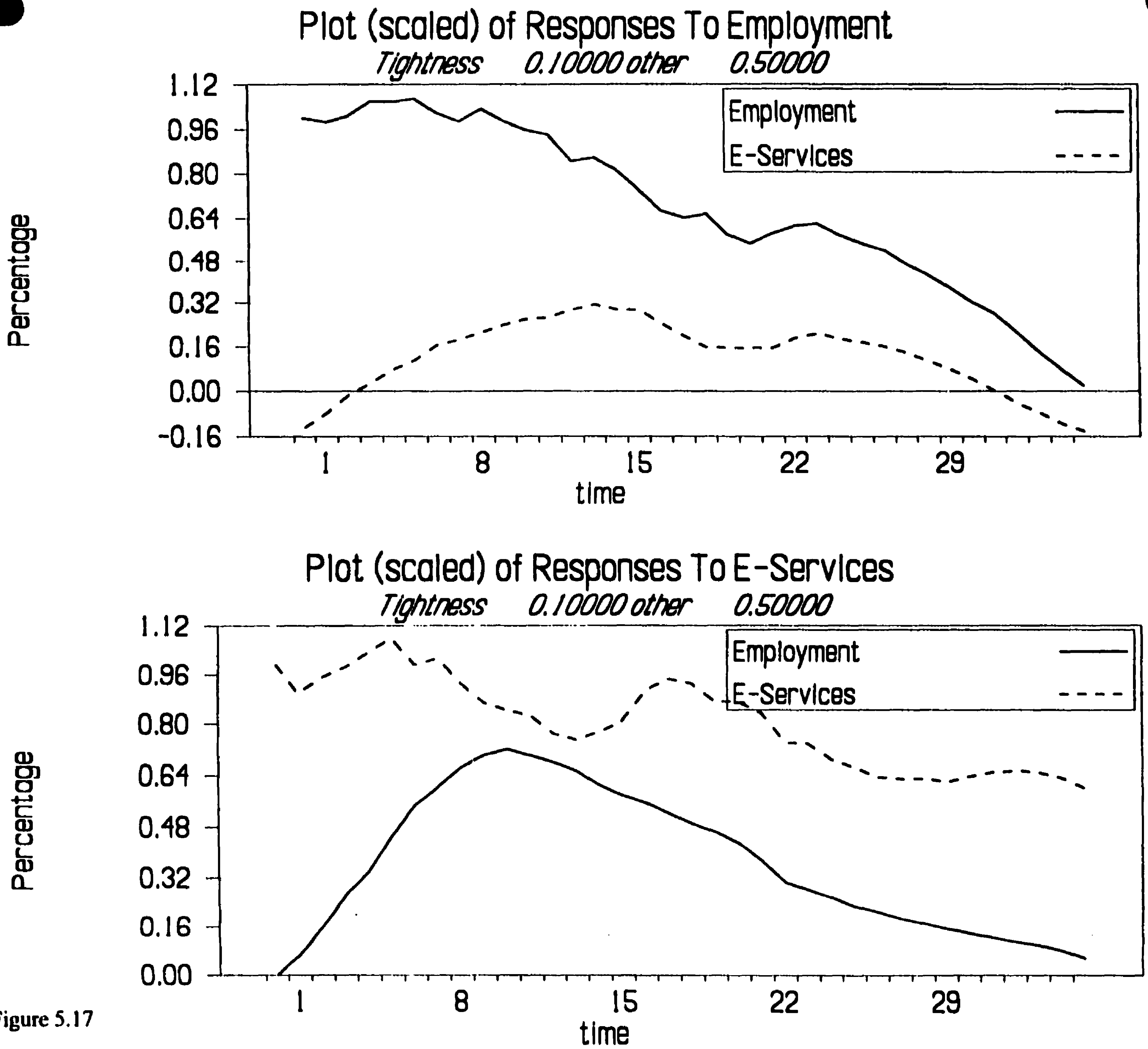


Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.00100
Employment
E-Services
Percentage
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
time



Plot (scaled) of Responses To E-Services
Tightness 0.10000 other 0.00100
Employment
E-Services
Percentage
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
8
15
22
29
time

Figure 5.16



Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.50000
Employment
E-Services
Percentage
time
1.12
0.96
0.80
0.64
0.48
0.32
0.16
0.00
-0.16
1
8
15
22
29
Plot (scaled) of Responses To E-Services
Tightness 0.10000 other 0.50000
Employment
E-Services
Percentage
time
1.12
0.96
0.80
0.64
0.48
0.32
0.16
0.00
1
8
15
22
29

Figure 5.17

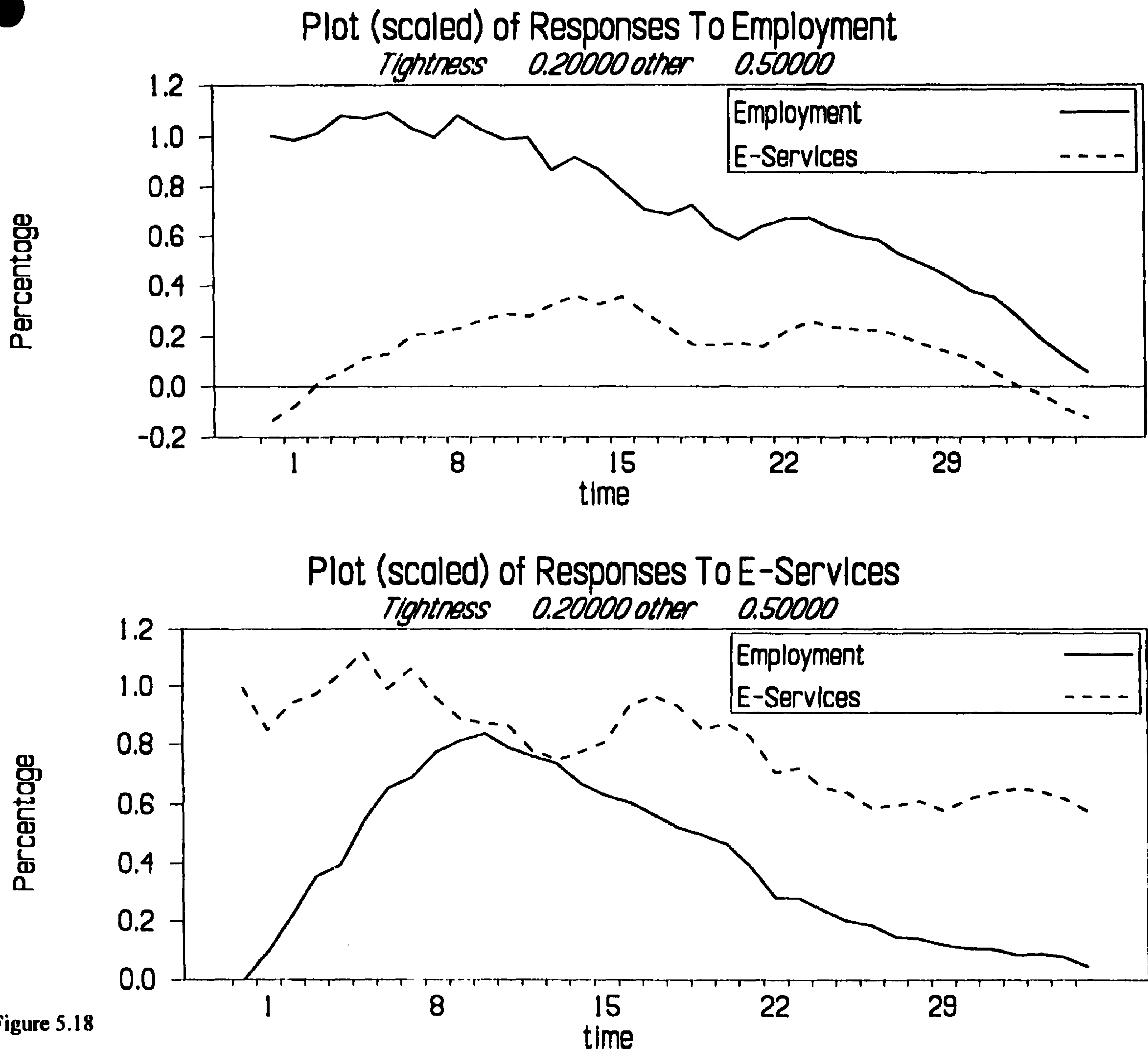
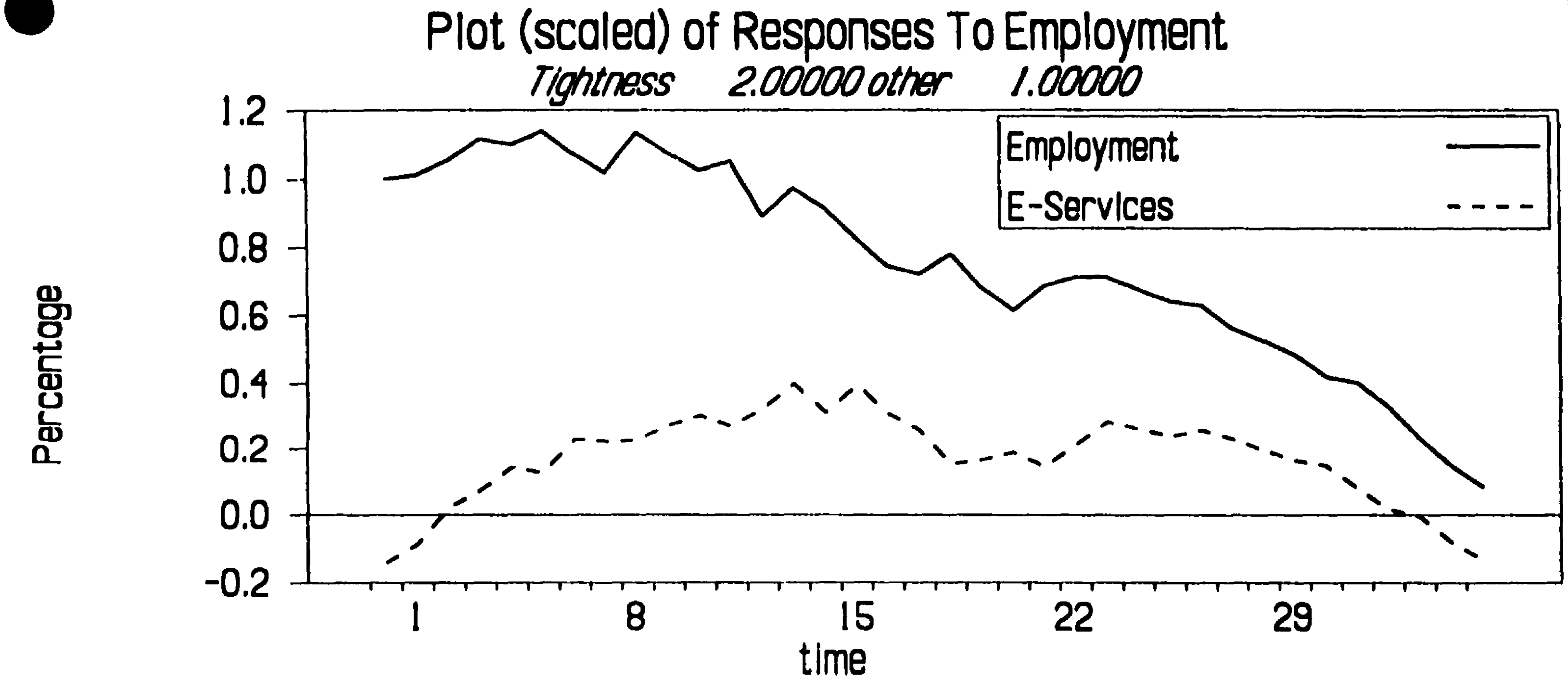

Plot (scaled) of Responses To Employment
Tightness 0.20000 other 0.50000
Employment
E-Services
Percentage
time
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
Plot (scaled) of Responses To E-Services
Tightness 0.20000 other 0.50000
Employment
E-Services
Percentage
time
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
8
15
22
29

Figure 5.18


Plot (scaled) of Responses To Employment
Tightness 2.00000 other 1.00000
Employment
E-Services
Percentage
time
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29

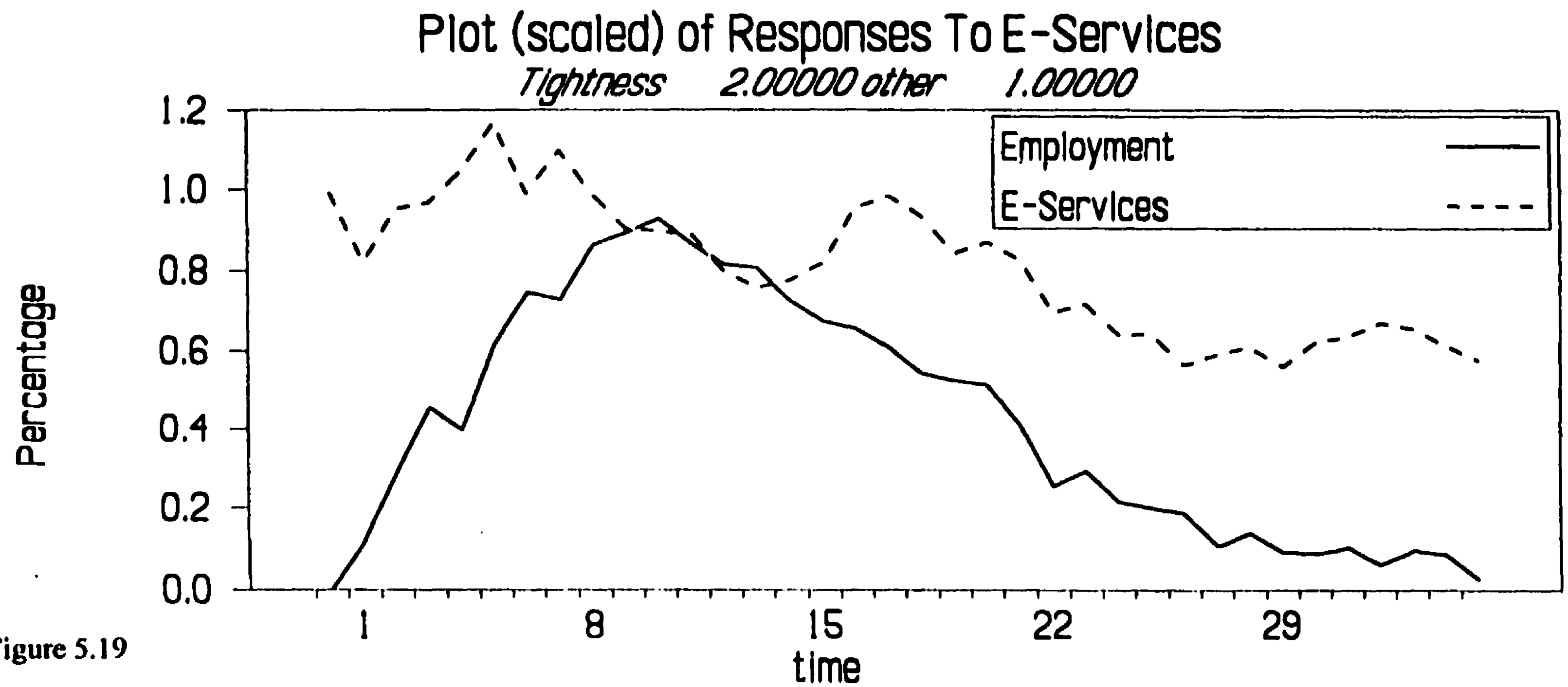

Plot (scaled) of Responses To E-Services
Tightness 2.00000 other 1.00000
Employment
E-Services
Percentage
time
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
8
15
22
29

Figure 5.19

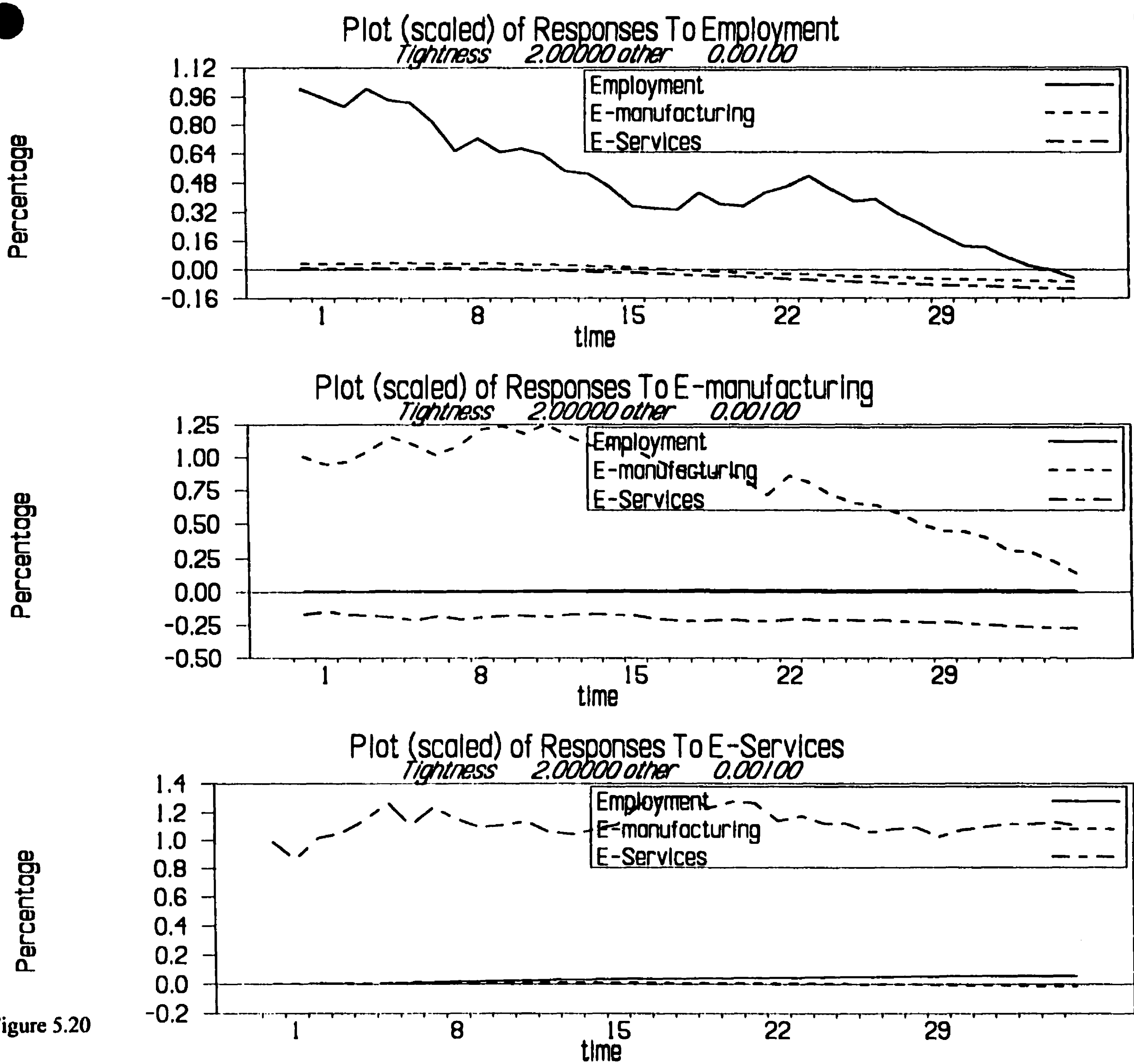
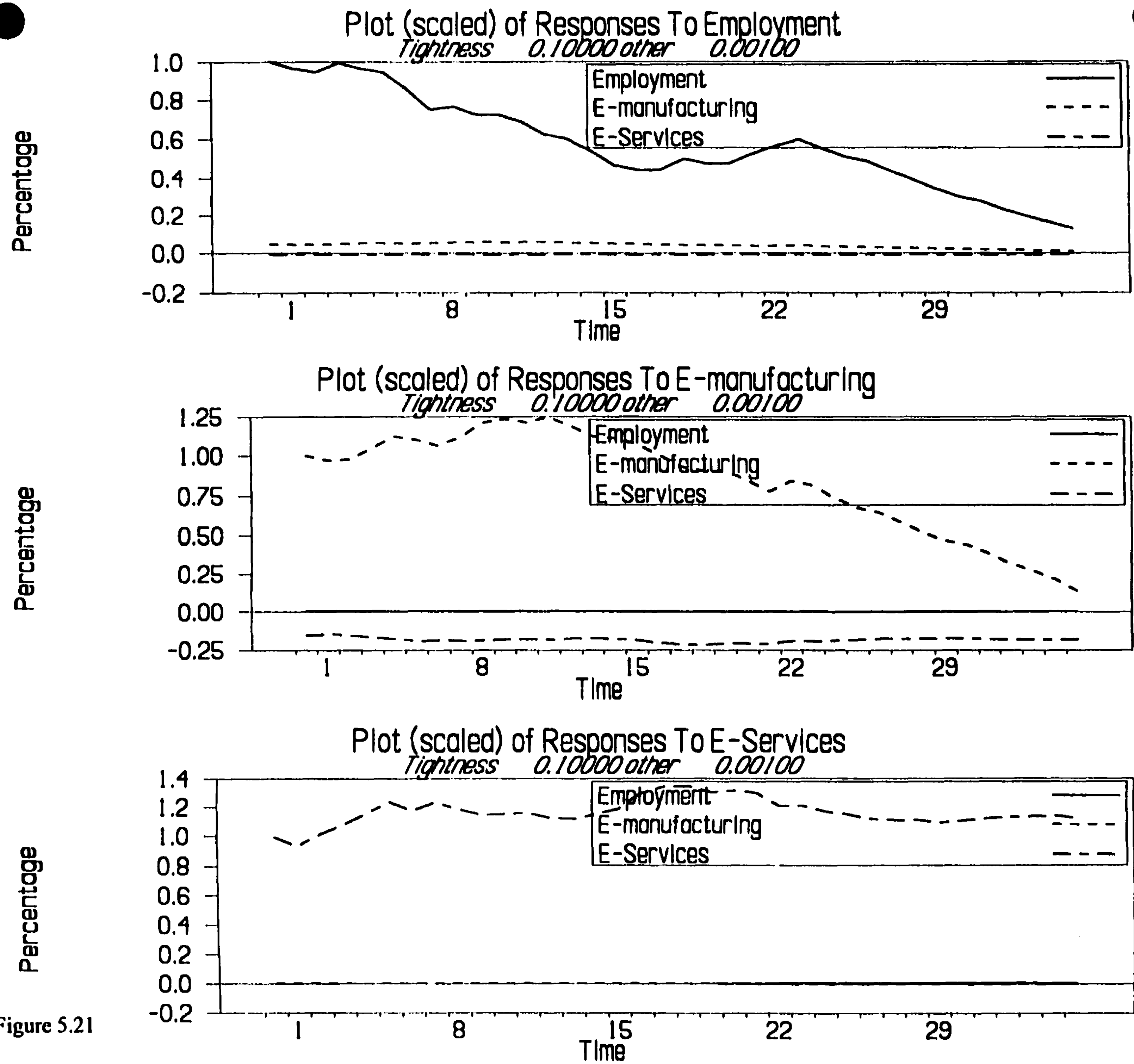
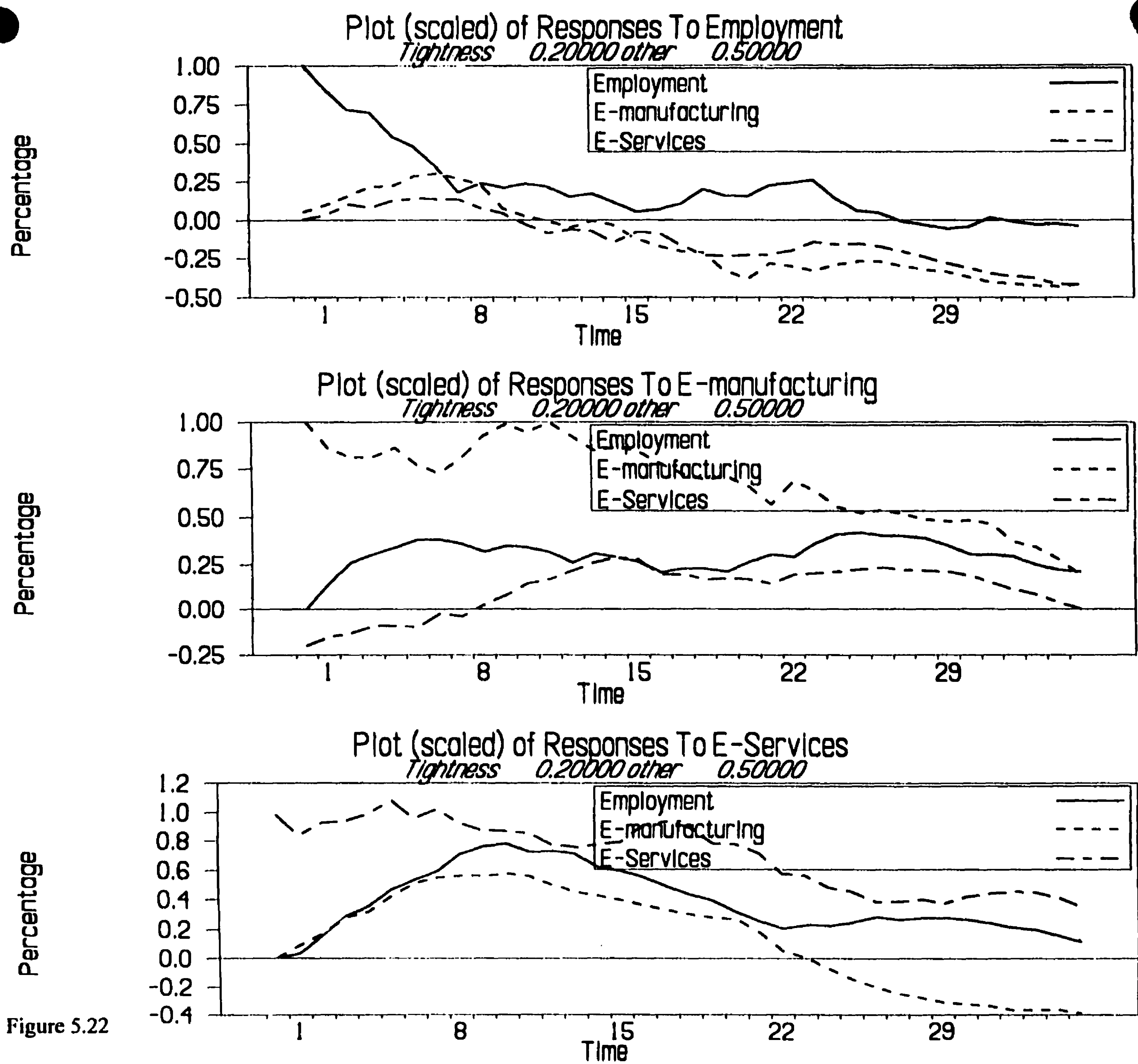

Plot (scaled) of Responses To Employment
Tightness 2.00000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
time
Plot (scaled) of Responses To E-manufacturing
Tightness 2.00000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
time
Plot (scaled) of Responses To E-Services
Tightness 2.00000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
time

Figure 5.20



Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
Time
Plot (scaled) of Responses To E-manufacturing
Tightness 0.10000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
1.25
1.00
0.75
0.50
0.25
0.00
-0.25
1
8
15
22
29
Time
Plot (scaled) of Responses To E-Services
Tightness 0.10000 other 0.00100
Employment
E-manufacturing
E-Services
Percentage
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
Time

Figure 5.21


Plot (scaled) of Responses To Employment
Tightness 0.20000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
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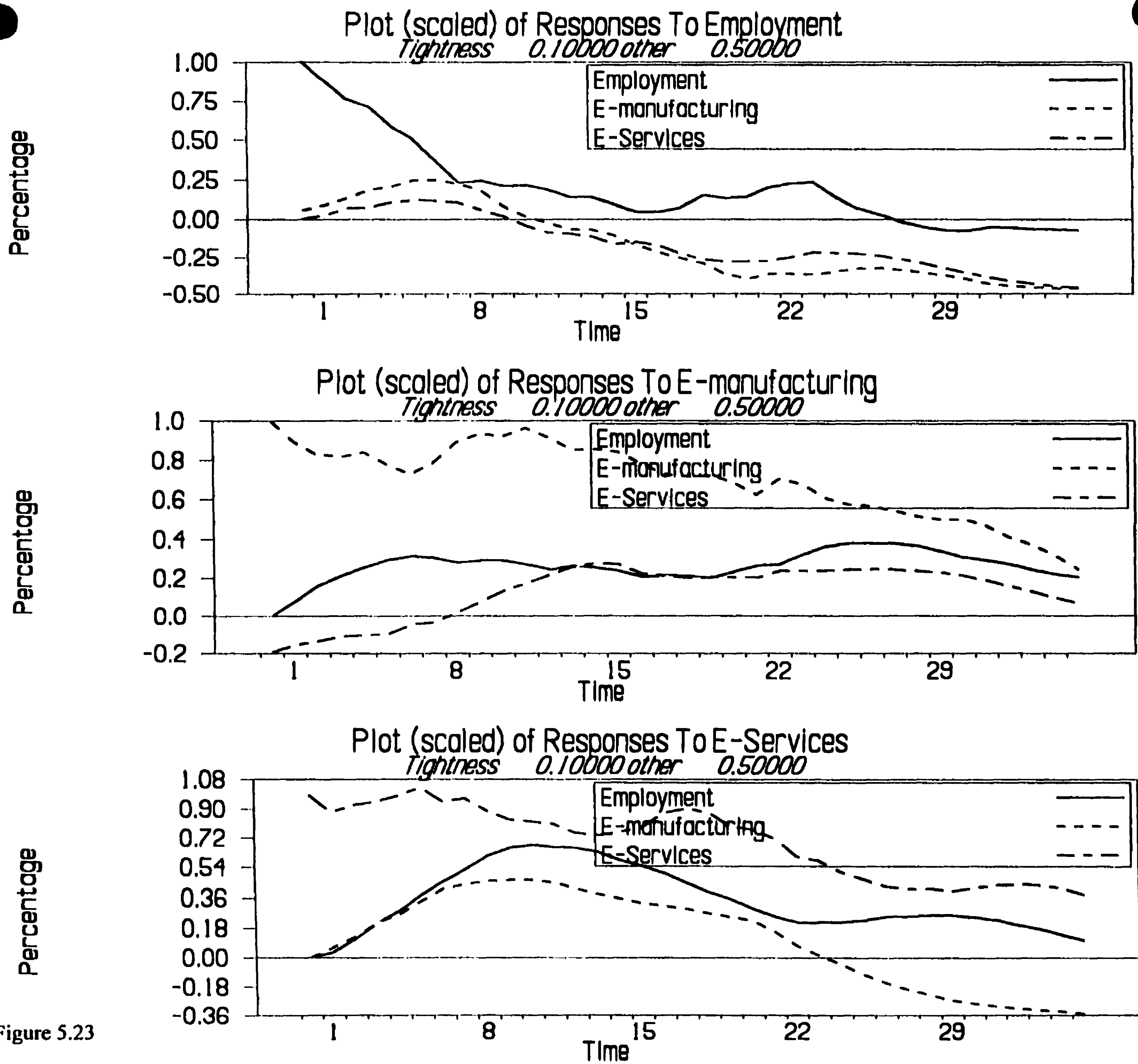
0.75
0.50
0.25
0.00
-0.25
-0.50
1
8
15
22
29
Time
Plot (scaled) of Responses To E-manufacturing
Tightness 0.20000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
1.00
0.75
0.50
0.25
0.00
-0.25
1
8
15
22
29
Time
Plot (scaled) of Responses To E-Services
Tightness 0.20000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
1
8
15
22
29
Time

Figure 5.22



Plot (scaled) of Responses To Employment
Tightness 0.10000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
1
8
15
22
29
Time
Plot (scaled) of Responses To E-manufacturing
Tightness 0.10000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
1
8
15
22
29
Time
Plot (scaled) of Responses To E-Services
Tightness 0.10000 other 0.50000
Employment
E-manufacturing
E-Services
Percentage
1.08
0.90
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0.36
0.18
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-0.18
-0.36
1
8
15
22
29
Time

Figure 5.23

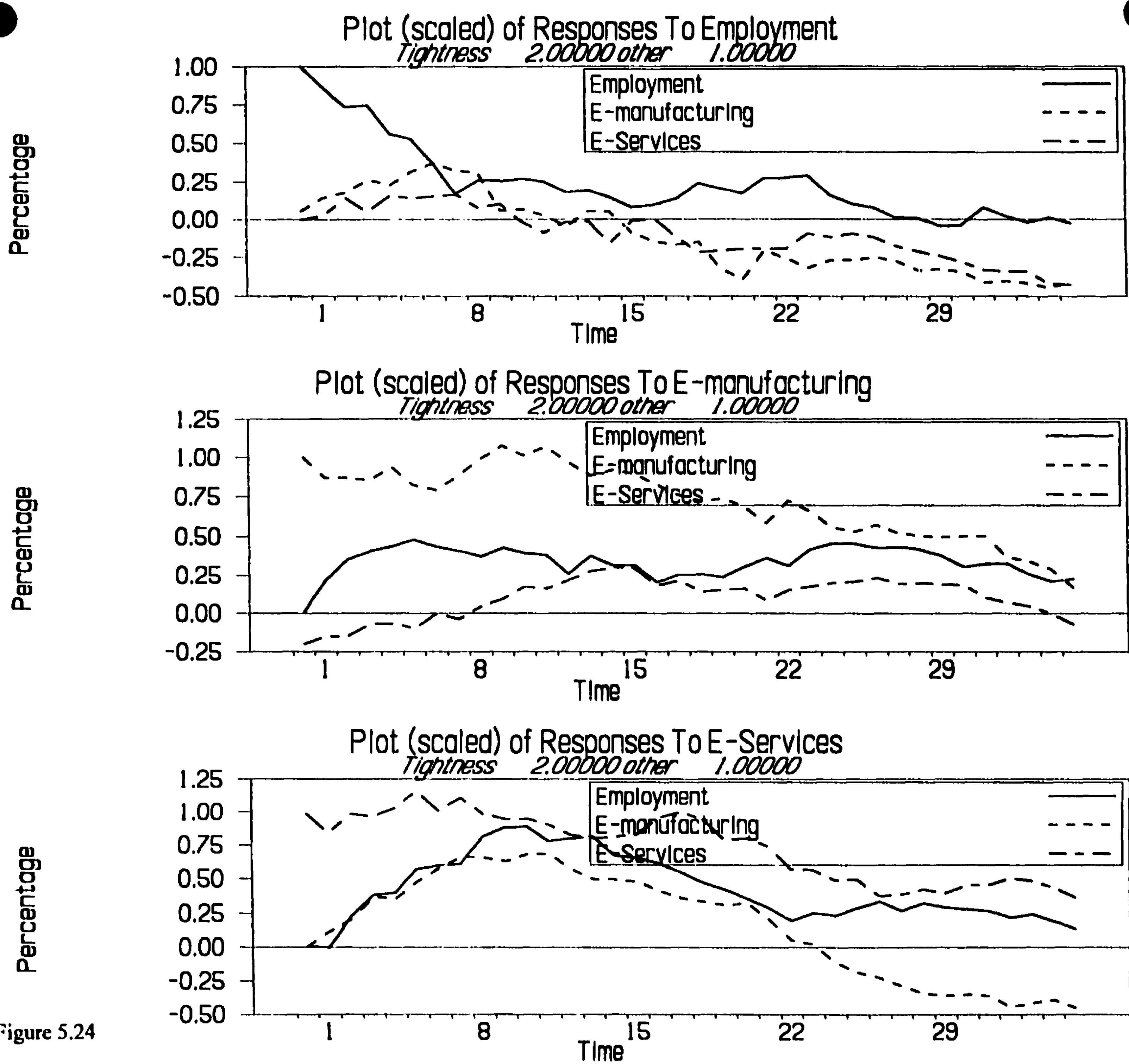

Plot (scaled) of Responses To Employment
Tightness 2.00000 other 1.00000
Employment
E-manufacturing
E-Services
Percentage
Time
Plot (scaled) of Responses To E-manufacturing
Tightness 2.00000 other 1.00000
Employment
E-manufacturing
E-Services
Percentage
Time
Plot (scaled) of Responses To E-Services
Tightness 2.00000 other 1.00000
Employment
E-manufacturing
E-Services
Percentage
Time

Figure 5.24

Chapter 6

The RBC Models

This chapter proposes two RBC models to investigate persistent unemployment. Both models incorporate sectoral labour mobility. Model I is driven by relative technology shocks, and model II is driven by representative agent relative taste shocks. This chapter presents and reports the results for both models.

6.1 Introduction

In the previous chapter, we studied the dynamic relationship that existed between total and sectoral employment. The emphasis was on the use of linear specification models. There is ongoing debate regarding the usefulness of linear versus non linear models. Our justification for using RBC models in this chapter is that linear models do not provide an accurate structural description of the dynamic relationship between total employment and reallocation shocks. Also, as a research strategy, we opt for stochastic dynamic general equilibrium (SDGE) models to deal with the Lucas and Sims critiques. These SDGE models provide intertemporal optimal paths for variables of interest that encompass the expectational behaviour of non-deep parameters.

In our view, linear and non-linear models should be regarded as complements instead of substitutes. RBC simulated employment series exhibit an inherent non-linearity. Prior to presenting the RBC models in this chapter, we test for nonlinear temporal dependence in total Canadian employment.

From a time series perspective, linear models neglect empirical testing for non-linearities. The non-linear Euler equations of a SDGE model are usually solved by finding a linear approximation around the steady state. Therefore, linear approximations are methodologically present in time series and in SDGE models. However, the propagation mechanism by which a shock impacts on the economy is generally absent in time series modelling and is, in most instances, specified to by an economic story that imposes identifying restrictions.

The literature on nonlinear dynamics has proposed a wide range of tests to detect, and models to investigate, nonlinearities in macroeconomic time series. Brock, Dechert and Scheinkman (BDS, 1987) derived and adopted a test for independence and identical distribution based on the correlation integral. The correlation integral was originally proposed by Grassberger and Procaccia (1984) as a U-statistic estimator to determine the fractal dimension of an attracting set. The U-statistic was first introduced by Hoeffdring (1948). He showed that this class of U-statistics could be approximated using a projection representation as the sum of i.i.d. random variables. U-statistics are generalizations of sample averages. Mizrach (1994) corrected for the failure of the BDS statistic in small samples and derived the simple nonparametric test (SNT) by changing the kernel used in the BDS statistic.

The SNT test was originally devised to discriminate between linear and non-linear time series models. If nonlinearities are present, models such as ARCH, GARCH, switching Markov, bilinear time series and others are used to capture the nonlinearities. Note that rejecting the null of i.i.d. on the residuals of fitted linear time series models does not imply that the alternative is only a non-linear time series model.[1] The rejection of the null simply implies that the linear specification is not accurate; no hints are given regarding its alternative. This thesis uses the SNT test to investigate nonlinearity in Canadian unemployment. If evidence of temporal nonlinearities is found in Canadian unemployment, using SDGE models is one option to pursue.[2] Given evidence of economic persistence, how could this persistence have been generated? To answer this, we propose the use of SDGE models.

6.2 U-Statistics and BDS statistic

This section briefly introduces the U- and the BDS statistics. For a detailed derivations, see Mizrach (1994) and Cromwell, Labys and Terraza (1994, pp. 32-36).

U-statistics are generalizations of sample averages. The components of a U-statistic include a kernel, a symmetric measurable function $h : R^m \to R$, and a permutation operator, $\sum_{n,m}$ that sums over the $\binom{n}{m}$ distinct combinations of m-elements in a sample space of size n. Let $\{x_i\}$ be a strictly stationary stochastic process with a distribution function F, and let $\{X_1, ..., X_n\}$ be a sample of size n. Define the canonical mapping,

$$U_n = U(X_1, ..., X_n) \equiv \binom{n}{m}^{-1} \sum_{n,m} h(X_1, ..., X_n) \tag{6.1}$$

Two examples follow to show how this U statistic relates to the sample moments. If

[1] This point is similar in essence to that of Poirier (1997).

[2] It may be argued that non-linear time series models can produce a better *fit* and indeed they might. However, our concern is not with the 'fit' of the data.

$m \equiv 1$, $h(x_i) \equiv x_i$, $\binom{n}{1}^{-1} = \frac{1}{n}$, then $U(X_1, ..., X_n) = \overline{X}$, i.e., the sample mean. If $m \equiv 2$, $h(x_i - x_j) \equiv \frac{(x_i - x_j)^2}{2}$, $\binom{n}{2}^{-1} = \frac{2}{n(n-1)}$, then $U(X_1, ..., X_n)$ equals the sample variance. Now, consider the vector valued version of (6.1). Let $x_t^m \in R^m$ be a random vector in R^m, and let $F(x_t^m)$ be its joint distribution. Define the kernel as, $h : R^m \times R^m \rightarrow R$,

$$h(x_t^m, x_s^m) = I[\| x_t^m - x_s^m \| < \varepsilon] \equiv I(x_t^m, x_s^m, \varepsilon) \tag{6.2}$$

where I is the indicator function, and $\| \, . \, \|$ denotes the max norm,

$$I(x_t^m, x_s^m, \varepsilon) = I[\max_i \prod_{i=0}^{m-1} |x_{t+j} - x_{s+j}| < \varepsilon] \tag{6.3}$$

The correlation integral is given by,

$$C(m, \varepsilon) = \int_X \int_X I(x_t^m, x_s^m, \varepsilon) dF(x_t^m) dF(x_s^m) \tag{6.4}$$

A consistent estimator of the correlation integral is given by,

$$C(m, N, \varepsilon) \equiv \frac{2}{N(N-1)} \sum_{t=1}^{N-1} \sum_{s=t+1}^{N} I(X_t^m, X_s^m, \varepsilon) \tag{6.5}$$

where $N = n - m + 1$. Note that $C(m, N, \varepsilon)$ is the expected number of m-vectors less than ε away from any given m-vector. In other words, $C(m, \varepsilon)$ measures the probability that any particular pair in the time series are 'ε-close'. The BDS test statistic is computed as,

$$\sqrt{N} \frac{C(m, N, \varepsilon) - C(1, N, \varepsilon)^m}{\sqrt{var(C(m, N, \varepsilon) - C(1, N, \varepsilon)^m)}} \rightarrow^d N(0, 1) \tag{6.6}$$

If the series is linear but exhibits autocorrelation, then the BDS will reject the null. Therefore in practice, the BDS is usually applied to the residual of a linear model.

6.3 The Simple Nonparametric Test (SNT)

The SNT has three advantages over the BDS. It involves simpler computation at the order of N rather than N^2. The variance of SNT is similar to that of a binomial random variable. And most importantly, the SNT is properly sized in small samples. At a sample size of 50 observations, the BDS rejects five times more frequently than it should under a conventional 5 percent test. This high rate of error of Type I led Mizrach (1991) to propose the SNT test,

By replacing the kernel in the BDS test statistic by $h : R \to R$,

$$h(x_t) = I[x_t < \varepsilon] = \left\{ \begin{array}{l} 1, \text{ if } x_t < \varepsilon \\ 0, \text{ otherwise} \end{array} \right\} \equiv I(x_t, \varepsilon) \tag{6.7}$$

Due to the choice of this kernel, the correlation integral (CI) at dimension m sums m-independent[3] events under the assumption of *i.i.d.*,

$$\theta(m, \varepsilon) = \int_{x \in X} \prod_{i=1}^{m} I(x_{t+i}, \varepsilon) dF(x_{t+i}) \tag{6.8}$$

A consistent estimator for the CI is,

$$\theta(m, N, \varepsilon) = \sum_{i=1}^{N} \prod_{i=0}^{m-1} I(x_{t+i}, \varepsilon)/N \tag{6.9}$$

The expected number of m-chains with a value of 1 in a sample of size N is,

$$\mu = N\theta(m, \varepsilon) = \sum_{x=0}^{N} x \binom{N}{x} \theta(m, \varepsilon)^x (1 - \theta(m, \varepsilon))^{N-x} \tag{6.10}$$

The variance is given by,

[3] To examine this 'spatial' correlation, the time series $x(t)$ must be embedded in m-space by constructing a vector. The choice of m for the dimensionality of the vectors is subjective. See Cromwell, Labys and Terraza (1994, p. 33) for details.

$$\sigma^2_{B_N} = \mu_2^{'} - \mu^2 = \sum_{x=0}^{N} x^2 \binom{N}{x} \theta(m,\varepsilon)^x (1-\theta(m,\varepsilon))^{N-x} - N^2\theta(m,\varepsilon)^2 \tag{6.11}$$

$$= N\theta(m,\varepsilon)(1-\theta(m,\varepsilon)) \tag{6.12}$$

Using both moments, Mizrach (1991) constructed the following statistic and showed that it has an asymptotic normal distribution,

$$SNT \equiv \sqrt{N}\frac{\theta(m,N,\varepsilon) - \theta(m-1,N,\varepsilon)\theta(1,N,\varepsilon)}{\theta(m-1,N,\varepsilon)\theta(1,N,\varepsilon)(1-\theta(m-1,N,\varepsilon))(1-\theta(1,N,\varepsilon))} \to^d N(0,1) \tag{6.13}$$

Mizrach (1994, pp. 381-382) studied the small sample properties of the SNT statistic and reported that it betters the BDS statistic in small samples.

To compute the SNT test, we use the log of the quarterly Canadian unemployment series. It covers the period from 1976:1 to 1999:4. Any linear dependency in the data should be removed and given that the autoregressive component captures it, we fit ARIMA$(p,1,0)$ models, where the choice of p is carried to minimize the Akaike criterion. We experimented with different values for p and concluded that $p = 4$ provides the minimum value for the Akaike statistic. Then, we added a dummy variable to offset the effect of the recessions in the data. Finally, we computed the residuals from the estimated linear ARMA$(4,1,0)$ that includes the dummy variable. The SNT test[4] is carried out on these residuals,

	SNT
$m=1$	-2.253
$m=2$	5.425
$m=3$	9.630

[4] We acknowledge the support of Bruce Mizrach in making the FORTRAN code available. We modified the code to compute the SNT directly. The estimation of the ARMA models were carried using E-Views. The SNT test was compiled on Linux 2.2.17-14.

We also investigated the robustness of these results with respect to the outliers in the series and reached a similar conclusion. Our conclusion also holds under alternative values for[5] m. To compare the results with those of Mizrach (1994), we focus on $m = 2$. Mizrach (1994, p. 384) reported evidence of non-linear temporal dependence in the French and Italian unemployment series. Here, the SNT rejects the null of i.i.d. for the Canadian unemployment.[6]

6.4 The RBC Models

The previous chapter documented employment persistence in Canadian data. We emphasized and reported evidence of the persistence effects of a sectoral shock to total employment. We present, simulate and report the results of two multi-sector RBC models. We report empirical regularities of sectoral Canadian multi-factor productivity data. The usefulness of this investigation is to be understood when calibrating the sectoral RBC models. Specifically, the transition probability matrix of the impulse to the models is inferred from the serial correlation of multi-factor productivity.

For simplicity, both models use a log-linear utility function that allows for a convex cost function $c(\Delta N_{1t}, \Delta N_{2t})$ to capture the costly movement of labour between sectors. Increasing labour in sector i is costly. Note that the $c(.,.)$ function can be viewed as capturing search unemployment (time invested in finding a job) or structural unemployment (training cost of switching between sectors). The log-linear utility implies an intertemporal elasticity of substitution of leisure equal to one. Given local

[5] Precisely, the conclusion is robust to and including $m = 5$.
[6] It may be argued that the SNT reflects dependence in the second moments from autoregressive conditional heteroscedasticity (ARCH). Here, we were satisfied as to the presence of non-linearity and decided to pursue the SDGE models.

nonsaturation and no externalities, competitive equilibria - which exists for this l_∞ commodity[7] space economy (Bewley (1972) theorems) - are Pareto Optima (using the competitive welfare theorems of Debreu (1954)). Given a single agent in this economy and convexity, there is a unique optimum to this maximization problem. This optimum is the unique competitive equilibrium allocation and supports the Pareto optimum. Therefore, one can solve for the social planner's problem using concave programming techniques.

Multi-sector RBC models have been proposed and studied in the literature. Long and Plosser (1983, 1987) presented a multi-sector model in which they traced the influence of a sector-specific shock on the aggregate fluctuations. Murphy, Shleifer and Vishny (1989) argued that labour immobility across sectors is of central importance in explaining cross-sectoral movement of outputs and labour inputs. Other models were proposed and we discussed them in Chapter 3, such as: Cooper and Haltiwanger (1990), Basu and Fernald (1997), Horvath (1997) and Swanson (1999b). Recently, Boldrin, Christiano and Fisher (2000) outlined that habit persistence and limited labour mobility are necessary to generate output persistence.

Weinberg (1999) studied the effects of long term changes in labour demand on wages using cross-industry variations in demand growth. The focus was on the responses of wages to low frequency shocks, defined as over five or ten year periods and

[7] The space l_∞consists of all sequences $x = (x_1, x_2, ...)$, $x_n \in R$, that are bounded in the norm $\| x \|_\infty = \sup_i | x_i |$.

This space is very important for the two welfare theorems. The space l_∞ ensures that assumptions 15.3 and 15.5 (Stokey and Lucas [with Prescott] (1989, p. 455)) hold for the preferences and technologies of interest. For infinite horizon stochastic optimal growth models, any space of the l_p spaces other than l_∞ causes serious difficulties. Stokey and Lucas (1989) defined this space (pp. 447-449), emphasized its role in the two welfare theorems (pp. 458-460), and explained its extension to stochastic growth models (p. 462).

labelled as persistent shocks. Weinberg (1999, p. 2) argued that the persistence of industrial shifts could be generated by changes in product demand, international trade patterns and technology changes. This study reported evidence of slow employment adjustment process (1999, p. 23). In this chapter, we argue that persistent aggregate unemployment is a result of sectoral phenomena - such as relative technology shocks or relative product demand shocks - and emerges due to adjustment costs to labour mobility across sectors. We integrate a two sector framework into a stochastic general dynamic equilibrium model to assess the validity of Lilien's hypothesis. We propose the following two RBC models.

Since our VAR result suggest that manufacturing reallocation shocks are influential in terms of total employment persistence, we focus our RBC models on the empirical regularities of models C-I and B-I in Chapter 5.

6.4.1 MODEL I (Sectoral Technology Shocks)

Many manufacturing processes can be characterized by fixed, or almost fixed, proportions.[8] Therefore, we assume the following: a) the representative firm's production function exhibits perfect complementarity in the labour input across sectors and constant returns to scale between labour and capital, b) the representative agent incurs a cost in terms of leisure to move labour across sectors, c) the sector-specific shock to the labour input in sector i is inversely symmetric to the one in sector j, and d) the cost function is quadratic. The first assumption reflects the high degree of labour specialization in each sector. This assumption justifies the existence of a cost to move

[8] See Ferguson (1969, p. 177).

between sectors (the second assumption). Assumption c) is necessary for the shocks to be 'pure' allocation shocks.

Assumptions c) and d) are to induce symmetry in the way labour adjusts across the sectors from the low productivity to the high productivity sector. Specifically, assumption c) reflects the following idea. Under our assumptions, a sector specific technology shock will not shift the aggregate production function. Since there are only two sectors, a relative shock to sector 1 implies a shock in reverse direction - and equal in magnitude - in sector 2. Therefore, labour demand increases in sector 1, and decreases in sector 2. This setup ensures that the aggregate production function is stable and any employment variation in the model is to be considered as structural, not aggregative. This symmetry is useful for investigating 'pure' sectoral' shock effects. These technology shocks shift the sectoral labour demands and leave the aggregate production function intact. Relative to sector 2, a shock to sector 1 increases the labour demand in sector 1 and decreases it in sector 2. Without symmetry, one can note isolate the effects of a sectoral shock from those of a general productivity shock, since all shocks would entail a mixture of both.

Representative agents' preferences are presented by a utility function which is time separable and state independent. We study the dynamics of a two-sector model in industries which are characterized by strong complementarities in the production process and a highly specialized labour input. The model is as follows.

$$\max_{(C_t, K_{t+1}, N_{1t}, N_{2t})_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \left[\beta^t \left(\ln C_t + \gamma \ln(T - N_{1t} - N_{2t} - c(\Delta N_{1t}, \Delta N_{2t}))\right)\right] \quad (6.14)$$

subject to

$$\begin{aligned}
Y_t &= AK_t^{\alpha}\left[\min(\theta_1 N_{1t}, \theta_2 N_{2t})\right]^{1-\alpha} && (6.15)\\
I_t &= K_{t+1} - (1-\delta)K_t && (6.16)\\
c(\Delta N_{1t}, \Delta N_{2t}) &= d\cdot(f(N_{1t} - N_{1t-1}))^2 + d\cdot(f(N_{2t} - N_{2t-1}))^2 && (6.17)\\
C_t + I_t &\leq Y_t && (6.18)\\
N_{1t} + N_{2t} + c(\Delta N_{1t}, \Delta N_{2t}) &\leq T && (6.19)\\
N_{1t} &\geq 0 \qquad N_{2t} \geq 0 && (6.20)
\end{aligned}$$

where $f(z) \equiv \max(z, 0)$ and $c(\Delta N_{1t}, \Delta N_{2t})$ denotes the cost function to move labour between sectors 1 and 2. So there is a cost only if there is an increase in employment. d denotes a cost parameter. T is the total time endowment of the agents. A is the aggregate shock (here constant). θ_i denotes the sector specific shock. The representative firm chooses the minimum level of employment. If employment increases in sector 1, it decreases in sector 2. Moving employment to sector 1 from sector 2 will impose a cost on the representative agent in terms of lost leisure. The shock θ_1 follows a Markov process[9] which is governed by the following transition probability matrix

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{21} \\ \lambda_{12} & \lambda_{22} \end{pmatrix} \qquad (6.21)$$

where $\lambda_{ij} = \Pr(z_t = j | z_{t-1} = i)$. The Bellman equation solved, subject to the above

[9] For the theoretical derivations and implications of Markov processes, see Norris (1997).

constraints by the social planner in this setup is

$$v(N_{1t-1}, N_{2t-1}, K_t, z_t) = \max_{(N_{1t}, N_{2t}, K_{t+1})} \quad [\ln C_t + \gamma \ln(T - N_{1t} - N_{2t}$$
$$-d \cdot (f(N_{1t} - N_{1t-1}))^2 - d \cdot (f(N_{2t} - N_{2t-1}))^2)$$
$$+\beta E_t v(N_{1t}, N_{2t}, K_{t+1}, z_{t+1})] \tag{6.22}$$

where z denotes the state of the economy (θ_1, θ_2). Given the symmetry of the problem imposed by the 'min' function between sector 1 and sector 2 technologies, we define the sector specific shock as $\theta_1 \equiv \frac{1}{\theta_2}$. Let $\theta \equiv \theta_1$. Under the symmetry condition, the Bellman equation for being in state 1 can be rewritten as,

$$v(N_{1t-1}, N_{2t-1}, K_t, 1) = \max_{(N_{1t}, N_{2t}, K_{t+1})} \quad [\ln C_t + \gamma \ln(T - N_{1t} - N_{2t}$$
$$-d \cdot (f(N_{1t} - N_{1t-1}))^2 - d \cdot (f(N_{2t} - N_{2t-1}))^2)$$
$$+\beta(\lambda_{11} v(N_{1t}, N_{2t}, K_{t+1}, 1) +$$
$$\lambda_{12} v(N_{1t}, N_{2t}, K_{t+1}, 2))] \tag{6.23}$$

We also impose a symmetry condition on the transition matrix Λ. The transition probability to move from state 1 to state 2 (λ_{12}) equals the transition probability to move from state 2 to state 1 (λ_{21}). In this setup as in others, the disequilibrium wage differentials that will exist between the workers across sectors are eliminated when the labour input is perfectly mobile and the cost function $c(\Delta N_{1t}, \Delta N_{2t})$ equals zero. Without adjustment costs, the first order conditions are,

$$N_t \; : \; \frac{(1-\alpha) A K_t^{\alpha} \theta^{1-\alpha} N_t^{-\alpha}}{C_t} - \frac{\gamma(1+\theta^2)}{\left(1 - \left(1+\theta^2\right) N_t\right)} = 0 \tag{6.24}$$

$$K_t \; : \; \frac{-1}{C_t} + \beta \frac{\alpha A K_{t+1}^{\alpha-1} (\theta N_t)^{1-\alpha} + 1 - \delta}{C_{t+1}} = 0 \tag{6.25}$$

In the steady state, the theoretical model has a stationary solution wherein the variables are constant. Solving for the steady state values for N_t and K_t respectively, one obtains,

$$N_{ss} = \left(\frac{\gamma(1+\theta^2)\left[A\theta^{1-\alpha} - \delta\left(\frac{\alpha A\theta^{1-\alpha}}{\rho+\delta}\right)\right]}{(1-\alpha)A\theta^{1-\alpha}} + (1+\theta^2) \right)^{-1} \tag{6.26}$$

$$K_{ss} = \left(\frac{\alpha A\theta^{1-\alpha}}{\rho+\delta}\right)^{\frac{1}{1-\alpha}} \cdot N_{ss} \tag{6.27}$$

Following a shock, employment is falling in sector 1 and rising in sector 2. It is possible that employment does not fall to the point of fixed proportion[10] in sector 1. In the current period, instead of firing all unproductive employment, keeping a part of this employment reduces the adjustment costs in the next period. Note that this employment produces no output. This situation reflects the possibility of labour hoarding. With adjustment costs, the derivative of the utility function with respect to sector 1 employment is,

$$\frac{\partial U_t}{\partial N_{1t}} = \frac{-\gamma}{L_t} + \beta\left[\lambda_{11}\frac{\gamma}{L_{t+1_{|s=1}}}d\Delta N_{1_{|s=1}} + \lambda_{12}\frac{\gamma}{L_{t+1_{|s=2}}}d\Delta N_{1_{|s=2}}\right] \geq 0 \tag{6.28}$$

$$\lambda_{11}\frac{\Delta N_{1_{|s=1}}}{L_{t+1_{|s=1}}} + \lambda_{12}\frac{\Delta N_{1_{|s=2}}}{L_{t+1_{|s=2}}} \geq \frac{1}{dL_t\beta} \tag{6.29}$$

$$\lambda_{11}\frac{N_{1t} - N_{1t-1}}{L_{t+1_{|s=1}}} + \lambda_{12}\frac{\theta^2\left(N_{1t} - N_{1t-1}\right)}{L_{t+1_{|s=2}}} \geq \frac{1}{dL_t\beta} \tag{6.30}$$

where L_t denotes leisure in period t. The last inequality is derived using Table 6.A. The first term on the right hand side of the first equation is the present cost of increasing labour in sector 1 in terms of lost leisure. This cost is a function of the weight of leisure in the utility function. The second term is the discounted value of the expected future marginal utility benefit arising as a consequence of increasing

[10]Due to the minimum function.

labour in sector 1 in the current period. Note that this depends on the state of the shock in the next period. In the case of an interior solution, a positive marginal benefit implies that firms in sector 1 are inclined to hoard labour. Hoarding labour in the current period reduces the adjustment costs in the next period. Equation (6.30) gives the marginal benefit from increasing employment in sector 1 above the level of fixed proportions. At the optimal solution, we verified that the effect of an increase in N_{1t} is negative, so that workers are always employed in fixed proportions between the two sectors.

The reason for maximizing over sector 1 labour and capital is as follows. Given the perfect complementarity between sector 1 and sector 2 labour, there will always exist a fixed proportion between them. Therefore, maximizing over the grid of sector 1 labour and then computing sector 2 labour from this value is similar to maximizing over both values of sector 1 and sector 2 labour.[11]

6.4.2 MODEL II (Sectoral Taste Shocks)

We assume the following: a) the representative firm's production technology is identical for both sectors, b) the representative agent incurs a cost in terms of leisure to move labour across sectors, c) the sector-specific tastes shocks to consumption are inversely symmetric, and d) the cost function is quadratic. In brief, we adopt the same assumptions as for model I except that there is no capital in this economy. We explicitly model the two goods' markets and study the dynamics of the economy subjected to tastes shocks.

[11]See section 6.9 for details.

The model used is as follows,

$$\max_{(C_{1t},C_{2t},N_{1t},N_{2t})_{t=0}^{\infty}} E\sum_{t=0}^{\infty}\left[\beta^t\left(\theta_1 \ln C_{1t} + \theta_2 \ln C_{2t} + \gamma \ln(T - N_{1t} - N_{2t} - c(\Delta N_{1t}, \Delta N_{2t}))\right)\right] \tag{6.31}$$

subject to

$$C_{1t} = A_1 N_{1t}^{1-\alpha} \tag{6.32}$$

$$C_{2t} = A_2 N_{2t}^{1-\alpha} \tag{6.33}$$

$$c(\Delta N_{1t}, \Delta N_{2t}) = d\cdot(f(N_{1t} - N_{1t-1}))^2 + d\cdot(f(N_{2t} - N_{2t-1}))^2 \tag{6.34}$$

$$N_{1t} + N_{2t} + c(\Delta N_{1t}, \Delta N_{2t}) \leq T \tag{6.35}$$

$$N_{1t} \geq 0 \qquad N_{2t} \geq 0 \tag{6.36}$$

where $f(z) \equiv \max(z, 0)$ and $c(\Delta N_{1t}, \Delta N_{2t})$ denotes the cost function to move labour between sectors 1 and 2. So there is a cost only if there is an increase in employment. d denotes a cost parameter. T is the total time endowment of the agents. A is a constant. We assume that $A = A_1 = A_2$. θ_i denotes the sector specific tastes shock. The shock θ_1 follows a Markov process which is governed by the following transition probability matrix,

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{21} \\ \lambda_{12} & \lambda_{22} \end{pmatrix} \tag{6.37}$$

where $\lambda_{ij} = \Pr(z_t = j | z_{t-1} = i)$. We also impose a symmetry condition on the transition matrix Λ. The transition probability to move from state 1 to state 2 (λ_{12}) equals the transition probability to move from state 2 to state 1 (λ_{21}). The Bellman equation solved by the social planner in this setup is,

$$\begin{aligned} v(N_{1t-1}, N_{2t-1}, z_t) = \max_{(N_{1t}, N_{2t})} \quad & [\theta_1 \ln C_{1t} + \theta_2 \ln C_{2t} + \gamma \ln(T - N_{1t} - N_{2t} \\ & -d \cdot (f(N_{1t} - N_{1t-1}))^2 - d \cdot (f(N_{2t} - N_{2t-1}))^2) \\ & +\beta E_t v(N_{1t}, N_{2t}, z_{t+1})] \end{aligned} \tag{6.38}$$

where z denotes the state of the economy (θ_1, θ_2). Given the symmetry of the problem imposed by assumption (c) one can define the sector specific shock as $\theta_1 \equiv \frac{1}{\theta_2}$. Let $\theta \equiv \theta_1$. Under the symmetry condition, the Bellman equation for being in state 1 and in state 2 can be rewritten as

$$\begin{aligned} v(N_{1t-1}, N_{2t-1}, 1) = \max_{(N_{1t}, N_{2t})} \quad & [\theta \ln C_{1t} + \theta^{-1} \ln C_{2t} \\ & +\gamma \ln(T - N_{1t} - N_{2t} \\ & -d \cdot (f(N_{1t} - N_{1t-1}))^2 - d \cdot (f(N_{2t} - N_{2t-1}))^2) \\ & +\beta(\lambda_{11} v(N_{1t}, N_{2t}, 1) + \lambda_{12} v(N_t, N_{2t}, 2))] \end{aligned} \tag{6.39}$$

$$\begin{aligned} v(N_{1t-1}, N_{2t-1}, 2) = \max_{(N_{1t}, N_{2t})} \quad & [\theta^{-1} \ln C_{1t} + \theta \ln C_{2t} \\ & +\gamma \ln(T - N_{1t} - N_{2t} \\ & -d \cdot (f(N_{1t} - N_{1t-1}))^2 - d \cdot (f(N_{2t} - N_{2t-1}))^2) \\ & +\beta(\lambda_{21} v(N_{1t}, N_{2t}, 1) + \lambda_{22} v(N_t, N_{2t}, 2))] \end{aligned} \tag{6.40}$$

This model [model II] is similar to model I in terms of wage differentials whenever the cost function is zero and labour is perfectly mobile. Note that the computation of real output in model II is done by solving the inter-temporal representative maximization problem,

$$\max_{C_1,C_2} L = \theta \ln C_1 + \frac{1}{\theta} \ln C_2 + \lambda(M - C_1 - PC_2) \tag{6.41}$$

$$\frac{\partial L}{\partial C_1} = \frac{\theta}{C_1} - \lambda = 0 \tag{6.42}$$

$$\frac{\partial L}{\partial C_2} = \frac{1}{\theta C_2} - \lambda P = 0 \tag{6.43}$$

$$\frac{\theta}{C_1} = \lambda = \frac{1}{\theta P C_2} \tag{6.44}$$

$$P = \frac{C_1}{\theta^2 C_2} \tag{6.45}$$

where P is the price of good 2 relative to good 1 and M refers to income. Similarly, $\frac{1}{P}$ is the price of good 1 relative to good 2. Nominal output equals $C_1 + PC_2$, and real output is computed at a base year price, $C_1 + P_{(0)}C_2$.

6.5 The Models' Intuition

Allowing a two-sector framework is one way to capture missing dynamics and to counter the weak propagation mechanism in the general equilibrium models adapted to analyze business cycle fluctuations. Assuming that optimizing agents encounter no market failure and that productivity shocks are serially independent across sectors, a sector-specific shock will have its primary effect on the originating sector depending on how large or small the sector is relative to the economy. Such a setup will help quantify aggregate level fluctuations due to independent sectoral shocks. Therefore, policy making can address unemployment in a more appropriate sectoral manner instead of just focusing on the aggregate economy. The mechanism by which workers lose jobs in response to an adverse technology shock and the slow process of re-employment, is the propagation mechanism of the persistent periods of slack.

The single consumer is assumed to be representative[12] of the society as a whole. A change in the level of her utility reflects and is equivalent to a change in the overall level of social welfare. An increase (decrease) in her utility[13] implies an improvement (loss) in social welfare. Dinwiddy and Teal (1988, p. 104) noted that "This convention is commonly used by economists wishing to abstract from questions of distribution in order to concentrate upon problems dealing with the allocation of resources." With only a representative consumer, questions regarding the distribution of wealth do not arise. If there are two or more consumers, with differing factor endowments and/or utility functions, then economic change will clearly have different consequences for each. For simplicity, assume the case of two consumers. If both gain or both lose, the calculation of welfare change is unambiguous. However, should one gain and the other lose, computing the value of welfare change is difficult without some explicit value judgments (e.g., the Nash equilibrium, the Bergson-Samuelson welfare function).

The aggregate production function exhibits constant returns to scale in model I. This assumption reflects the empirical assessment of the Canadian production structure reached in Paquet and Robidoux (1997). Once the Solow residuals were corrected for capacity utilization in the U.S. and Canada, Paquet and Robidoux (1997) concluded that - over the period from 1962Q1 to 1993Q4 and from 1970Q1 to 1993Q4 for the U.S. and Canada, respectively - the U.S. and Canadian market structures are well described by constant returns to scale. For model II, each sectoral production function is constant. If one adds a fixed and sector specific amount of capital, say $\overline{K}^{\alpha}$,

[12]For an excellent and comprehensive development of the representative agent in macroeconomics modeling, refer to Hartley (1997).

[13]The actual numerical value of utility is irrelevant. A change in the utility level provides a measure of the direction of welfare change.

to each production function, then each production function exhibits constant returns to scale.

Model I emphasizes sectoral *relative* technology shocks. The argument is based on the following. While technological change leads to job losses in certain industries - specifically, in the manufacturing sector - it does not imply that employment must fall at the aggregate level. Therefore, we adopted a relative technology shock to keep the aggregate level insulated from the shock. The only reason for unemployment here is the labour reallocation process, which is not instantaneous.

Critics against the use of technological change as a major cause of Canada's higher unemployment rate, argue that, with similar technological trends in the U.S.A. and Canada, it is unlikely that technological change can lead to high unemployment in Canada when it does not have that effect in the U.S. (see Sharpe (1999, p. 31)). We view this argument as flawed for the following reason. It is widely accepted that both countries face and enjoy similar technological trends; however, the Canadian economy suffers gaps across the spectrum of industries. Some industries are non-existent in the Canadian economy. These gaps impinge on workers, making labour movement across industries more difficult and time consuming. For example, the aerospace and manufacturing industries suffer from - and exhibit - these gaps. In this thesis, we argue that, faced with a similar technology shock, the Canadian economy will incur higher persistence in terms of output and unemployment. This persistence is due - in part - to the nature of existent institutional structures.[14]

For model I, the shock is symmetric. Due to the presence of the 'min' function in

[14]We also investigate the size of the relative technology shock in section 6.8.

the production function, at the steady state

$$\theta N_1 = \theta^{-1} N_2 \tag{6.46}$$

$$N_2 = \theta^2 N_1 \tag{6.47}$$

and total labour supply equals $N_1 + N_2 = (1+\theta^2)N_1$. In model II, total employment equals the sum of employment in both sectors.

For model I, the following table summarizes the change in sectoral employment as a function of the state of the economy.

Table 6.A

MODEL I	Change of employment in sector 1	Change of employment in sector 2
Previous state was low in sector 1 Present state is low in sector 1	$N_{1,t} - N_{1,t-1}$	$\theta^2(N_{1,t} - N_{1,t-1})$
Previous state was high in sector 1 Present state is high in sector 1	$N_{1,t} - \theta^2 N_{1,t-1}$	$\theta^2 N_{1,t} - N_{1,t-1}$

During recessions, matching workers to jobs is time-consuming and costly in terms of time lost. In the models, and following an adverse relative sectoral shock, jobs are destroyed in one sector and new ones are created in the other sector. Workers search and are willing to move to the sector with the high demand for labour. This search process increases non-cyclical unemployment. As time goes on, unsuccessful workers (in finding a job) suffer a loss of skills or find themselves with the wrong skills to move to the other sector. This process raises non-cyclical unemployment. Therefore, an adverse shock results in increasing the natural rate of unemployment and decreasing output. In this thesis, the aim is not to explain the search or the loss of skills processes. Through a sectoral shock, the focus is on explaining the increase in the natural rate of unemployment. In model I, the impulse is a relative technology shock, while in model II, the impulse is a relative taste shock that increases the product demand in one sector and reduces it in the other.

In a two-sector model without adjustment costs to labour mobility between sectors, there is no change in structural unemployment. Given the market clearing nature of RBC models augmented by the perfect mobility of labour assumption, a symmetric productivity shock reduces labour demand in one sector and simultaneously increases it in the other sector. To explain the sharp rise in unemployment during recessions, one is inclined to make use of adjustment costs to labour mobility. These costs impinge on labour mobility following an adverse productivity shock. If one is to interpret these costs as 'searching costs' or 'acquiring new skills costs', then the natural rate of unemployment will increase during recessions. Note that the former costs explain the increase in frictional unemployment, while the latter explains the increase in structural unemployment. The end-result is that an adverse sectoral supply shock (sectoral productivity shock) will increase unemployment and reduce output.

If one is able to quantify the magnitude of the increase in the natural rate of unemployment relative to the general level of unemployment from the model, then a clear policy response is in sight. At the aggregate level, the problem is the following. The unemployment rate increases sharply during recessions. Part of this increase is due to an increase in the natural rate[15] and part is due to cyclical unemployment. In this thesis, we suggest that a good explanation of the former is the reallocation

[15]In this thesis, changes in the natural rate includes any transitional changes in unemployment resulting from the reallocation of labour between sectors.

of labour. Therefore, a best policy response is to deal independently with each part of the unemployment increase. If most of the increase in unemployment is due to the cyclical component, then an aggregate demand policy could alleviate the burden. If the increase in unemployment is due to a fluctuation in the natural rate, then a supply policy such as eliminating (or reducing) barriers to labour market adjustment and costly regulations will reduce unemployment. Next, we study two important issues. The first relates to the size of the shock and the second advances the issue of calibrating the transition matrix Λ.

6.6 Size and Economic Fluctuations

This section explains our interest in simulating our RBC models with different shocks size. Bianchi and Zoega (1996) emphasized the size of the shock issue. They asked the question: "Does the size of the shock matter in explaining unemployment persistence?" Using statistical analysis based on switching regression models (Markovian regime shifts in the mean) and non-parametric density estimation techniques (as an exploratory tool to investigate the data) they identified and quantified the size of the shift in the unemployment series mean of 17 OECD countries. The annual data covered the period 1960-1993. They criticized the use of linear time series models in which the mean is constant (time invariant), as is the case with ARMA models. Therefore, they proposed a time series Markov switching regime type model, in which the unemployment mean is a function of the state of the economy. The model was labeled as 'the shifting mean value (SMV) model'. The methodology is as follows: First, test for time invariant parameters using stability tests on the recursive least squares. Next, use the nonparametric density estimation and the bootstrap multimodality tests to test for the number of the states in the density of the frequency distribution of unemployment rate series. Then, estimate the switching regression model to detect the timing of the shift points. Once the dates at which the shocks occurred were identified, they removed the changes in the mean and concluded that there was little evidence of unemployment persistence in most countries. They found that large annual changes in the unemployment mean (large shocks) are consistent with the hysteresis models of unemployment (see Chapter 4). Most of the persistence was accounted for by a few large shocks rather than by numerous small shocks. They suggested further investigation into the non-linearity properties of unemployment (a time variant mean of unemployment). For Canada, a shift was found in 1975. Note that in Canada, the unemployment insurance reform took place in 1972.

The point is that the size of the shock matters. On a technical issue, the size of each industry can be measured as the proportion of the industry output relative to the total economy-wide output. The size of each industry shock can be proxied by the mean of the industry Solow residuals (corrected for capital utilization) à la Burnside, Eichenbaum and Rebelo (1995). Once computed, the respective mean can be used to calibrate the size of the industry shock. However, in this thesis, the size of the shock is calibrated such that the models' steady state workweek hours match the one in the business cycle data. Over a range from small to large, values around the size of this shock are investigated. We use $\theta = \{1.1, 1.15, 1.2, 1.25, 1.3\}$, i.e., we investigate shocks with size of 10 percent to 30 percent.

6.7 Multi-Factor Productivity Data

This section highlights the usefulness of the Canadian Solow residuals for calibrating the transition probability matrix Λ. Table 6.1 identifies the CANSIM source of Canadian value-added multifactor productivity across sectors, specifically for goods, manufacturing and services. Table 6.2 presents basic descriptive statistics for total factor productivity, as well as for detrended GDP. Table 6.3 shows the correlation matrix between each of the productivity series and detrended GDP. The shocks are generated using a Markov transition probability matrix. The probability to stay in the same state λ_{11} is usually set to equal the serial correlation coefficient of the sectoral Solow residual. The serial correlation coefficients for different sectors' multifactor productivity are,

Table 6.B

Annual Data	First Serial Correlation
Multifactor Productivity: Sector GOODS	0.861
Multifactor Productivity: Sector MANUFACTURING	0.875
Multifactor Productivity: Sector SERVICES	0.892

Source: Table 6.4.

We choose an upper bound value of 0.92 for λ_{11} in the transition matrix Λ. This value equals the first serial correlation of GDP over the period from 1961 to 1998. Values of 0.92 and 0.72 are chosen to calibrate the probability to stay in the same state for all models quarterly and annually, respectively. Given the relatively small value of λ_{11}, one can use $(0.92)^4 \simeq 0.72$ as a good approximation. For symmetry purpose, we set $\lambda_{22} = \lambda_{11}$. The values of λ_{12} and λ_{21} are computed directly from λ_{11} and λ_{22}.

Greenwood et al. (1994, p. 9) used $Z = \{\exp^{\zeta}, \exp^{-\zeta}\}$ as values for the shock in a two-state world. ζ denoted the standard deviation of the sectoral Solow residual.

However, the use of the exponential form requires passing the HP filter on the model-generated data to de-trend it (since the study assumed an exponential trend in the shocks). Here, there is no need to pass the HP filter on the models generated data, since there is no trend present.

Table 6.1

CANSIM SOURCE	
Multifactor Productivity: Sector Goods	I700601
Multifactor Productivity: Sector Manufacturing	I700606
Multifactor Productivity: Sector Services	I700602

Table 6.2

DESCRIPTIVE STATISTICS
HP FILTERED GDP and MULTIFACTOR PRODUCTIVITY

Series	Obs	Mean	Std Error	Minimum	Maximum	CV
GDP	36	0.000	0.031	-0.060	0.045	
GOODS	36	89.78	10.56	64.40	103.50	0.11761
MANUF	36	83.99	14.47	54.10	105.10	0.17222
SERV	36	92.50	6.85	76.90	100.90	0.07402

Table 6.3

Correlation Matrix between GDP and MULTIFACTOR PRODUCTIVITY
HP FILTERED

	GDP	Goods	Manufacturing	Services
GDP	1.00000			
Goods	0.27750	1.00000		
Manufacturing	0.24606	0.99038	1.00000	
Services	0.49571	0.93505	0.91468	1.00000

Table 6.4

AUTOCORRELATIONS
HP FILTERED

	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.74062	0.42863	0.12036	-0.0786	-0.17629	-0.1690
GOODS	0.86150	0.74388	0.65160	0.57931	0.51717	0.45888
MANUF	0.87547	0.75754	0.65741	0.59064	0.54040	0.49102
SERV	0.89202	0.76224	0.63591	0.52803	0.43223	0.34775

6.8 Models Calibration

Independent evidence on an appropriate value for D (the adjustment cost parameter) is not available.[16] For our calibration of D, we follow the pioneering work of Cardia (1991) and Greenwood, Hercowitz and Krusell (1992) in setting the adjustment cost parameter so that the generated series match the variance of employment in the business cycle data. Using an open economy dynamic general equilibrium model, Cardia (1991, p. 423) chose to calibrate the adjustment cost parameter to 0.5 because this value reproduced the observed volatility for the investment series. Here, we are interested in explaining unemployment and use the values of the adjustment cost parameter as $D = \{5, 10, 15\}$.

When dealing with sector level data, Long and Plosser (1987) argued that using monthly data will reduce the potential role for shocks that influence some sectors with some time delay. On the other hand, using quarterly data will mislabel a portion of the shock that is already propagated to other sectors within the quarter. Here, we will explore the quarterly and the annual frequencies. To compare the results from both frequencies (annual and quarterly), the time endowment is set to one unit for the quarterly frequency and to four units for the annual frequency.

The value of A (constant) was computed in each model such that the model possess a steady state on the grid mesh. It is computed as a function of the steady state values of the decision variables. The following table reports the value of A for each frequency for model I. Note that A is not a function of the adjustment cost

[16] Note that $d = 0.5\ D$. In the literature, d is used as the adjustment cost parameter. Here, we calibrate and report our results in terms of D. Similar use of notation was reported by Cardia (1991).

parameter D.

Table 6.C

Model I	$\theta = 1.10$	$\theta = 1.15$	$\theta = 1.20$	$\theta = 1.25$	$\theta = 1.30$
Annual - A	4.762	4.918	5.078	5.242	5.410
Quarterly - A	3.155	3.259	3.365	3.474	3.586

Over the period from 1980 to 1996, the calibrated parameters for the Canadian economy at both frequencies are taken from Section 2.12, and are given in Table 6.D,

Table 6.D

$\alpha = 0.35$	$\delta = 0.06$	$\gamma = 2/3$

α is the capital' share in income, δ denotes the capital depreciation parameter and γ denotes the momentary leisure shape parameter. The leisure shape parameter $\gamma = 2/3$ implies that two-thirds of the household time is allocated to non-market activities and the elasticity of the labour supply equals 2. The same value was used by Prescott (1986). Calibrated parameters differ for both frequencies and are set out in Table 6.E,

Table 6.E

Quarterly	$\rho = 0.01$	$\beta = 0.99$	$\lambda_{11} = 0.92$	$T = 1$
Annual	$\rho = 0.04$	$\beta = 0.96$	$\lambda_{11} = 0.72$	$T = 4$

where ρ denotes the time rate of preference and β denotes the discount factor. T is the units of time endowment in each period.

Each model is simulated with all combinations of $D = \{5, 10, 15\}$ and $\theta = \{1.1, 1.15, 1.2, 1.25, 1.3\}$. Therefore, in total, 60 models were simulated. The rationale for these simulations is to investigate the sensitivity of the results to calibrated parameters and to the frequency.

Values of $\theta = \{1.10, 1.15, 1.20, 1.25, 1.30\}$ around $\theta = 1.20$ are chosen so that the model yields a steady state value of N equal to 0.20 which matches the average workweek as a fraction of total hours over the time period. Since the week contains 168 hours, 20 percent for hours of work time implies 33.6 hours on the job. Note also that a workweek of 40 hours implies that N^* equals 0.238, a value which is not far from the chosen 0.20.

We use a random number generator to determine the incidence of a shock. To simulate the time series, the procedure is as follows. First, assume that the economy is resting in state 1 with probability λ_{11} to stay in the same state for the next period. Second, generate a uniformly distributed random number. If the random number is higher than λ_{11}, then the economy will move to state 2. If state 1 is the state wherein sector 2 enjoys the high value of θ (high productivity in model I and high product demand in model II) and sector 1 collects $1/\theta$, then when the economy moves to state 2, the role of θ is switched for both sectors. The random number generator is used to simulate the models. For example, assume as described that the economy is in state 1 and sector 2 is the high θ sector ($\theta = 1.2$). If the value of the random number is higher than λ_{11}, then sector 1 enjoys a shock of $\theta = 1.2$, which implies that sector 2 is experiencing a shock of $\theta = 1/1.20 = 0.83$. For model I, this shock translates into a 20 percent increase in the labour demand in sector 1 and a 17 percent decrease in the demand for labour in sector 2. For model II, this shock translates into a 20 percent increase in the demand for sector 1 goods and a 17 percent decrease in the demand for sector 2 goods. The range of analysis is chosen to cover the range from a small shock (10 percent) to a relatively large shock (30 percent).

6.9 Algorithm, Robustness and Validity

In the context of RBC models, Romer (1996, p. 158) pointed out that his model (1996, p. 152) cannot be solved analytically. This model assumed two types of shocks, technology and government,[17] and included a mixture of non-linear and linear elements. Our models - in this thesis - possess a mixture of non-linear and linear elements such as a Leontiff production function, a log-linear preference function and convex adjustment costs. Note also that given the inherent asymmetry of the $f(.)$ function, the adjustment costs function is positive only if the change in employment is positive. Consequently, it is highly unlikely that our models can be solved analytically. We proceed further by solving the models numerically.

Solving the models using a numerical approach lead to the study of different numerical methods, as outlined in Taylor and Uhlig (1990). They compared seven different numerical methods, namely the value-function grid, the quadrature value-function grid, the linear-quadratic, backsolving, the extended-path, the parametrizing expectations and the least-squares projections. One of their conclusions was that if the measuring stick is the 'closeness' of the numerical solution to the true decision rule, then grid methods are "... likely to do very well." Taylor and Uhlig (1990, p. 16). They pointed that when computing time is the measuring stick, linear-quadratic approximation methods exhibit financially significant savings in terms of computing time. In our case, we accepted the burden of computing time and choose 'closeness' as a measuring stick. Therefore, we choose the value-function grid method.

[17]Romer dropped the government sector and also assumed complete capital depreciation to solve the model analytically.

The method relies on approximating the continuous valued problem by a discrete-valued one. The method evaluates and iterates on the Bellman equation over a grid of points with respect to the choice variables. The choice variables are capital and labour in model I. For model II, the choice variables are sector 1 and sector 2 labour.

Model I was maximized over 20,000 grid points of capital and sector 1 labour. The value for sector 2 labour was computed from sector 1 labour. Sector 2 employment is computed as $N_2 = \theta^2 N_1$. Total employment was set to $N = (1 + \theta^2)N_1$. The mesh size for model I differed across the frequencies, annually and quarterly. For capital, it is set to 0.2 and 0.02 for annual and quarterly frequencies, respectively. For sector 1 labour, the mesh is set to 0.009 and 0.0003 for annual and quarterly frequencies, respectively. Model II was maximized over 22,500 grid points of sector 1 and sector 2 labour. The mesh size was set to 0.006 for all sub-models. All grids were centered around the steady state. At first, we simulated a representative of each model [model I and model II]. After a process of trial and error, we located for each model the steady state on the grid. Then we changed the extremum of the grid to center it around this steady state. Finally, we carried out our sensitivity analysis.

Judd (1998, pp. 413-414) devised an error bound on the value function. Once an approximate solution is computed, the computation of the error bound on the Bellman equation is carried out. The contraction property used to iterate the value function implies that each iteration satisfy the inequality,

$$\| V^{sol} - V^k \|_\infty \leq \frac{1}{1-\beta} \| V^{k+1} - V^k \|_\infty \tag{6.48}$$

One stops the value function iteration at the first iterate such that,

$$\| V^{k+1} - V^{k} \|_{\infty} \leq \epsilon^{V} \quad (1-\beta) \tag{6.49}$$

The last inequality becomes the convergence rule given one's goal ϵ^V. This implies that the initial convergence stopping rule is $\epsilon = \epsilon^V(1-\beta)$. In our program, we set the stopping rule to $1.E-10$. This rule implies that the following values for ϵ^V were used,

Table 6.F

	Quarterly ($\beta = 0.99$)	Annual ($\beta = 0.96$)
ϵ^V	1.E-12	4.E-12

When $| V^k - V^{k-1} | < 1.E - 10$, iterations stop and the policy rules are computed from the steady state. Once they are computed, the variables are simulated and their properties are investigated.[18]

We have examined the robustness of the results to variations of the parameters within their support. There are two types of sensitivity analysis: global and local. Local sensitivity analysis focuses on local perturbations of the parameters. Our focus here is to study local robustness (next section). Global sensitivity analysis focuses on 'how robust the simulation results are to changes of the parameters in a small neighbourhood of a particular vector of calibrated parameters?' For the global approach, see Pagan and Ullah (1999).

We studied the models' results in the neighbourhood of local parameter perturbation. We simulated the models by fixing all calibrated parameters but one. We

[18]Each sub-model is run seven times to ensure that convergence is reached. All models are programmed in Fortran77 and run on a Linux/Unix operating systems based machines using the g77/f77 compilers. We acknowledge the tolerance of the Computer Science department and the permission to run these programs on their Unix/Linux machines.

decided to investigate the effect of adjustment cost sizes, relative shock sizes and the frequency used on the results. Therefore, we simulated each model [model I and model II] under three adjustment cost sizes, five relative shock sizes and two frequencies (quarterly and annually). All parameter variations were taken in a small local neighbourhood around the steady state (see section 6.8 for the values used).

As for the validity of the results, the following quotes best present our view of this calibration exercise. "A calibrationist takes the opposite view: the model, as a DGP [Data Generating Process] for the data, is false. That is, as the sample size grows, it is known that the generated data by the model will be at increasingly greater variance with the observed time series. An economic model is seen, at best, as an approximation to the true DGP which need not be either accurate or realistic and, as such, should not be regarded as a null hypothesis to be statistically tested." (Prescott (1991, p. 5)). Also on the same issue, "In confronting the model with the data, a calibrationist wants to indicate the dimensions where the approximation is poor and suggest modifications to the theoretical model in order to obtain a better approximation." Canova (1994, p. S124). The conclusion of this chapter points to the dimensions where the models were successful.

6.10 Local Sensitivity Analysis

Kim and Pagan (1995, pp. 380-381) proposed two approaches (local and global) to sensitivity analysis in computable general equilibrium models. Since our focus is on local sensitivity analysis, we computed the "sensitivity elasticities" for the models' parameters. These elasticities are based on the Taylor series expansion of a function of the calibrated parameters $g(\theta)$ around θ^* featured in the model. Formally,

$$g(\theta) \simeq g(\theta^*) + \left[\frac{\partial g}{\partial \theta}\right]_{\theta=\theta^*} (\theta - \theta^*) \tag{6.50}$$

In terms of proportionate changes,

$$\frac{g(\theta) - g(\theta^*)}{g(\theta^*)} \simeq \sum_{j=1}^{p} \eta_j \left[\frac{(\theta_j - \theta_j^*)}{\theta_j^*}\right] \tag{6.51}$$

where,

$$\eta_j \equiv \left\{ \left[\frac{\partial g}{\partial \theta_j}\right] \left[\frac{\theta_j}{g}\right] \right\}_{\theta=\theta^*} \tag{6.52}$$

η_j is the sensitivity elasticity for the jth coefficient. These elasticities are computed numerically by perturbing the coefficients of interest. Tables 6.G and 6.H report the models elasticities, where g is defined as the ratio of the standard deviations of model output to sample GDP. Table 6.G reports the sensitivity elasticities for the adjustment cost parameter D.

Table 6.G

MODEL I $\theta^{*} = 1.2$		**MODEL II** $\theta^{*} = 1.2$	
ANNUAL	η	**ANNUAL**	η
D=10	0.5268	D=10	0.0998
D=15	0.4613	D=15	0.0773
QUARTER	η	**QUARTER**	η
D=10	0.9072	D=10	-0.040
D=15	0.5104	D=15	0.1046

From the above results, at low levels of adjustment cost [range 5 to 10], if one changes D by 1 percent, model I (annual frequency and shock size $\theta = 1.2$) implies a change of 0.526 percent in the ratio of the model output standard deviation relative to business cycle data GDP standard deviation. For similar conditions (i.e., same frequency and fixed shock size), model II implies a change of 0.099 percent in the ratio of the model output standard deviation relative to business cycle data GDP standard deviation. Model II (annual frequency) sensitivity results suggest that the model implications are insensitive to the adjustment cost parameter.

Overall, model I results are more sensitive (relative to model II) to changes in the adjustment cost parameter. In the absence of formal educational institutions that facilitate labour mobility across sectors (i.e., high adjustment cost parameter D=15), a 1 percent change in D influences considerably the model output variability. If the parameter D can be thought of as an index that measures the absence, the rigidity or the presence of institutions that facilitate labour mobility in the economy, then a small policy change can influence the severity of output lost during a recession that is generated by a sectoral technological change.

Overall, the sensitivity elasticities for model II imply that regardless of the shape of the adjustment cost parameter, the effects of a sectoral tastes shock are robust in terms of output variability. Table 6.H reports the sensitivity elasticities for the size of the shock at the annual frequency.

Table 6.H

MODEL I		MODEL II	
ANNUAL	η	ANNUAL	η
D=5		**D=5**	
$\theta = 1.15$	7.632	$\theta = 1.15$	1.030
$\theta = 1.2$	5.853	$\theta = 1.2$	0.607
$\theta = 1.25$	4.489	$\theta = 1.25$	0.541
$\theta = 1.3$	4.024	$\theta = 1.3$	0.048
D=10		**D=10**	
$\theta = 1.15$	7.466	$\theta = 1.15$	0.239
$\theta = 1.2$	5.496	$\theta = 1.2$	0.432
$\theta = 1.25$	4.428	$\theta = 1.25$	0.413
$\theta = 1.3$	3.750	$\theta = 1.3$	0.556
D=15		**D=15**	
$\theta = 1.15$	6.988	$\theta = 1.15$	0.324
$\theta = 1.2$	5.409	$\theta = 1.2$	0.098
$\theta = 1.25$	4.257	$\theta = 1.25$	0.346
$\theta = 1.3$	3.691	$\theta = 1.3$	0.208

With the exception of the case of low adjustment cost and low size of the shock (i.e., $D = 5$ and $\theta = 1.15$), model II results are insensitive to the change in the size of the shock. The size of the sectoral technology shock in model I is very important to the model's results on output variability. Overall and almost at all levels of adjustment costs, output variability is very sensitive to the size of the sectoral technology shock.

A pattern that emerges from Table 6.H is that, as the size of the sectoral technology shock increases, the elasticity decreases. This implies that output variability is very sensitive to large sectoral technology shocks. Appendix B presents sensitivity analysis[19] for model I. Appendix B, Figure 2, illustrates the sensitivity of consumption and output to the capital depreciation parameter δ. Appendix B, Figure 3, shows that labour supply is an increasing function of the size of the sectoral technology shock. As θ increases, unemployment and the labour supply increase.

6.11 Stochastic General Equilibrium Results

This section reports and analyses the results of the simulated models, their characteristics and ability to match business cycle data. First, the section is divided by type of results, tables and figures. Finally, the sub-section 'average labour productivity' investigates the merits of each model relative to its performance in replicating observed labour productivity characteristics. In what follows, 'output' is used to describe the real GDP simulated series, and 'GDP' is used to refer to the real business cycle data.

6.11.1 Results (Tables)

Tables 6.5 to 6.15 report the empirical regularities of the Canadian business cycle data. Table 6.5 identifies the data source and their CANSIM labels. Data cover the period 1976 to 1999 and are for gross domestic product (GDP), employment (EMP), consumption (CONS) and investment (INVST). GDP is measured from the expenditure side at 1992 market prices. Consumption is measured as expenditure on consumer goods and services. Investment is measured as business gross fixed capital

[19]To investigate the sensitivity of model I, Appendix B undertakes parameter sensitivity analysis. This was done using MATHCAD programs. I acknowledge the support of Stephen Millard at the Bank of England in providing me with the prototype MATHCAD program for the basic real bussiness cycle model used in Millard et al. (1999).

formation. All are in 1992 dollars. Employment is measured as actual hours. Note that measuring employment as the total number of people above 15 years of age who are employed, reduces employment variability with respect to GDP. Relative to GDP, actual hours are more variable than total employment. Figure 6.1 illustrates the time series of GDP, consumption and investment.

Tables 6.6 and 6.7 report basic descriptive statistics for the cyclical component of each series at each frequency. The cyclical component is computed as deviation from the trend, where the trend is extracted by the Hodrick-Prescott filter. Prior to filtering, all series were in log form. In terms of volatility: investment is the most volatile, followed by employment, gross domestic product and then consumption.

For Canadian data covering the period from 1976 to 1998, the volatility measures are,

Table 6.I

	Standard Deviation relative to GDP	
	QUARTERLY	**ANNUAL**
σ_{GDP}	1.6%	2.56%
$\sigma_{EMP}/\sigma_{GDP}$	1.09	1.04
$\sigma_{INVST}/\sigma_{GDP}$	3.29	3.29
$\sigma_{CONS}/\sigma_{GDP}$	0.82	0.94
$Corrl(APN_t, GDP_t)$	0.074	0.079
$Corrl(APN_t, GDP_{t+2})$	0.183	0.711

Source: Tables 6.6 and 6.7. APN denotes labour productivity.

Tables 6.8 and 6.9 show the cross correlations of each series with GDP at different lags. All series (consumption, investment, employment and labour productivity) are procyclical. Consumption, investment and employment are coincident, whereas labour productivity is leading.

Tables 6.10 and 6.11 report the correlation matrix of the series. Ranking the variables using the correlation with GDP - from highest to lowest - results in employment, consumption and investment. Tables 6.12 and 6.13 report the serial autocorrelations of each series for the detrended data. For all series, the autocorrelations are significantly different from zero. Tables 6.14 and 6.15 are the autocorrelations for the growth series. The Canadian GDP growth rate is significantly serially autocorrelated at lag 1 with a value of 0.276 and 0.381 for annual and quarter frequencies, respectively.

Tables 6.16 to 6.33 report the results of the simulated data for model I (relative technology shock). Tables 6.16 and 6.17 show basic descriptive statistics for output generated by model I. Each row represents the results of a simulated model at different parameter specifications: three different adjustment cost parameters (parameter D) and five different shock size parameters (parameter θ).

At the annual and quarterly levels, the highest variation for output is produced by the model which includes the highest shock size ($\theta = 1.3$) and the highest adjustment cost parameter ($D = 15$). The last rows of Tables 6.16 and 6.17 show that model I produces 13.5 percent and 4.42 percent output variability, for the annual and the quarterly simulations, respectively. The selection of the following models is based primarily on their ability to match output variability. From tables 6.16 to 6.23, the models which match cyclical variability (Tables 6.6 and 6.7) are given in Tables 6.J and 6.K,

Table 6.J

Model I - ANNUAL	St-Dev GDP	Relative to Output EMPL	INVST	CONS
DATA	2.56%	1.03	3.29	0.94
Model I - D = 5 - Theta = 1.15	4.53	1.34	3.48	0.59
Model I - D = 5 - Theta = 1.2	5.99	1.34	3.45	0.57
Model I - D = 10 - Theta = 1.1	4.24	1.30	3.21	0.63
Model I - D = 15 - Theta = 1.1	5.19	1.26	3.08	0.66

Source: Table 6.6 and Tables 6.16, 6.18, 6.19 and 6.20.

For the quarterly frequency simulation,

Table 6.K

Model I - QUARTERLY	St-Dev GDP	Relative to Output EMPL	INVST	CONS
DATA	1.6%	1.09	3.29	0.82
Model I - D = 5 - Theta = 1.2	1.37	1.46	3.38	0.58
Model I - D = 10 - Theta = 1.1	1.31	1.42	2.63	0.63
Model I - D = 10 - Theta = 1.15	1.86	1.43	2.78	0.51
Model I - D = 15 - Theta = 1.1	1.62	1.40	2.70	0.57

Source: Table 6.7 and Tables 6.17, 6.21, 6.22 and 6.23.

Tables 6.24 to 6.29 show the correlation matrix of the simulated models. For annual simulations (tables 6.24 to 6.26), employment correlation with output increases if θ is higher for a given level of adjustment costs. The same pattern emerges for the correlation between investment and output. However, consumption exhibits no correlation pattern with output. Tables 6.27 to 6.29 show that such patterns disappear at quarterly level simulations.

Tables 6.30 to 6.33 report the output autocorrelations at different lags for all model I simulations. At the annual level, a comparison between Tables 6.12 (real business cycle data) and 6.30 (simulated model I data) reveal that lower adjustment costs generate a near match for the first lag (K=1) autocorrelation. However, no model is able to approximate reality for the subsequent lags. In the output growth data (Tables 6.32 and 6.33), all models again come short of producing a near match.

Tables 6.34 to 6.57 report the results of the simulated data for model II (relative tastes shock). Tables 6.34 and 6.35 present basic descriptive statistics for model II simulations. Each row in the tables shows output statistics for each model. As in model I, higher adjustment costs result in higher output volatility. For the highest values of adjustment costs and shock sizes (i.e., $D = 15$ and $\theta = 1.3$), output variability is 1.75 percent and 2.4 percent for annual and quarterly frequencies, respectively. However, as compared with model I, output variability is cut at least by half. Relative to model II, model I yields lower output variability.

Tables 6.36 to 6.41 relate the variability to the output of the simulated series. The results are summarized in tables 6.L and 6.M. Compared with GDP, annual frequency models underestimate output volatility and show an increasing pattern for D and θ. Quarterly models overestimate output volatility and show a pattern that peaks at $\theta = 1.2$. At the annual level, to generate an output volatility matching the data, one needs higher values for the parameters D and θ. At the quarterly level, to generate output volatility matching to data, one needs lower values for the parameters D and θ. In other words, a small shock and a smaller adjustment cost parameter for model II can match output volatility in quarterly data. As expected, in all quarterly submodels of model II, employment volatility is small and is due to adjustment costs. At the annual frequency of model II, models $D = 5$ and $D = 10$, when combined with the highest value of the relative taste shock, produce a near match for employment volatility relative to GDP.

Table 6.L

Model II - ANNUAL	St-Dev GDP	Relative to Output EMPL	APN	CONS
DATA	2.56%	1.03	0.367	0.94
Model II - D = 5 - Theta = 1.15	1.54	0.61	0.874	0.79
Model II - D = 5 - Theta = 1.2	1.58	0.70	0.912	0.81
Model II - D = 10 - Theta = 1.1	1.61	0.74	0.534	0.82
Model II - D = 10 - Theta = 1.3	1.72	1.02	0.755	0.91
Model II - D = 15 - Theta = 1.1	1.67	0.77	0.429	0.82
Model II - D = 15 - Theta = 1.3	1.74	1.03	0.641	0.92

Source: Table 6.6 and Tables 6.36, 6.37 and 6.38.

For the quarter frequency simulation,

Table 6.M

Model II - QUARTERLY	St-Dev GDP	Relative to Output EMPL	APN	CONS
DATA	1.60%	1.09	0.13	0.82
Model II - D = 5 - Theta = 1.2	2.37	0.45	1.07	0.79
Model II - D = 10 - Theta = 1.2	2.38	0.56	1.05	0.81
Model II - D = 10 - Theta = 1.25	2.32	0.83	1.32	0.91
Model II - D = 15 - Theta = 1.1	1.90	0.58	1.07	0.95

Source: Table 6.7 and Tables 6.39, 6.40 and 6.41.

Tables 6.42 to 6.53 show the correlation matrix of the simulated model II data. For the annual frequency, a pattern emerges for the correlation of output with employment. The higher the size of the shock, the lower $\rho(E,Y)$, $\rho(C,Y)$ and $\rho(APN,Y)$ are. The higher the adjustment costs parameter, the higher is $\rho(E,Y)$. For a given adjustment cost, a higher size of the shock drives the average productivity of labour from being procyclical to countercyclical. For the annual frequency, the highest $\rho(E,Y)$ [equals 0.94] is recorded in model II - D = 15 - $\theta = 1.1$.

For the quarterly frequency, average productivity of labour is countercyclical regardless of the size of the shock and the adjustment cost parameter values. The correlation of output with employment is relatively small, reaching at most 0.22 in model II with D = 15 and $\theta = 1.3$.

By construction, the correlation between sector 1 and sector 2 consumption is negative and increases with the value of the shock. Note that this correlation is higher with a smaller adjustment cost. A higher adjustment cost reduces the value of $\rho(C_1, C_2)$. Model II correctly predicts a negative correlation between sector 1 and sector 2 consumption movements. For the annual frequency, output, employment and total consumption are all positively correlated. Tables 6.54 to 6.57 report the output autocorrelations at different lags for all model II simulations. For the annual frequency, Table 6.54 shows success in producing a similar first lag autocorrelation in the data.

6.11.2 Results (Figures)

Figure 6.1 illustrates the time series behaviour of the aggregate Canadian variables: GDP, consumption and investment. Figures 6.2 to 6.5 graph the simulated output autocorrelation at both frequencies for both models. For models I and II, a near perfect match of the first and second serial autocorrelation is achieved with the annual simulation. Model I quarterly simulations explain (at best) two-thirds of the first lag autocorrelation. This result is for D = 15, $\theta = 1.25$ and $\theta = 1.3$. Both sub-models reach two-thirds of the first-order serial autocorrelation of GDP. For model II, almost half of the first lag of quarterly output serial autocorrelation can be explained by relative taste shocks combined with sectoral reallocation and adjustment costs. For quarterly data, one-third of the autocorrelation can be explained by model II.

Figures 6.6 to 6.11 graph impulse responses for model I. Figures 6.6 to 6.10 are for employment and figures 6.11 and 6.12 are for output and consumption. Figures 6.6 to 6.10 capture the essence of adjustment costs. Following a technology shock, total employment decreases. The time it takes to revert to its original state is due to the adjustment costs. The higher the adjustment cost is (parameter D), the longer it takes employment to adjust. For model I, quarterly frequency (Figure 6.6), the small value for $D = 5$ implies a 7.3 percent reduction in employment and two quarters to adjust. For higher values for D , a 20 percent technology shock induces a 14 percent reduction in employment. One can deduce the importance of the effect of adjustment costs on employment variability. The severity of the fall of employment is positively correlated with the adjustment costs. Figure 6.6 illustrates that the decrease in employment double across the given range of adjustment costs.

From Figure 6.11, a 20 percent technology shock produces a reduction in output of 7 percent. For the higher value of D, the shock induces an 11 percent reduction in output.

Unemployment persistence is generated at higher values for D. Quarterly, it takes 9 periods at most for employment to adjust following a shock (Figure 6.6). In this setup, persistent unemployment could be explained by a technology shock followed by adjustment costs to reallocate between sectors.

Figures 6.12 to 6.21 illustrate impulse responses for model II. Figures 6.12 to 6.17 are for consumption by sector, by shock size and by adjustment cost respectively. Figure 6.12 shows that sector 2 consumption takes at least four years (for a smaller shock value, see Figure 6.13) to adjust following a change in agents' tastes. Given the nature of a small shock, sector 1 consumption adjusts quickly relative to the other sector. For higher adjustment costs (Figure 6.14), sector 2 consumption takes five periods to adjust fully. For higher shock size (Figures 6.16 and 6.17), consumption in sector 1 takes from two to five periods to adjust.

Figures 6.18 to 6.21 illustrate employment impulse responses. Following a 20 percent relative taste shock, employment decreases at most by 4 percent. Employment takes at most 4 periods to return to its steady state level.

6.11.3 Average Productivity of Labour (APN)

In most simulated RBC models, the correlation between the average productivity of labour (APN) and GDP is positive. A positive technology shock increases the demand for labour and output. Such shocks are responsible for the generated positive labour productivity, a result that matches the observed positive correlation in Real Business Cycle data.[20] In periods of booms, workers produce more output during each hour worked than they do during a recession.

For model I, following a relative technology shock, the reallocative process of employment across sectors reduces total employment and increases the average productivity of labour. A slow reallocation process, due to the presence of adjustment costs, results in decreasing average productivity of labour. Therefore, the average productivity of labour is countercyclical. This result shows that sectoral technology driven shocks can generate countercyclical average labour productivity.

One of the strong points of the basic RBC model is that, to generate a procyclical APN, one needs an aggregate productivity shock. Without an aggregate productivity

[20] See Abel, Bernanke and Smith (1999, p. 299). Also, see Tables 10 and 11 in this chapter' appendix.

shock (i.e., a non-shifting production function), an increase in labour during booms will reduce the average productivity of labour because of the diminishing marginal product of labour. Therefore, a stable aggregate production function generates a countercyclical average productivity of labour. This result is reached in model I. The challenge then becomes: how to generate procyclical APN without productivity shocks? The answer is the impulse mechanism in model II.

Model II focuses on changing labour demand without changing the production function. In model II, households' relative tastes change and they demand higher quantities of a specific good (sector 2 good) relative to the other (sector 1 good). Firms answer by supplying more of the desired good and by increasing their derived demand for labour in this sector. Here, there is no productivity shock. Figures 6.22 to 6.25 illustrate the impulse responses of labour productivity for both models.

The following results are for model II,

Table 6.N

APN CORRELATION WITH OUTPUT ANNUAL					
	T+2	**T+1**	**T**	**T-1**	**T-2**
Model II - D = 5 - Theta = 1.2	0.0677	0.0056	0.9257	0.0916	0.0920
Model II - D = 10 - Theta = 1.2	-0.0006	-0.0756	0.8721	0.1738	0.1360
Model II - D = 15 - Theta = 1.2	0.0063	0.0191	0.9024	0.1896	0.1006

Model II is successful in generating the observed procyclical labour productivity. Model II offers a non-technology driven explanation for procyclical productivity. However, the results show a high correlation with output and that labour productivity is coincident, as opposed to leading in observed data.

What is interesting is the apparent overshooting of the adjustment process, evident in Figures 6.24, 6.25 and 6.26. For model I, a relative technology shock reduces total employment and output. Since output equals consumption plus investment, this reduction in output must be matched by a reduction in consumption and/or investment. Given the preference for smoothing consumption by the representative household, a large reduction in consumption to match the loss of output is undesirable. Therefore, investment falls by more than the reduction in consumption. This reduction in investment produces a reduction of capital over subsequent periods, linked by the law of motion for capital (i.e., the time-to-build characteristic). The reduction in capital acts as a negative wealth effect that impacts on the households' decisions. The representative agent responds by increasing labour supply and reducing consumption and leisure. This effect, when combined with the cost of adjustment in terms of leisure lost to move across sectors, produces overshooting (see Figure 6.26). Note that this characteristic is similar to the empirical regularity found in Chapter 5 by the Blanchard-Quah identification for the VAR model C-I. The size and the timing of overshooting are positively correlated with the size of the shock and with the cost of adjustment parameter.

6.12 Conclusions

Sensitivity analysis was undertaken with regard to the size of the shock, the frequency - quarterly and annually - of the shock and with regard to the adjustment cost parameter for all simulated models. The success of the RBC models is defined in the literature as their ability to mimic general business cycle correlations/moments. In this chapter, we added the criterion of explaining the observed unemployment persistence.

Our simulations examined the dynamics between sectoral shocks and unemployment. Specifically, they tried to answer the questions: How much of the increase in structural unemployment in recessions is due to sectoral reallocation? Which impulse and propagation mechanisms, if any, can generate persistence in unemployment similar to that in the data?

At the absolute level, sectoral reallocation and adjustment costs combined with relative taste/technology shocks produced a range of variations in unemployment. Depending on the size of the shock and the degree of difficulty in moving across sectors, volatility in unemployment was found to be between 10 percent to 37 percent. Note that this range is smaller than the one suggested by Lilien (1982). Our results do encompass the Campbell and Kuttner (1996, p.113) observation that sectoral reallocation is responsible for *at least* 27 percent of aggregate unemployment variation.

For model I, employment correlation with output increases if θ is higher for a given level of adjustment costs. The same pattern emerges for the correlation between investment and output. Also, higher adjustment costs result in higher output volatility. For model II, the higher the size of the shock, the lower are $\rho(E,Y)$, $\rho(C,Y)$ and $\rho(APN,Y)$. The higher the adjustment costs parameter, the higher is $\rho(E,Y)$. For a given adjustment cost, a higher size of the shock can change average productivity of labour from being procyclical to countercyclical.

Model I dominates model II with respect to higher unemployment variance. Model II performs poorly in terms of output volatility. Model I results are more sensitive to the calibrated parameters and one should read its results with caution. A smaller taste shock and a smaller adjustment cost parameter for model II can generate a match for the data on output volatility at the quarterly level. Model II successfully produces procyclical labour productivity without recourse to a technology shock. However, the generated labour productivity is cyclically coincident, and not leading as in the data. Both models show partial success in matching empirical regularities.

Both models successfully generate unemployment persistence. It takes a smaller technology shock and a relatively larger taste shock to generate a similar decrease in employment. The results presented are conditioned on the calibrated parameters and the models' formal specification. For both models, the adjustment mechanism is similar. Also, a symmetry by which a shock influences the economy is present. Leisure utility is lost from employment search. However, the models also differ in many aspects. Model I includes a capital stock, whereas model II does not. Model II encompasses two well defined goods sectors.

The absolute value of the adjustment costs parameter D is of no significant importance. However, as our results suggest, employment variance varies with the adjustment costs parameter. A policy - such as training - aimed at reducing these costs will significantly reduce the variance of employment.

One merit of our framework - among many - is its ability to produce the increase in employment following the adjustment process. This theoretical success in capturing the empirical wealth effect is emphasized in Figure 6.26. Note that this characteristic is similar to the empirical regularity found in Chapter 5 by the Blanchard-Quah identification for the VAR model C-I.

Given the simulated results, an observed unemployment persistence is equally likely to be the product of a technology shock or a taste shock. In the absence of institutions that ease labour mobility across sectors (higher adjustment costs) unemployment displays persistence regardless of the source of the shock. A smaller adjustment cost tends to generate higher persistence for a technology shock than for a taste shock. Comparing shocks of the same magnitude to technology and tastes, the former produces higher employment volatility, longer unemployment persistence and a deeper recession.

6.13 Appendix A: Tables and Figures

Table 6.5

CANSIM SOURCE	LABEL
GROSS DOMESTIC PRODUCT	D14872
EMPLOYMENT	D980662
CONSUMPTION	D14842
INVESTMENT	D14851

Label	: D14872
Title	: G.D.P. AT 1992 PRICES, EXPENDITURE-BASED / GROSS DOMESTIC PRODUCT AT MARKET PRICES
Subtitle	: GROSS DOMESTIC PRODUCT AT 1992 PRICES, EXPENDITURE-BASED. BY QUARTER, IN MILLIONS OF 1992 DOLLARS, SEASONALLY ADJUSTED AT ANNUAL RATES
Factor	: MILLION
Unit	: DOLLARS
Source	: SDDS 1901 STC 13-001
Update	: 11 April, 2000
Period	: 1961Q1 - 1999Q4
Frequency	: quarterly

Label	: D14842
Title	: G.D.P. AT 1992 PRICES, EXPENDITURE-BASED / PERSONAL EXPENDITURE ON CONSUMER GOODS & SERVICES
Subtitle	: GROSS DOMESTIC PRODUCT AT 1992 PRICES, EXPENDITURE-BASED. BY QUARTER, IN MILLIONS OF 1992 DOLLARS, SEASONALLY ADJUSTED AT ANNUAL RATES
Factor	: MILLION
Unit	: DOLLARS
Source	: SDDS 1901 STC 13-001
Update	: 11 April, 2000
Period	: 1961Q1 - 1999Q4
Frequency	: quarterly

Label	: D14851
Title	: G.D.P. AT 1992 PRICES, EXPENDITURE-BASED / BUSINESS GROSS FIXED CAPITAL FORMATION
Subtitle	: GROSS DOMESTIC PRODUCT AT 1992 PRICES, EXPENDITURE-BASED. BY QUARTER, IN MILLIONS OF 1992 DOLLARS, SEASONALLY ADJUSTED AT ANNUAL RATES
Factor	: MILLION
Unit	: DOLLARS
Source	: SDDS 1901 STC 13-001
Update	: 11 April, 2000
Period	: 1961Q1 - 1999Q4
Frequency	: quarterly

Label	: D980662
Title	: CDA LF CHARACTERISTICS MONTHLY SA / ACTUAL HOURS SA CDA
Subtitle	: CANADA, LABOUR FORCE CHARACTERISTICS, MONTHLY FROM JAN 1976, SEASONALLY ADJUSTED. INCLUDES LF CHARACTERISTICS BY AGE & SEX; LABOUR FORCE, UNEMPLOYMENT & UNEMPLOYMENT RATE BY INDUSTRY; EMPLOYMENT BY INDUSTRY, OCCUPATION & CLASS OF WORKER; HOURS OF WORK BY INDUSTRY.
Factor	: THOUSAND
Unit	: HRS./WEEK
Source	: SDDS 3701 STC (71-001)
Update	: 28 March, 2000
Period	: January 1976 - Febuary 2000
Frequency	: monthly

Table 6.6

DESCRIPTIVE STATISTICS					
CYCLICAL COMPONENT					ANNUAL
Series	Obs	Mean	Std Error	Minimum	Maximum
CGDP	24	0.00000	0.02569	-0.04377	0.05031
CEMP	24	0.00000	0.02666	-0.03654	0.05521
CINVST	24	0.00000	0.08470	-0.13113	0.16106
CCONS	24	0.00000	0.02407	-0.05096	0.04870

Table 6.7

DESCRIPTIVE STATISTICS					
CYCLICAL COMPONENT				QUARTERLY	
Series	Obs	Mean	Std Error	Minimum	Maximum
CGDP	96	0.00000	0.01607	-0.05372	0.02939
CEMP	96	0.00000	0.01752	-0.05115	0.03936
CINVST	96	0.00000	0.05299	-0.09831	0.16151
CCONS	96	0.00000	0.01316	-0.04134	0.03010

Table 6.8

ANNUAL	CORRELATION WITH GDP				
HP FILTERED					
	T+2	T+1	T	T-1	T-2
CONS	0.0515	0.5687	0.9033	0.7113	0.3570
INVST	-0.1065	0.3282	0.7838	0.7182	0.5075
EMP	-0.0880	0.4543	0.9351	0.7831	0.3534
APN	0.7116	0.5121	0.0797	-0.4130	-0.5302

Table 6.9

QUARTERLY	CORRELATION WITH GDP				
HP FILTERED					
	T+2	T+1	T	T-1	T-2
CONS	0.7132	0.8332	0.8699	0.7702	0.6627
INVST	0.4075	0.5872	0.6484	0.6129	0.5153
EMP	0.5619	0.7693	0.8825	0.8728	0.7714
APN	0.1835	0.0980	0.0741	-0.1213	-0.2608

Table 6.10

	CORRELATION MATRIX			ANNUAL
HP FILTERED				
	GDP	EMP	INVST	CONS
GDP	1.000000			
INVESTMENT	0.783799	1.000000		
CONSUMPTION	0.903289	0.692864	1.000000	
EMPLOYMENT	0.935138	0.876700	0.832255	1.000000

Table 6.11

	CORRELATION MATRIX			QUARTERLY
HP FILTERED				
	GDP	EMP	INVST	CONS
GDP	1.000000			
INVESTMENT	0.648365	1.000000		
CONSUMPTION	0.869922	0.667140	1.000000	
EMPLOYMENT	0.882469	0.704124	0.776721	1.000000

Table 6.12

HP FILTERED	AUTOCORRELATIONS					ANNUAL
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.6605	0.1712	-0.2409	-0.4043	-0.4812	-0.4467
CONSUMPTION	0.7500	0.3076	-0.1424	-0.4523	-0.6230	-0.6459
INVESTMENT	0.6381	0.1891	-0.2830	-0.5087	-0.5135	-0.3696
EMPLOYMENT	0.6582	0.1079	-0.3347	-0.4808	-0.4381	-0.3235

Table 6.13

HP FILTERED	AUTOCORRELATIONS				QUARTERLY	
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.8890	0.7068	0.5144	0.3099	0.1427	0.0063
CONSUMPTION	0.8207	0.7028	0.5562	0.3758	0.2469	0.1111
INVESTMENT	0.8720	0.6785	0.4414	0.2182	0.0587	-0.0289
EMPLOYMENT	0.8441	0.6864	0.5074	0.3895	0.2397	0.0627

Table 6.14

Growth Rates	AUTOCORRELATIONS					ANNUAL
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.2768	-0.0862	-0.3340	-0.1697	-0.1611	-0.2407
CONSUMPTION	0.3943	0.0168	-0.2639	-0.2794	-0.3003	-0.4319
INVESTMENT	0.1651	0.0304	-0.2469	-0.2646	-0.2224	-0.2372
EMPLOYMENT	0.3692	-0.1053	-0.3906	-0.3057	-0.0848	-0.2130

Table 6.15

Growth Rates	AUTOCORRELATIONS				QUARTERLY	
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.3815	0.0442	0.0346	-0.1462	-0.1547	-0.1392
CONSUMPTION	-0.0874	0.0720	0.1841	-0.2053	-0.0343	0.0059
INVESTMENT	0.2617	0.1758	-0.0437	-0.2484	-0.2855	-0.1652
EMPLOYMENT	0.0225	0.0710	-0.1663	0.0916	0.0970	0.0319

Table 6.16

DESCRIPTIVE STATISTICS FOR SIMULATED OUTPUT						ANNUAL
	Obs	Mean	St-Dev	MIN	MAX	CV
MODEL I - D = 5 - THETA = 1.1	1100	11.3662	0.3444	10.1090	11.9747	0.0303
MODEL I - D = 5 - THETA = 1.15	1100	11.2768	0.5114	9.8745	12.1052	0.0453
MODEL I - D = 5 - THETA = 1.2	1100	11.1544	0.6690	9.5694	12.2682	0.0600
MODEL I - D = 5 - THETA = 1.25	1100	11.0293	0.8064	9.1756	12.5110	0.0731
MODEL I - D = 5 - THETA = 1.3	1100	10.9157	0.9443	8.7159	12.5436	0.0865
MODEL I - D = 10 - THETA = 1.1	1100	11.2521	0.4771	9.6995	12.1339	0.0424
MODEL I - D = 10 - THETA = 1.15	1100	11.0968	0.6967	9.4016	12.5779	0.0628
MODEL I - D = 10 - THETA = 1.2	1100	10.8977	0.8874	8.7898	12.6638	0.0814
MODEL I - D = 10 - THETA = 1.25	1100	10.7008	1.0590	8.2678	12.8543	0.0990
MODEL I - D = 10 - THETA = 1.3	1100	10.5236	1.2170	7.7788	13.0890	0.1156
MODEL I - D = 15 - THETA = 1.1	1100	11.1584	0.5790	9.4212	12.3796	0.0519
MODEL I - D = 15 - THETA = 1.15	1100	10.9412	0.8156	8.9754	12.6557	0.0745
MODEL I - D = 15 - THETA = 1.2	1100	10.6993	1.0295	8.1698	13.1034	0.0962
MODEL I - D = 15 - THETA = 1.25	1100	10.4359	1.2104	7.6666	13.2503	0.1160
MODEL I - D = 15 - THETA = 1.3	1100	10.1989	1.3786	7.1738	13.3993	0.1352

Table 6.17

DESCRIPTIVE STATISTICS FOR SIMULATED OUTPUT					QUARTERLY	
Series	Obs	Mean	St-Dev	MIN	MAX	CV
MODEL I - D = 5 - THETA = 1.1	1100	1.8095	0.0009	1.8094	1.8247	0.0005
MODEL I - D = 5 - THETA = 1.15	1100	1.8976	0.0034	1.8675	1.8986	0.0018
MODEL I - D = 5 - THETA = 1.2	1100	1.9818	0.0271	1.8650	1.9947	0.0137
MODEL I - D = 5 - THETA = 1.25	1100	2.0042	0.0415	1.8377	2.0321	0.0207
MODEL I - D = 5 - THETA = 1.3	1100	2.0017	0.0484	1.8035	2.0335	0.0242
MODEL I - D = 10 - THETA = 1.1	1100	2.0096	0.0264	1.8438	2.0275	0.0131
MODEL I - D = 10 - THETA = 1.15	1100	2.0037	0.0373	1.8445	2.0334	0.0186
MODEL I - D = 10 - THETA = 1.2	1100	2.0038	0.0501	1.7985	2.0403	0.0250
MODEL I - D = 10 - THETA = 1.25	1100	1.9992	0.0603	1.7529	2.0406	0.0302
MODEL I - D = 10 - THETA = 1.3	1100	1.9964	0.0714	1.7066	2.0485	0.0358
MODEL I - D = 15 - THETA = 1.1	1100	2.0068	0.0325	1.8274	2.0303	0.0162
MODEL I - D = 15 - THETA = 1.15	1100	2.0037	0.0469	1.8130	2.0391	0.0234
MODEL I - D = 15 - THETA = 1.2	1100	1.9996	0.0603	1.7534	2.0431	0.0302
MODEL I - D = 15 - THETA = 1.25	1100	2.0058	0.0743	1.7097	2.0643	0.0371
MODEL I - D = 15 - THETA = 1.3	1100	2.0029	0.0885	1.6533	2.0711	0.0442

Table 6.18

ANNUAL		St-DEV RELATIVE TO OUTPUT		
	St-Dev			
	OUTPUT	EMP	INVST	CONS
MODEL I - D = 5 - THETA = 1.1	0.03030	1.36510	3.63069	0.60058
MODEL I - D = 5 - THETA = 1.15	0.04535	1.34857	3.48052	0.59246
MODEL I - D = 5 - THETA = 1.2	0.05998	1.34972	3.45472	0.57523
MODEL I - D = 5 - THETA = 1.25	0.07311	1.35061	3.44253	0.57113
MODEL I - D = 5 - THETA = 1.3	0.08650	1.34612	3.46030	0.56606

Table 6.19

ANNUAL		St-DEV RELATIVE TO OUTPUT		
	St-Dev			
	OUTPUT	EMP	INVST	CONS
MODEL I - D = 10 - THETA = 1.1	0.04240	1.30363	3.21659	0.63696
MODEL I - D = 10 - THETA = 1.15	0.06278	1.30403	3.22101	0.63024
MODEL I - D = 10 - THETA = 1.2	0.08143	1.30101	3.25222	0.61899
MODEL I - D = 10 - THETA = 1.25	0.09896	1.29697	3.22683	0.62214
MODEL I - D = 10 - THETA = 1.3	0.11564	1.29728	3.22997	0.61579

Table 6.20

ANNUAL		St-DEV RELATIVE TO OUTPUT		
	St-Dev			
	OUTPUT	EMP	INVST	CONS
MODEL I - D = 15 - THETA = 1.1	0.05189	1.26721	3.08228	0.66702
MODEL I - D = 15 - THETA = 1.15	0.07454	1.26960	3.07409	0.65671
MODEL I - D = 15 - THETA = 1.2	0.09623	1.27587	3.08671	0.64760
MODEL I - D = 15 - THETA = 1.25	0.11598	1.27744	3.08975	0.64340
MODEL I - D = 15 - THETA = 1.3	0.13517	1.27515	3.09557	0.64136

Table 6.21

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	INVST	CONS
MODEL I - D = 5 - THETA = 1.1	0.00052	0.00019	4.71369	3.20435
MODEL I - D = 5 - THETA = 1.15	0.00178	1.45783	2.54962	1.62565
MODEL I - D = 5 - THETA = 1.2	0.01367	1.46641	3.38891	0.58105
MODEL I - D = 5 - THETA = 1.25	0.02072	1.46056	2.87428	0.44345
MODEL I - D = 5 - THETA = 1.3	0.02419	1.45537	2.84703	0.42092

Table 6.22

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	INVST	CONS
MODEL I - D = 10 - THETA = 1.1	0.01314	1.42570	2.63552	0.63265
MODEL I - D = 10 - THETA = 1.15	0.01862	1.43973	2.78979	0.51223
MODEL I - D = 10 - THETA = 1.2	0.02502	1.41958	2.77362	0.48737
MODEL I - D = 10 - THETA = 1.25	0.03016	1.42279	2.83022	0.43561
MODEL I - D = 10 - THETA = 1.3	0.03577	1.41238	2.76274	0.46718

Table 6.23

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	INVST	CONS
MODEL I - D = 15 - THETA = 1.1	0.01619	1.40983	2.70117	0.57294
MODEL I - D = 15 - THETA = 1.15	0.02342	1.40413	2.69224	0.52227
MODEL I - D = 15 - THETA = 1.2	0.03015	1.40516	2.71212	0.48784
MODEL I - D = 15 - THETA = 1.25	0.03706	1.40886	2.73788	0.50101
MODEL I - D = 15 - THETA = 1.3	0.04419	1.39254	2.74680	0.50085

Table 6.24

CORRELATION MATRIX				ANNUAL	
MODEL I - D = 5 - THETA = 1.1					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.88098	1.00000			
OUTPUT	0.95819	-0.86356	1.00000		
INVST	0.96516	-0.86570	0.88941	1.00000	
CONS	0.46947	-0.42975	0.67920	0.26860	1.00000
MODEL I - D = 5 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.91760	1.00000			
OUTPUT	0.95672	-0.89350	1.00000		
INVST	0.97703	-0.90161	0.89973	1.00000	
CONS	0.51916	-0.50181	0.73224	0.36158	1.00000
MODEL I - D = 5 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.92608	1.00000			
OUTPUT	0.95663	-0.90217	1.00000		
INVST	0.98476	-0.90788	0.90962	1.00000	
CONS	0.53305	-0.53592	0.74844	0.40527	1.00000
MODEL I - D = 5 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.92368	1.00000			
OUTPUT	0.95771	-0.90195	1.00000		
INVST	0.98675	-0.91180	0.91233	1.00000	
CONS	0.54201	-0.53850	0.75494	0.42024	1.00000
MODEL I - D = 5 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.92948	1.00000			
OUTPUT	0.95728	-0.90873	1.00000		
INVST	0.98860	-0.91539	0.91377	1.00000	
CONS	0.53380	-0.54423	0.75096	0.41797	1.00000

Table 6.25

CORRELATION MATRIX			ANNUAL		
MODEL I - D = 10 - THETA = 1.1					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.88789	1.00000			
OUTPUT	0.95174	-0.85585	1.00000		
INVST	0.97614	-0.87203	0.89040	1.00000	
CONS	0.57980	-0.52912	0.79098	0.42578	1.00000
MODEL I - D = 10 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.90297	1.00000			
OUTPUT	0.95373	-0.87645	1.00000		
INVST	0.98146	-0.88225	0.89404	1.00000	
CONS	0.58099	-0.56069	0.79287	0.43585	1.00000
MODEL I - D = 10 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.90724	1.00000			
OUTPUT	0.95232	-0.88094	1.00000		
INVST	0.98573	-0.89050	0.89842	1.00000	
CONS	0.56969	-0.55683	0.78930	0.43948	1.00000
MODEL I - D = 10 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.91136	1.00000			
OUTPUT	0.95340	-0.88450	1.00000		
INVST	0.98598	-0.89545	0.89814	1.00000	
CONS	0.57750	-0.56241	0.79385	0.44558	1.00000
MODEL I - D = 10 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.91759	1.00000			
OUTPUT	0.95333	-0.89345	1.00000		
INVST	0.98705	-0.90043	0.90146	1.00000	
CONS	0.57985	-0.57789	0.79564	0.45503	1.00000

Table 6.26

CORRELATION MATRIX				ANNUAL	
MODEL I - D = 15 - THETA = 1.1					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.88113	1.00000			
OUTPUT	0.95025	-0.85398	1.00000		
INVST	0.97627	-0.85618	0.88155	1.00000	
CONS	0.60359	-0.56849	0.81444	0.44404	1.00000
MODEL I - D = 15 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.89259	1.00000			
OUTPUT	0.95097	-0.86278	1.00000		
INVST	0.98233	-0.87226	0.88871	1.00000	
CONS	0.60969	-0.57677	0.82084	0.46763	1.00000
MODEL I - D = 15 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.90354	1.00000			
OUTPUT	0.95198	-0.87670	1.00000		
INVST	0.98471	-0.88485	0.89322	1.00000	
CONS	0.61037	-0.59006	0.82058	0.47598	1.00000
MODEL I - D = 15 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.90694	1.00000			
OUTPUT	0.95258	-0.88286	1.00000		
INVST	0.98563	-0.88556	0.89555	1.00000	
CONS	0.61289	-0.60383	0.82165	0.48220	1.00000
MODEL I - D = 15 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.91241	1.00000			
OUTPUT	0.95280	-0.88956	1.00000		
INVST	0.98584	-0.89107	0.89619	1.00000	
CONS	0.61143	-0.60867	0.82025	0.48133	1.00000

Table 6.27

CORRELATION MATRIX					QUARTERLY
MODEL I - D = 5 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.98826	1.00000			
OUTPUT	0.96076	-0.93973	1.00000		
INVST	0.29819	-0.21291	0.18875	1.00000	
CONS	0.64381	-0.68259	0.75176	-0.50568	1.00000
MODEL I - D = 5 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.99274	1.00000			
OUTPUT	0.97436	-0.96627	1.00000		
INVST	0.96528	-0.94849	0.91877	1.00000	
CONS	-0.01716	-0.00492	0.16213	-0.24061	1.00000
MODEL I - D = 5 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.96016	1.00000			
OUTPUT	0.97872	-0.93683	1.00000		
INVST	0.99128	-0.94795	0.95531	1.00000	
CONS	0.40979	-0.39475	0.57755	0.31044	1.00000
MODEL I - D = 5 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.96176	1.00000			
OUTPUT	0.97844	-0.93828	1.00000		
INVST	0.99481	-0.95605	0.96188	1.00000	
CONS	0.44707	-0.42275	0.61507	0.37601	1.00000

Table 6.28

CORRELATION MATRIX					QUARTERLY
MODEL I - D = 10 - THETA = 1.1					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.93162	1.00000			
OUTPUT	0.97034	-0.89712	1.00000		
INVST	0.96330	-0.89862	0.90372	1.00000	
CONS	0.47682	-0.42662	0.64951	0.26145	1.00000
MODEL I - D = 10 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.93965	1.00000			
OUTPUT	0.97516	-0.90914	1.00000		
INVST	0.98490	-0.92959	0.93919	1.00000	
CONS	0.42714	-0.37180	0.60255	0.29185	1.00000
MODEL I - D = 10 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.94121	1.00000			
OUTPUT	0.97343	-0.90422	1.00000		
INVST	0.99127	-0.93307	0.94718	1.00000	
CONS	0.44235	-0.38110	0.62721	0.34429	1.00000
MODEL I - D = 10 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.94852	1.00000			
OUTPUT	0.97255	-0.91802	1.00000		
INVST	0.99557	-0.94721	0.95878	1.00000	
CONS	0.42214	-0.37775	0.61428	0.36474	1.00000
MODEL I - D = 10 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.94969	1.00000			
OUTPUT	0.97302	-0.91666	1.00000		
INVST	0.99446	-0.94918	0.95330	1.00000	
CONS	0.45957	-0.40184	0.64604	0.38533	1.00000

Table 6.29

CORRELATION MATRIX					QUARTERLY
MODEL I - D = 15 - THETA = 1.1					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.91794	1.00000			
OUTPUT	0.96808	-0.88149	1.00000		
INVST	0.97768	-0.90463	0.92301	1.00000	
CONS	0.44252	-0.37394	0.63212	0.28531	1.00000
MODEL I - D = 15 - THETA = 1.15					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.92057	1.00000			
OUTPUT	0.97045	-0.88046	1.00000		
INVST	0.98848	-0.92028	0.94030	1.00000	
CONS	0.47523	-0.37947	0.66207	0.36747	1.00000
MODEL I - D = 15 - THETA = 1.2					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.93467	1.00000			
OUTPUT	0.97161	-0.89881	1.00000		
INVST	0.99316	-0.93470	0.94984	1.00000	
CONS	0.48349	-0.40935	0.66943	0.40354	1.00000
MODEL I - D = 15 - THETA = 1.25					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.92798	1.00000			
OUTPUT	0.97642	-0.89864	1.00000		
INVST	0.98765	-0.92045	0.94491	1.00000	
CONS	0.48333	-0.41817	0.64965	0.36503	1.00000
MODEL I - D = 15 - THETA = 1.3					
	EMP	UNEMP	OUTPUT	INVST	CONS
EMP	1.00000				
UNEMP	-0.93035	1.00000			
OUTPUT	0.97425	-0.89536	1.00000		
INVST	0.98920	-0.92228	0.94452	1.00000	
CONS	0.46507	-0.39665	0.64260	0.35527	1.00000

Table 6.30

ANNUAL	AUTOCORRELATIONS OF SIMULATED OUTPUT LEVEL					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL I - D = 5 - THETA = 1.1	0.6704	0.4653	0.3233	0.2702	0.2185	0.1875
MODEL I - D = 5 - THETA = 1.15	0.6683	0.4708	0.3458	0.3007	0.2542	0.2314
MODEL I - D = 5 - THETA = 1.2	0.6644	0.4757	0.3465	0.2961	0.2418	0.2197
MODEL I - D = 5 - THETA = 1.25	0.6661	0.4693	0.3431	0.2977	0.2458	0.2242
MODEL I - D = 5 - THETA = 1.3	0.6663	0.4755	0.3479	0.3049	0.2488	0.2237
MODEL I - D = 10 - THETA = 1.1	0.7704	0.6101	0.4849	0.4113	0.3376	0.2988
MODEL I - D = 10 - THETA = 1.15	0.7586	0.5982	0.4772	0.4108	0.3387	0.2959
MODEL I - D = 10 - THETA = 1.2	0.7596	0.5971	0.4725	0.4058	0.3354	0.2883
MODEL I - D = 10 - THETA = 1.25	0.7544	0.5898	0.4699	0.4035	0.3386	0.2960
MODEL I - D = 10 - THETA = 1.3	0.7518	0.5880	0.4680	0.4046	0.3352	0.2908
MODEL I - D = 15 - THETA = 1.1	0.8136	0.6737	0.5572	0.4824	0.4040	0.3523
MODEL I - D = 15 - THETA = 1.15	0.8069	0.6653	0.5530	0.4810	0.4093	0.3553
MODEL I - D = 15 - THETA = 1.2	0.8013	0.6537	0.5363	0.4636	0.3890	0.3375
MODEL I - D = 15 - THETA = 1.25	0.7942	0.6452	0.5299	0.4575	0.3851	0.3337
MODEL I - D = 15 - THETA = 1.3	0.7909	0.6420	0.5259	0.4553	0.3820	0.3327

Table 6.31

QUARTERLY	AUTOCORRELATIONS OF SIMULATED OUTPUT LEVEL					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL I - D = 5 - THETA = 1.1	0.8703	0.7423	0.6180	0.4995	0.3887	0.2877
MODEL I - D = 5 - THETA = 1.15	0.1257	0.0340	0.0599	0.0350	0.0368	0.0301
MODEL I - D = 5 - THETA = 1.2	0.2934	0.0940	0.1112	0.0961	0.0891	0.0707
MODEL I - D = 5 - THETA = 1.25	0.4203	0.1709	0.1112	0.0810	0.0682	0.0512
MODEL I - D = 5 - THETA = 1.3	0.4228	0.1787	0.1175	0.0819	0.0755	0.0623
MODEL I - D = 10 - THETA = 1.1	0.5400	0.2923	0.1966	0.1192	0.0870	0.0694
MODEL I - D = 10 - THETA = 1.15	0.5204	0.2611	0.1654	0.1134	0.0799	0.0678
MODEL I - D = 10 - THETA = 1.2	0.5420	0.3040	0.2088	0.1564	0.1298	0.1111
MODEL I - D = 10 - THETA = 1.25	0.5295	0.2890	0.1956	0.1412	0.1146	0.0931
MODEL I - D = 10 - THETA = 1.3	0.5319	0.2885	0.1955	0.1426	0.1200	0.1010
MODEL I - D = 15 - THETA = 1.1	0.6009	0.3526	0.2417	0.1691	0.1176	0.0929
MODEL I - D = 15 - THETA = 1.15	0.6066	0.3727	0.2638	0.1968	0.1575	0.1243
MODEL I - D = 15 - THETA = 1.2	0.5956	0.3580	0.2514	0.1874	0.1481	0.1195
MODEL I - D = 15 - THETA = 1.25	0.5984	0.3579	0.2400	0.1650	0.1256	0.0950
MODEL I - D = 15 - THETA = 1.3	0.6073	0.3753	0.2644	0.1962	0.1572	0.1251

Table 6.32

ANNUAL	AUTOCORRELATIONS OF SIMULATED OUTPUT GROWTH					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL I - D = 5 - THETA = 1.1	0.0539	-0.0855	0.0127	-0.0296	0.0097	-0.0145
MODEL I - D = 5 - THETA = 1.15	0.0523	-0.0805	0.0125	-0.0283	0.0094	-0.0138
MODEL I - D = 5 - THETA = 1.2	0.0522	-0.0759	0.0122	-0.0276	0.0090	-0.0137
MODEL I - D = 5 - THETA = 1.25	0.0439	-0.0611	0.0109	-0.0226	0.0076	-0.0115
MODEL I - D = 5 - THETA = 1.3	0.0423	-0.0557	0.0104	-0.0207	0.0072	-0.0105
MODEL I - D = 10 - THETA = 1.1	0.0537	-0.0811	0.0129	-0.0283	0.0097	-0.0136
MODEL I - D = 10 - THETA = 1.15	0.0536	-0.0767	0.0128	-0.0273	0.0094	-0.0134
MODEL I - D = 10 - THETA = 1.2	0.0456	-0.0610	0.0115	-0.0222	0.0080	-0.0115
MODEL I - D = 10 - THETA = 1.25	0.0436	-0.0538	0.0112	-0.0198	0.0076	-0.0103
MODEL I - D = 10 - THETA = 1.3	0.0427	-0.0507	0.0109	-0.0186	0.0073	-0.0097
MODEL I - D = 15 - THETA = 1.1	0.0553	-0.0810	0.0133	-0.0279	0.0099	-0.0136
MODEL I - D = 15 - THETA = 1.15	0.0478	-0.0637	0.0122	-0.0226	0.0087	-0.0114
MODEL I - D = 15 - THETA = 1.2	0.0457	-0.0560	0.0118	-0.0204	0.0080	-0.0105
MODEL I - D = 15 - THETA = 1.25	0.0448	-0.0515	0.0116	-0.0187	0.0078	-0.0096
MODEL I - D = 15 - THETA = 1.3	0.0430	-0.0460	0.0111	-0.0168	0.0073	-0.0091

Table 6.33

QUARTERLY	AUTOCORRELATIONS OF SIMULATED OUTPUT GROWTH					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL I - D = 5 - THETA = 1.1	0.1484	-0.0591	0.0123	-0.0108	0.0044	-0.0026
MODEL I - D = 5 - THETA = 1.15	0.1476	-0.0609	0.0127	-0.0113	0.0047	-0.0028
MODEL I - D = 5 - THETA = 1.2	0.1458	-0.0619	0.0131	-0.0116	0.0051	-0.0028
MODEL I - D = 5 - THETA = 1.25	0.1462	-0.0640	0.0130	-0.0123	0.0048	-0.0033
MODEL I - D = 5 - THETA = 1.3	0.1439	-0.0630	0.0129	-0.0123	0.0046	-0.0033
MODEL I - D = 10 - THETA = 1.1	0.1487	-0.0649	0.0133	-0.0123	0.0051	-0.0032
MODEL I - D = 10 - THETA = 1.15	0.1484	-0.0654	0.0132	-0.0125	0.0050	-0.0033
MODEL I - D = 10 - THETA = 1.2	0.1483	-0.0654	0.0131	-0.0126	0.0049	-0.0034
MODEL I - D = 10 - THETA = 1.25	0.1447	-0.0637	0.0129	-0.0124	0.0047	-0.0034
MODEL I - D = 10 - THETA = 1.3	0.1506	-0.0661	0.0130	-0.0127	0.0048	-0.0035
MODEL I - D = 15 - THETA = 1.1	0.1530	-0.0666	0.0133	-0.0129	0.0053	-0.0033
MODEL I - D = 15 - THETA = 1.15	0.1488	-0.0651	0.0131	-0.0124	0.0050	-0.0033
MODEL I - D = 15 - THETA = 1.2	0.1518	-0.0669	0.0131	-0.0128	0.0049	-0.0034
MODEL I - D = 15 - THETA = 1.25	0.1459	-0.0657	0.0128	-0.0131	0.0046	-0.0037
MODEL I - D = 15 - THETA = 1.3	0.1518	-0.0686	0.0129	-0.0137	0.0045	-0.0041

Table 6.34

DESCRIPTIVE STATISTICS FOR SIMULATED OUTPUT						ANNUAL
	Obs	Mean	St-Dev	MIN	MAX	CV
MODEL II - D = 5 - THETA = 1.1	1100	2.3625	0.0348	1.3721	2.3859	0.0147
MODEL II - D = 5 - THETA = 1.15	1100	2.2383	0.0345	1.3193	2.2697	0.0154
MODEL II - D = 5 - THETA = 1.2	1100	2.1285	0.0336	1.2729	2.1599	0.0158
MODEL II - D = 5 - THETA = 1.25	1100	2.0344	0.0329	1.2320	2.0677	0.0162
MODEL II - D = 5 - THETA = 1.3	1100	1.9520	0.0316	1.1957	1.9846	0.0162
MODEL II - D = 10 - THETA = 1.1	1100	2.3632	0.0382	1.3721	2.3869	0.0162
MODEL II - D = 10 - THETA = 1.15	1100	2.2364	0.0365	1.3193	2.2645	0.0163
MODEL II - D = 10 - THETA = 1.2	1100	2.1294	0.0354	1.2729	2.1665	0.0166
MODEL II - D = 10 - THETA = 1.25	1100	2.0336	0.0344	1.2320	2.0691	0.0169
MODEL II - D = 10 - THETA = 1.3	1100	1.9508	0.0337	1.1958	1.9914	0.0173
MODEL II - D = 15 - THETA = 1.1	1100	2.3616	0.0396	1.3721	2.3792	0.0168
MODEL II - D = 15 - THETA = 1.15	1100	2.2367	0.0380	1.3193	2.2688	0.0170
MODEL II - D = 15 - THETA = 1.2	1100	2.1281	0.0363	1.2729	2.1602	0.0171
MODEL II - D = 15 - THETA = 1.25	1100	2.0332	0.0352	1.2320	2.0735	0.0173
MODEL II - D = 15 - THETA = 1.3	1100	1.9506	0.0340	1.1957	1.9904	0.0175

Table 6.35

DESCRIPTIVE STATISTICS FOR SIMULATED OUTPUT						QUARTERLY
	Obs	Mean	St-Dev	MIN	MAX	CV
MODEL II - D = 5 - THETA = 1.1	1100	0.9725	0.0187	0.9469	1.3721	0.0193
MODEL II - D = 5 - THETA = 1.15	1100	0.9187	0.0201	0.8913	1.3193	0.0218
MODEL II - D = 5 - THETA = 1.2	1100	0.8711	0.0207	0.8369	1.2729	0.0237
MODEL II - D = 5 - THETA = 1.25	1100	0.8315	0.0184	0.7959	1.2320	0.0221
MODEL II - D = 5 - THETA = 1.3	1100	0.7975	0.0198	0.7634	1.1958	0.0249
MODEL II - D = 10 - THETA = 1.1	1100	0.9725	0.0187	0.9469	1.3721	0.0193
MODEL II - D = 10 - THETA = 1.15	1100	0.9183	0.0205	0.8845	1.3193	0.0223
MODEL II - D = 10 - THETA = 1.2	1100	0.8700	0.0208	0.8410	1.2729	0.0239
MODEL II - D = 10 - THETA = 1.25	1100	0.8305	0.0193	0.7925	1.2320	0.0232
MODEL II - D = 10 - THETA = 1.3	1100	0.8001	0.0188	0.7566	1.1958	0.0235
MODEL II - D = 15 - THETA = 1.1	1100	0.9711	0.0193	0.9400	1.3721	0.0199
MODEL II - D = 15 - THETA = 1.15	1100	0.9172	0.0206	0.8845	1.3193	0.0225
MODEL II - D = 15 - THETA = 1.2	1100	0.8694	0.0209	0.8341	1.2729	0.0241
MODEL II - D = 15 - THETA = 1.25	1100	0.8303	0.0200	0.7856	1.2320	0.0241
MODEL II - D = 15 - THETA = 1.3	1100	0.7993	0.0198	0.7498	1.1958	0.0248

Table 6.36

ANNUAL	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 5 - THETA = 1.1	0.01471	0.49288	0.78874	0.80662
MODEL II - D = 5 - THETA = 1.15	0.01540	0.61861	0.79824	0.87462
MODEL II - D = 5 - THETA = 1.2	0.01580	0.70018	0.81158	0.91292
MODEL II - D = 5 - THETA = 1.25	0.01615	0.78216	0.83136	0.97700
MODEL II - D = 5 - THETA = 1.3	0.01618	0.89325	0.87516	1.03098

Table 6.37

ANNUAL	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 10 - THETA = 1.1	0.01616	0.74219	0.82849	0.53436
MODEL II - D = 10 - THETA = 1.15	0.01633	0.81416	0.85198	0.58730
MODEL II - D = 10 - THETA = 1.2	0.01663	0.88952	0.87491	0.65895
MODEL II - D = 10 - THETA = 1.25	0.01691	0.95843	0.89695	0.72126
MODEL II - D = 10 - THETA = 1.3	0.01728	1.02536	0.91870	0.75539

Table 6.38

ANNUAL	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 15 - THETA = 1.1	0.01676	0.77755	0.82979	0.42975
MODEL II - D = 15 - THETA = 1.15	0.01700	0.85300	0.85426	0.48851
MODEL II - D = 15 - THETA = 1.2	0.01707	0.90052	0.87408	0.53059
MODEL II - D = 15 - THETA = 1.25	0.01731	0.96991	0.89884	0.59509
MODEL II - D = 15 - THETA = 1.3	0.01745	1.03225	0.92537	0.64171

Table 6.39

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 5 - THETA = 1.1	0.01925	0.44854	0.95076	1.05351
MODEL II - D = 5 - THETA = 1.15	0.02183	0.39552	0.83894	1.04216
MODEL II - D = 5 - THETA = 1.2	0.02372	0.45902	0.79260	1.07527
MODEL II - D = 5 - THETA = 1.25	0.02214	0.72272	0.90264	1.30005
MODEL II - D = 5 - THETA = 1.3	0.02486	0.66825	0.80398	1.12970

Table 6.40

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 10 - THETA = 1.2	0.02386	0.56452	0.81555	1.05845
MODEL II - D = 10 - THETA = 1.25	0.02325	0.83677	0.91062	1.32669
MODEL II - D = 10 - THETA = 1.3	0.02346	1.02233	0.96987	1.35236

Table 6.41

QUARTERLY	St-Dev OUTPUT	St-DEV RELATIVE TO OUTPUT EMP	CONS	APN
MODEL II - D = 15 - THETA = 1.1	0.01989	0.58273	0.95526	1.07666
MODEL II - D = 15 - THETA = 1.15	0.02248	0.58303	0.86254	1.07730
MODEL II - D = 15 - THETA = 1.2	0.02409	0.67845	0.84438	1.13547
MODEL II - D = 15 - THETA = 1.25	0.02412	0.91168	0.91699	1.35331
MODEL II - D = 15 - THETA = 1.3	0.02481	1.09027	0.96979	1.35352

Table 6.42

CORRELATION MATRIX — ANNUAL

MODEL II - D = 5 - THETA = 1.1

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7658	1.0000					
APN	0.3783	-0.7638	1.0000				
OUTPUT	0.7246	-0.8899	0.9108	1.0000			
C1	0.1359	-0.1853	-0.2296	-0.1379	1.0000		
C2	0.5770	-0.7015	0.8810	0.9229	-0.5087	1.0000	
CONS	0.7621	-0.9425	0.8162	0.9366	0.2179	0.7294	1.0000

MODEL II - D = 5 - THETA = 1.15

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.6555	1.0000					
APN	0.0184	-0.5929	1.0000				
OUTPUT	0.5844	-0.8298	0.8205	1.0000			
C1	0.1467	-0.1255	-0.3519	-0.2306	1.0000		
C2	0.3673	-0.5632	0.7970	0.8713	-0.6784	1.0000	
CONS	0.6519	-0.8895	0.6719	0.9054	0.2044	0.5804	1.0000

MODEL II - D = 5 - THETA = 1.2

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.6691	1.0000					
APN	-0.1343	-0.4397	1.0000				
OUTPUT	0.5379	-0.7832	0.7615	1.0000			
C1	0.1037	-0.1035	-0.3666	-0.2726	1.0000		
C2	0.3000	-0.4644	0.7234	0.8285	-0.7646	1.0000	
CONS	0.5976	-0.8484	0.6111	0.8980	0.1785	0.4977	1.0000

MODEL II - D = 5 - THETA = 1.25

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7014	1.0000					
APN	-0.2774	-0.2789	1.0000				
OUTPUT	0.4800	-0.7420	0.7082	1.0000			
C1	0.1084	-0.0842	-0.3699	-0.2848	1.0000		
C2	0.2183	-0.3915	0.6646	0.7850	-0.8174	1.0000	
CONS	0.5430	-0.8028	0.5684	0.9069	0.1457	0.4509	1.0000

Table 6.43

MODEL II - D = 5 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7354	1.0000					
APN	-0.3934	-0.1167	1.0000				
OUTPUT	0.4642	-0.7061	0.6304	1.0000			
C1	0.0662	-0.0755	-0.2717	-0.2293	1.0000		
C2	0.2040	-0.3286	0.5390	0.7089	-0.8490	1.0000	
CONS	0.4967	-0.7457	0.5322	0.9238	0.1609	0.3848	1.0000

Table 6.44

CORRELATION MATRIX ANNUAL

MODEL II - D = 10 - THETA = 1.1

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.8410	1.0000					
APN	0.4530	-0.7344	1.0000				
OUTPUT	0.9011	-0.9126	0.7927	1.0000			
C1	0.4058	-0.3310	-0.0964	0.2160	1.0000		
C2	0.8120	-0.8440	0.8370	0.9645	-0.0494	1.0000	
CONS	0.9259	-0.9218	0.7244	0.9809	0.4016	0.8948	1.0000

MODEL II - D = 10 - THETA = 1.15

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7905	1.0000					
APN	0.1725	-0.5804	1.0000				
OUTPUT	0.8459	-0.8898	0.6693	1.0000			
C1	0.3015	-0.2461	-0.1521	0.1320	1.0000		
C2	0.7161	-0.7796	0.7116	0.9299	-0.2419	1.0000	
CONS	0.8673	-0.8957	0.5955	0.9732	0.3565	0.8203	1.0000

MODEL II - D = 10 - THETA = 1.2

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7247	1.0000					
APN	-0.0611	-0.4576	1.0000				
OUTPUT	0.7929	-0.8591	0.5580	1.0000			
C1	0.2406	-0.2108	-0.1480	0.0969	1.0000		
C2	0.6322	-0.7077	0.5894	0.8913	-0.3649	1.0000	
CONS	0.8093	-0.8651	0.4941	0.9716	0.3297	0.7587	1.0000

MODEL II - D = 10 - THETA = 1.25

	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.6963	1.0000					
APN	-0.2183	-0.3366	1.0000				
OUTPUT	0.7547	-0.8305	0.4739	1.0000			
C1	0.2210	-0.1742	-0.1875	0.0609	1.0000		
C2	0.5355	-0.6270	0.5152	0.8367	-0.4957	1.0000	
CONS	0.7748	-0.8361	0.4085	0.9712	0.2971	0.6820	1.0000

Table 6.45

MODEL II - D = 10 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.6784	1.0000					
APN	-0.3236	-0.2252	1.0000				
OUTPUT	0.7431	-0.7949	0.3915	1.0000			
C1	0.1734	-0.1486	-0.1365	0.0613	1.0000		
C2	0.5108	-0.5691	0.4084	0.7926	-0.5600	1.0000	
CONS	0.7535	-0.7985	0.3499	0.9785	0.2658	0.6498	1.0000

Table 6.46

CORRELATION MATRIX				ANNUAL			
MODEL II - D = 15 - THETA = 1.1							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.8897	1.0000					
APN	0.5786	-0.7718	1.0000				
OUTPUT	0.9473	-0.9301	0.8073	1.0000			
C1	0.4248	-0.4264	0.1121	0.3399	1.0000		
C2	0.9050	-0.8865	0.8255	0.9789	0.1404	1.0000	
CONS	0.9531	-0.9372	0.7735	0.9893	0.4734	0.9386	1.0000
MODEL II - D = 15 - THETA = 1.15							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.8149	1.0000					
APN	0.2225	-0.5796	1.0000				
OUTPUT	0.8979	-0.8945	0.6271	1.0000			
C1	0.3915	-0.3161	-0.1450	0.2370	1.0000		
C2	0.8000	-0.8201	0.6892	0.9531	-0.0683	1.0000	
CONS	0.9163	-0.8992	0.5625	0.9837	0.4079	0.8830	1.0000
MODEL II - D = 15 - THETA = 1.2							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7857	1.0000					
APN	0.0420	-0.4663	1.0000				
OUTPUT	0.8688	-0.8796	0.5296	1.0000			
C1	0.2791	-0.2589	-0.1458	0.1544	1.0000		
C2	0.7397	-0.7584	0.5775	0.9183	-0.2492	1.0000	
CONS	0.8806	-0.8869	0.4738	0.9803	0.3464	0.8222	1.0000
MODEL II - D = 15 - THETA = 1.25							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7384	1.0000					
APN	-0.1547	-0.3346	1.0000				
OUTPUT	0.8338	-0.8474	0.4151	1.0000			
C1	0.2739	-0.2180	-0.1790	0.1436	1.0000		
C2	0.6601	-0.6998	0.4797	0.8803	-0.3430	1.0000	
CONS	0.8483	-0.8505	0.3620	0.9820	0.3280	0.7749	1.0000

Table 6.47

MODEL II - D = 15 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.7182	1.0000					
APN	-0.2836	-0.2399	1.0000				
OUTPUT	0.8138	-0.8357	0.3253	1.0000			
C1	0.2425	-0.1909	-0.1251	0.1568	1.0000		
C2	0.6115	-0.6607	0.3696	0.8309	-0.4192	1.0000	
CONS	0.8218	-0.8339	0.2906	0.9857	0.3212	0.7251	1.0000

Table 6.48

CORRELATION MATRIX				QUARTERLY			
MODEL II - D = 5 - THETA = 1.1							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9303	1.0000					
APN	-0.3316	0.3722	1.0000				
OUTPUT	0.1081	-0.0355	0.9020	1.0000			
C1	0.0501	-0.0255	-0.1777	-0.1638	1.0000		
C2	0.0328	-0.0045	0.6834	0.7347	-0.7896	1.0000	
CONS	0.1247	-0.0475	0.6084	0.6986	0.5914	0.0280	1.0000
MODEL II - D = 5 - THETA = 1.15							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9102	1.0000					
APN	-0.2967	0.3436	1.0000				
OUTPUT	0.0942	-0.0111	0.9228	1.0000			
C1	0.0407	-0.0130	-0.3770	-0.3762	1.0000		
C2	0.0208	0.0032	0.7345	0.7739	-0.8779	1.0000	
CONS	0.1235	-0.0213	0.5732	0.6479	0.4621	0.0189	1.0000
MODEL II - D = 5 - THETA = 1.2							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9301	1.0000					
APN	-0.3795	0.3833	1.0000				
OUTPUT	0.0677	-0.0306	0.8972	1.0000			
C1	0.1122	-0.0155	-0.4801	-0.4596	1.0000		
C2	-0.0491	-0.0028	0.7447	0.7765	-0.9165	1.0000	
CONS	0.1661	-0.0451	0.5318	0.6568	0.3679	0.0348	1.0000
MODEL II - D = 5 - THETA = 1.25							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.8716	1.0000					
APN	-0.6501	0.4527	1.0000				
OUTPUT	-0.1050	-0.0658	0.8237	1.0000			
C1	0.4224	-0.0232	-0.5308	-0.3853	1.0000		
C2	-0.3780	-0.0049	0.7226	0.6684	-0.9439	1.0000	
CONS	0.2580	-0.0822	0.3328	0.6235	0.4812	-0.1648	1.0000

Table 6.49

MODEL II - D = 5 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9423	1.0000					
APN	-0.4791	0.5541	1.0000				
OUTPUT	0.1545	-0.0351	0.7930	1.0000			
C1	0.0230	-0.0188	-0.4373	-0.4780	1.0000		
C2	0.0328	0.0034	0.6117	0.7128	-0.9567	1.0000	
CONS	0.1883	-0.0533	0.5369	0.7339	0.2459	0.0467	1.0000

Table 6.50

CORRELATION MATRIX				QUARTERLY			
MODEL II - D = 10 - THETA = 1.1							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9303	1.0000					
APN	-0.3316	0.3722	1.0000				
OUTPUT	0.1081	-0.0355	0.9020	1.0000			
C1	0.0501	-0.0255	-0.1777	-0.1638	1.0000		
C2	0.0328	-0.0045	0.6834	0.7347	-0.7896	1.0000	
CONS	0.1247	-0.0475	0.6084	0.6986	0.5914	0.0280	1.0000
MODEL II - D = 10 - THETA = 1.15							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9653	1.0000					
APN	-0.4019	0.3735	1.0000				
OUTPUT	0.0574	-0.0700	0.8910	1.0000			
C1	0.0817	-0.0289	-0.3663	-0.3586	1.0000		
C2	-0.0251	-0.0175	0.7209	0.7735	-0.8690	1.0000	
CONS	0.1198	-0.0899	0.5602	0.6704	0.4523	0.0482	1.0000
MODEL II - D = 10 - THETA = 1.2							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9024	1.0000					
APN	-0.3776	0.4611	1.0000				
OUTPUT	0.1797	-0.0397	0.8429	1.0000			
C1	0.0690	-0.0280	-0.4347	-0.4178	1.0000		
C2	0.0341	0.0016	0.7007	0.7615	-0.9070	1.0000	
CONS	0.2386	-0.0630	0.5071	0.6806	0.3812	0.0435	1.0000
MODEL II - D = 10 - THETA = 1.25							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9102	1.0000					
APN	-0.6606	0.5312	1.0000				
OUTPUT	-0.0083	-0.0960	0.7558	1.0000			
C1	0.3270	-0.0398	-0.4603	-0.3384	1.0000		
C2	-0.2658	-0.0048	0.6591	0.6547	-0.9329	1.0000	
CONS	0.2479	-0.1215	0.3515	0.6768	0.4636	-0.1134	1.0000

Table 6.51

MODEL II - D = 10 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9113	1.0000					
APN	-0.6778	0.6569	1.0000				
OUTPUT	0.1525	-0.1020	0.6225	1.0000			
C1	0.3050	-0.0307	-0.3766	-0.1991	1.0000		
C2	-0.2069	-0.0109	0.5517	0.5369	-0.9336	1.0000	
CONS	0.3303	-0.1125	0.3335	0.7897	0.4440	-0.0935	1.0000

Table 6.52

CORRELATION MATRIX			QUARTERLY				
MODEL II - D = 15 - THETA = 1.1							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.8977	1.0000					
APN	-0.3973	0.3909	1.0000				
OUTPUT	0.1701	-0.1176	0.8366	1.0000			
C1	0.0978	-0.0567	-0.1606	-0.1133	1.0000		
C2	0.0446	-0.0383	0.6586	0.7333	-0.7586	1.0000	
CONS	0.2049	-0.1343	0.5711	0.7362	0.5890	0.0797	1.0000
MODEL II - D = 15 - THETA = 1.15							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9547	1.0000					
APN	-0.4005	0.4117	1.0000				
OUTPUT	0.1675	-0.1301	0.8362	1.0000			
C1	0.0567	-0.0610	-0.3199	-0.3109	1.0000		
C2	0.0528	-0.0294	0.6763	0.7598	-0.8541	1.0000	
CONS	0.1986	-0.1672	0.5367	0.6959	0.4662	0.0619	1.0000
MODEL II - D = 15 - THETA = 1.2							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9426	1.0000					
APN	-0.4931	0.4698	1.0000				
OUTPUT	0.1475	-0.1347	0.7875	1.0000			
C1	0.0840	-0.0483	-0.3745	-0.3651	1.0000		
C2	0.0100	-0.0296	0.6465	0.7413	-0.8955	1.0000	
CONS	0.2089	-0.1692	0.4881	0.7041	0.4040	0.0453	1.0000
MODEL II - D = 15 - THETA = 1.25							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9353	1.0000					
APN	-0.6728	0.5352	1.0000				
OUTPUT	0.0432	-0.1750	0.7093	1.0000			
C1	0.3237	-0.0535	-0.4452	-0.3055	1.0000		
C2	-0.2423	-0.0272	0.6412	0.6456	-0.9244	1.0000	
CONS	0.2803	-0.2033	0.3333	0.7086	0.4554	-0.0814	1.0000

Table 6.53

MODEL II - D = 15 - THETA = 1.3							
	EMP	UNEMP	APN	OUTPUT	C1	C2	CONS
EMP	1.0000						
UNEMP	-0.9210	1.0000					
APN	-0.6820	0.6746	1.0000				
OUTPUT	0.2214	-0.1575	0.5611	1.0000			
C1	0.3109	-0.0435	-0.3765	-0.1689	1.0000		
C2	-0.1809	-0.0238	0.5410	0.5332	-0.9239	1.0000	
CONS	0.3852	-0.1696	0.2918	0.8152	0.4332	-0.0554	1.0000

Table 6.54

ANNUAL	AUTOCORRELATIONS OF SIMULATED OUTPUT LEVEL					
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.6605	0.1712	-0.2409	-0.4043	-0.4812	-0.4467
MODEL II - D = 5 - THETA = 1.1	0.3649	0.1563	0.0707	0.0419	0.0295	0.0149
MODEL II - D = 5 - THETA = 1.15	0.3899	0.1719	0.0994	0.0691	0.0525	0.0324
MODEL II - D = 5 - THETA = 1.2	0.3972	0.1724	0.0873	0.0671	0.0541	0.0328
MODEL II - D = 5 - THETA = 1.25	0.3880	0.1710	0.0909	0.0732	0.0578	0.0335
MODEL II - D = 5 - THETA = 1.3	0.3808	0.1839	0.0968	0.0794	0.0605	0.0404
MODEL II - D = 10 - THETA = 1.1	0.5759	0.3517	0.2198	0.1422	0.0945	0.0615
MODEL II - D = 10 - THETA = 1.15	0.5810	0.3611	0.2313	0.1469	0.0923	0.0604
MODEL II - D = 10 - THETA = 1.2	0.5786	0.3594	0.2312	0.1567	0.1042	0.0695
MODEL II - D = 10 - THETA = 1.25	0.5759	0.3494	0.2154	0.1479	0.0946	0.0619
MODEL II - D = 10 - THETA = 1.3	0.5818	0.3544	0.2254	0.1544	0.1017	0.0692
MODEL II - D = 15 - THETA = 1.1	0.6327	0.4171	0.2844	0.1943	0.1365	0.0933
MODEL II - D = 15 - THETA = 1.15	0.6357	0.4207	0.2844	0.1934	0.1320	0.0910
MODEL II - D = 15 - THETA = 1.2	0.6380	0.4208	0.2865	0.1987	0.1382	0.0966
MODEL II - D = 15 - THETA = 1.25	0.6339	0.4161	0.2836	0.2019	0.1422	0.0995
MODEL II - D = 15 - THETA = 1.3	0.6338	0.4183	0.2841	0.2043	0.1436	0.1021

Table 6.55

ANNUAL	AUTOCORRELATIONS OF SIMULATED OUTPUT GROWTH					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL II - D = 5 - THETA = 1.1	0.1447	-0.0737	0.0143	-0.0156	0.0060	-0.0046
MODEL II - D = 5 - THETA = 1.15	0.1515	-0.0737	0.0141	-0.0152	0.0059	-0.0045
MODEL II - D = 5 - THETA = 1.2	0.1530	-0.0708	0.0138	-0.0143	0.0053	-0.0043
MODEL II - D = 5 - THETA = 1.25	0.1559	-0.0694	0.0136	-0.0138	0.0051	-0.0040
MODEL II - D = 5 - THETA = 1.3	0.1588	-0.0678	0.0134	-0.0132	0.0048	-0.0038
MODEL II - D = 10 - THETA = 1.1	0.1756	-0.0909	0.0147	-0.0179	0.0072	-0.0050
MODEL II - D = 10 - THETA = 1.15	0.1837	-0.0908	0.0143	-0.0173	0.0067	-0.0048
MODEL II - D = 10 - THETA = 1.2	0.1873	-0.0881	0.0141	-0.0163	0.0063	-0.0047
MODEL II - D = 10 - THETA = 1.25	0.1879	-0.0842	0.0139	-0.0154	0.0059	-0.0043
MODEL II - D = 10 - THETA = 1.3	0.1975	-0.0860	0.0134	-0.0150	0.0058	-0.0041
MODEL II - D = 15 - THETA = 1.1	0.1876	-0.0961	0.0147	-0.0182	0.0075	-0.0049
MODEL II - D = 15 - THETA = 1.15	0.1911	-0.0930	0.0144	-0.0171	0.0070	-0.0047
MODEL II - D = 15 - THETA = 1.2	0.1955	-0.0906	0.0141	-0.0163	0.0067	-0.0043
MODEL II - D = 15 - THETA = 1.25	0.2003	-0.0889	0.0137	-0.0155	0.0064	-0.0041
MODEL II - D = 15 - THETA = 1.3	0.2032	-0.0864	0.0135	-0.0147	0.0060	-0.0037

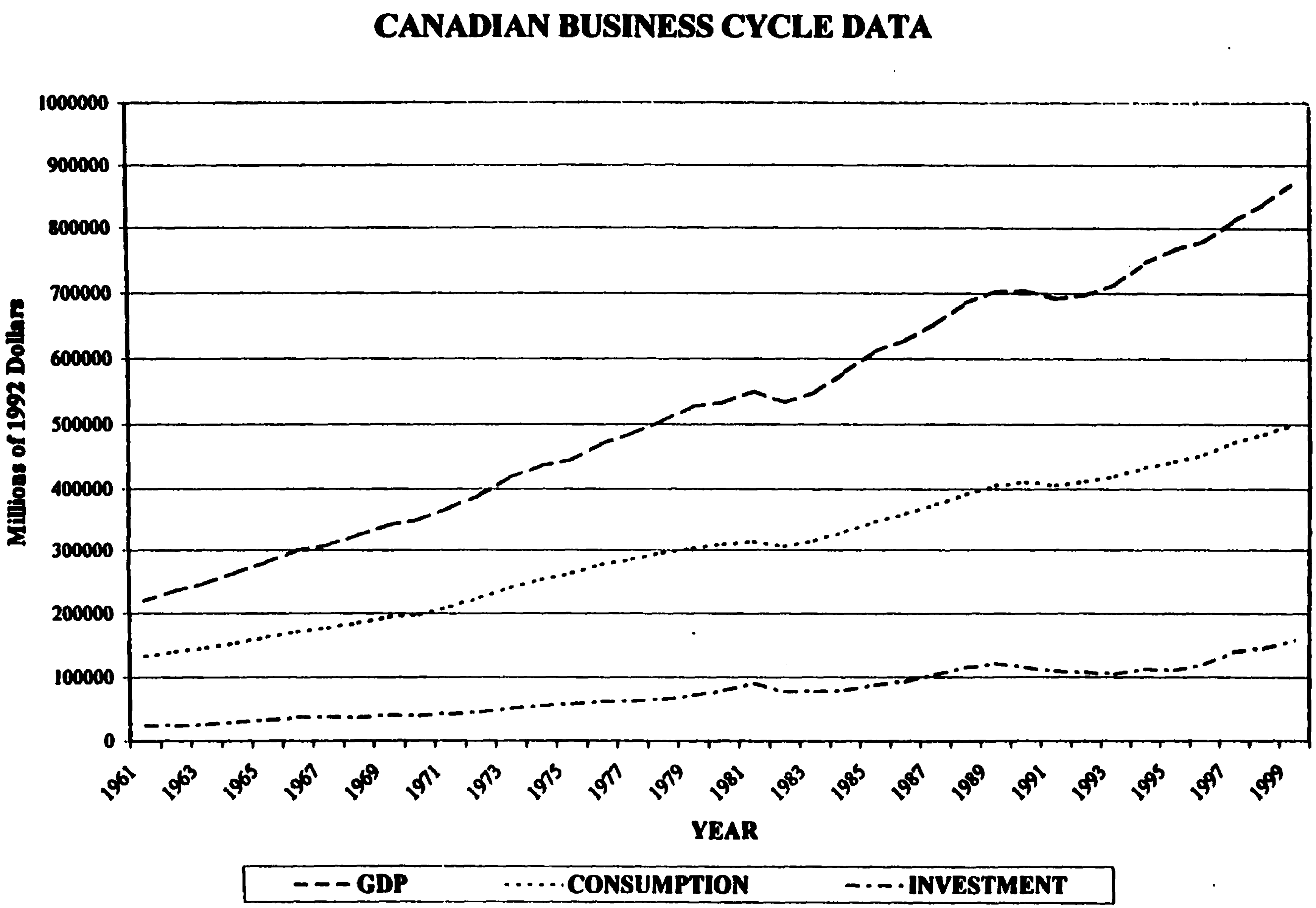
Table 6.56

QUARTERLY	AUTOCORRELATIONS OF SIMULATED OUTPUT LEVEL					
	K=1	K=2	K=3	K=4	K=5	K=6
GDP	0.8890	0.7068	0.5144	0.3099	0.1427	0.0063
MODEL II - D = 5 - THETA = 1.1	0.4649	0.3722	0.3108	0.2655	0.2237	0.1902
MODEL II - D = 5 - THETA = 1.15	0.5141	0.4201	0.3511	0.2999	0.2527	0.2157
MODEL II - D = 5 - THETA = 1.2	0.5077	0.4111	0.3440	0.2952	0.2496	0.2143
MODEL II - D = 5 - THETA = 1.25	0.4052	0.2955	0.2248	0.1929	0.1659	0.1386
MODEL II - D = 5 - THETA = 1.3	0.4631	0.3576	0.2798	0.2341	0.2047	0.1723
MODEL II - D = 10 - THETA = 1.1	0.4649	0.3722	0.3108	0.2655	0.2237	0.1902
MODEL II - D = 10 - THETA = 1.15	0.4977	0.3986	0.3328	0.2846	0.2401	0.2045
MODEL II - D = 10 - THETA = 1.2	0.5335	0.4253	0.3427	0.2890	0.2503	0.2141
MODEL II - D = 10 - THETA = 1.25	0.3947	0.2995	0.2144	0.1624	0.1417	0.1213
MODEL II - D = 10 - THETA = 1.3	0.3407	0.2142	0.1330	0.0890	0.0814	0.0692
MODEL II - D = 15 - THETA = 1.1	0.4688	0.3661	0.2899	0.2427	0.2089	0.1797
MODEL II - D = 15 - THETA = 1.15	0.5231	0.4199	0.3363	0.2826	0.2445	0.2068
MODEL II - D = 15 - THETA = 1.2	0.4979	0.4240	0.3406	0.2931	0.2554	0.2198
MODEL II - D = 15 - THETA = 1.25	0.3895	0.2420	0.1923	0.1462	0.1285	0.1083
MODEL II - D = 15 - THETA = 1.3	0.3684	0.1982	0.1182	0.0805	0.0701	0.0610

Table 6.57

QUARTERLY	AUTOCORRELATIONS OF SIMULATED OUTPUT GROWTH					
	K=1	K=2	K=3	K=4	K=5	K=6
MODEL II - D = 5 - THETA = 1.1	0.2188	-0.0418	0.0078	-0.0039	0.0024	0.0000
MODEL II - D = 5 - THETA = 1.15	0.2270	-0.0397	0.0074	-0.0032	0.0025	0.0004
MODEL II - D = 5 - THETA = 1.2	0.2329	-0.0385	0.0066	-0.0031	0.0020	0.0002
MODEL II - D = 5 - THETA = 1.25	0.2398	-0.0370	0.0061	-0.0027	0.0019	0.0003
MODEL II - D = 5 - THETA = 1.3	0.2465	-0.0352	0.0059	-0.0021	0.0021	0.0006
MODEL II - D = 10 - THETA = 1.1	0.2188	-0.0418	0.0078	-0.0039	0.0024	0.0000
MODEL II - D = 10 - THETA = 1.15	0.2270	-0.0397	0.0074	-0.0032	0.0024	0.0004
MODEL II - D = 10 - THETA = 1.2	0.2329	-0.0386	0.0066	-0.0032	0.0020	0.0001
MODEL II - D = 10 - THETA = 1.25	0.2397	-0.0370	0.0060	-0.0028	0.0018	0.0002
MODEL II - D = 10 - THETA = 1.3	0.2438	-0.0364	0.0053	-0.0030	0.0014	-0.0001
MODEL II - D = 15 - THETA = 1.1	0.2187	-0.0419	0.0077	-0.0040	0.0023	-0.0001
MODEL II - D = 15 - THETA = 1.15	0.2269	-0.0398	0.0073	-0.0033	0.0024	0.0003
MODEL II - D = 15 - THETA = 1.2	0.2327	-0.0386	0.0065	-0.0032	0.0020	0.0001
MODEL II - D = 15 - THETA = 1.25	0.2397	-0.0371	0.0060	-0.0028	0.0018	0.0002
MODEL II - D = 15 - THETA = 1.3	0.2438	-0.0365	0.0052	-0.0030	0.0014	-0.0002

1/



CANADIAN BUSINESS CYCLE DATA
Millions of 1992 Dollars
1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
1961
1963
1965
1967
1969
1971
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
YEAR
GDP
CONSUMPTION
INVESTMENT

Figure 6.1

AUTOCORRELATION of OUTPUT - ANNUAL

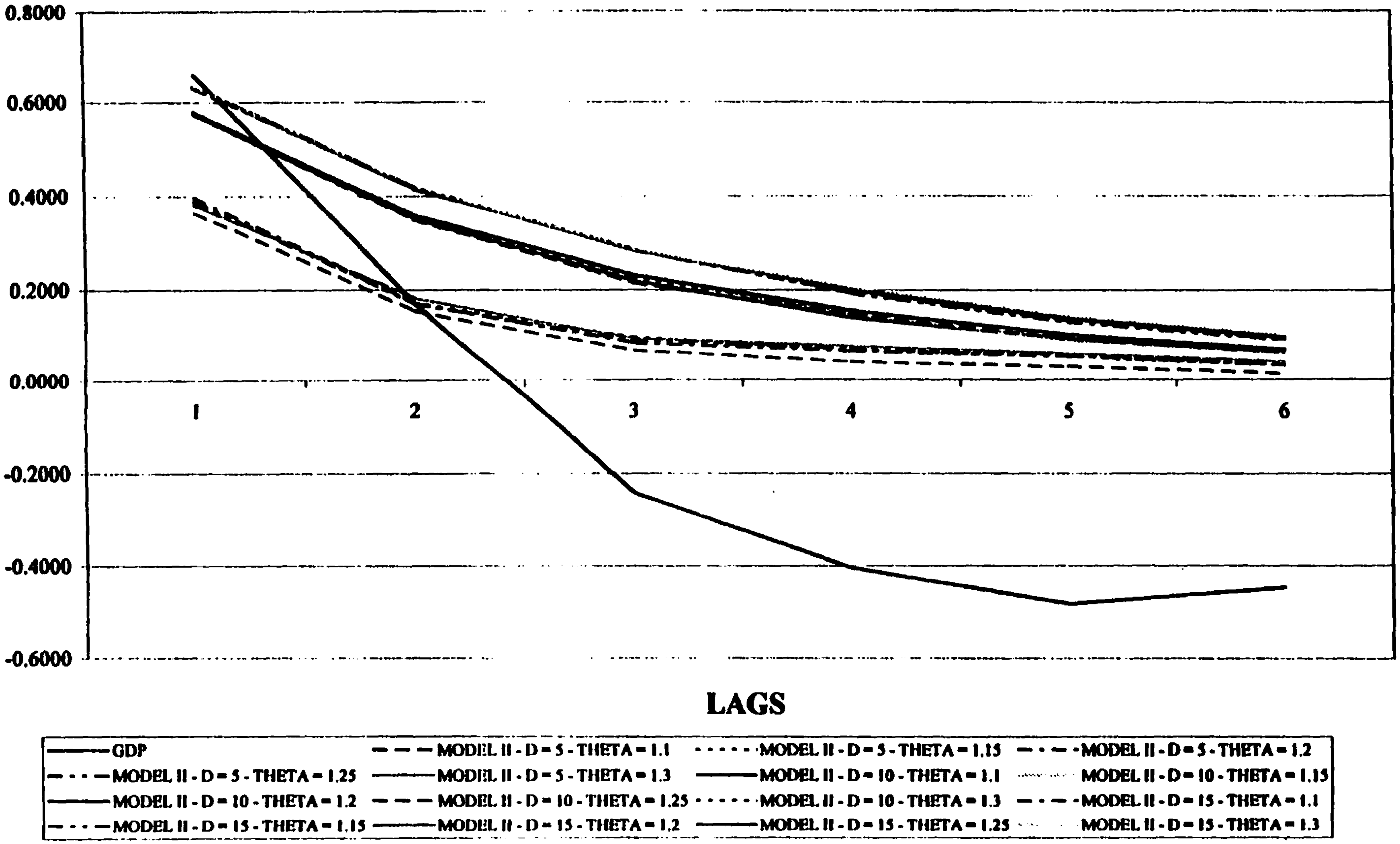


Figure 6.2

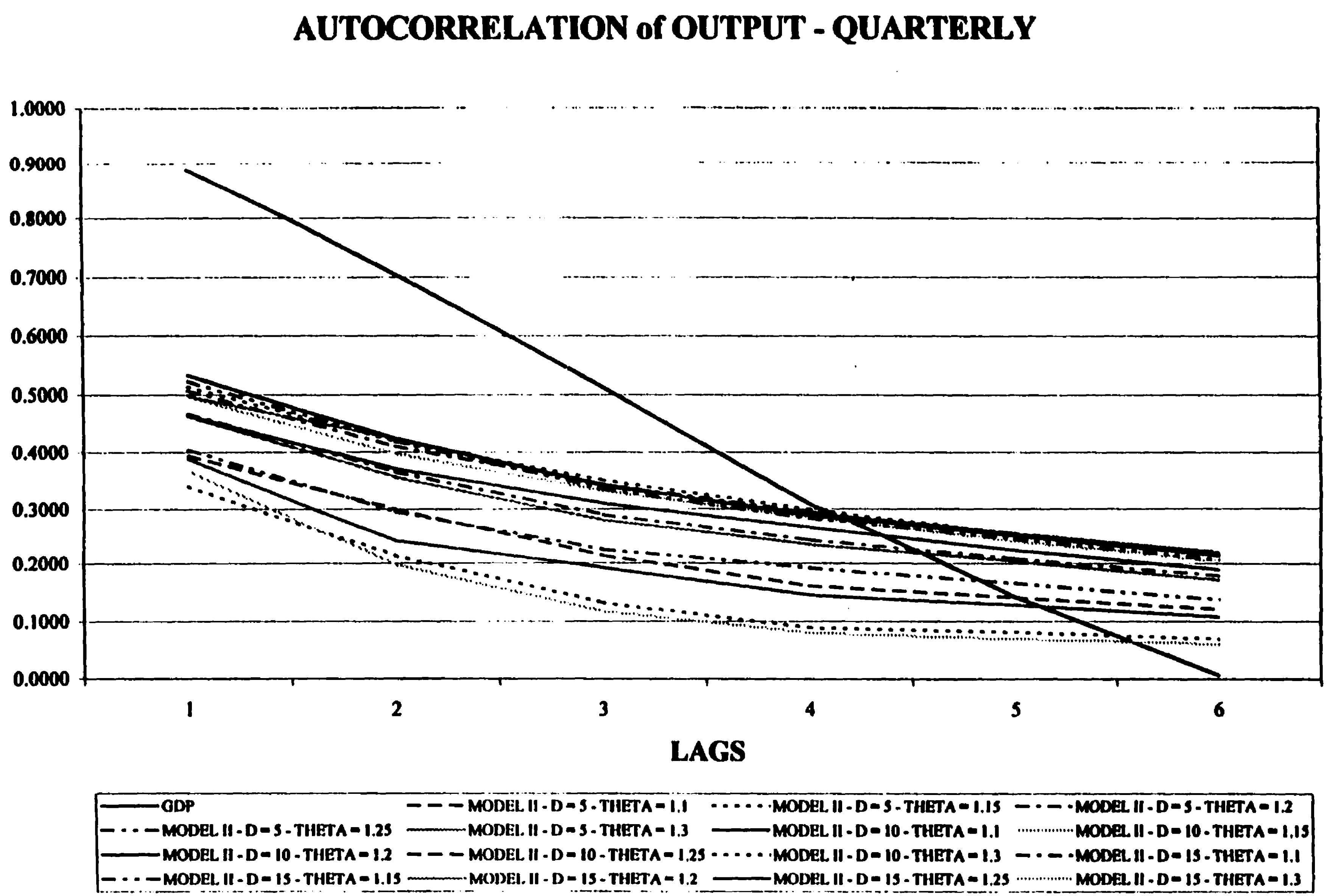
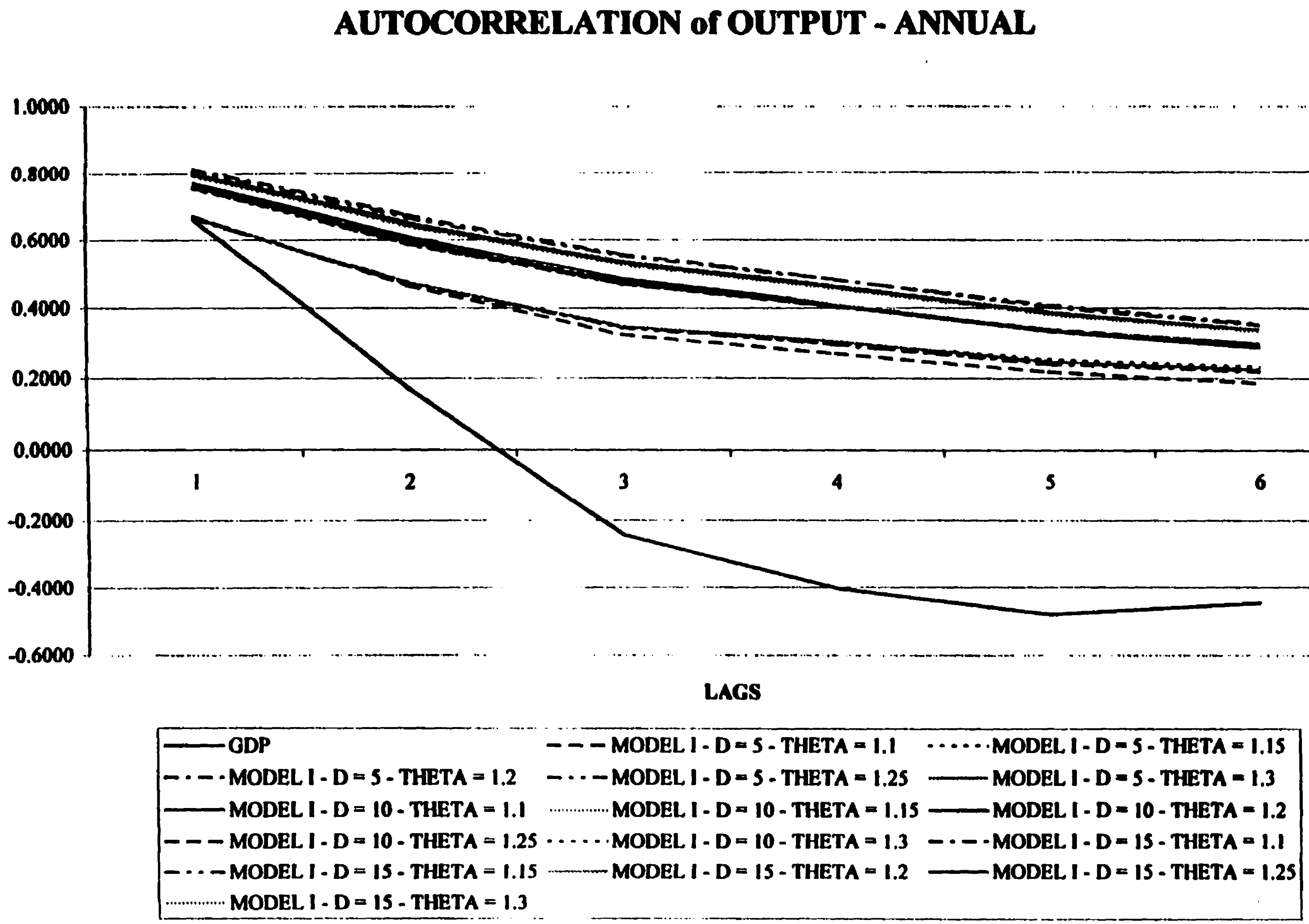

AUTOCORRELATION of OUTPUT - QUARTERLY
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
1
2
3
4
5
6
LAGS
GDP
MODEL II - D = 5 - THETA = 1.1
MODEL II - D = 5 - THETA = 1.15
MODEL II - D = 5 - THETA = 1.2
MODEL II - D = 5 - THETA = 1.25
MODEL II - D = 5 - THETA = 1.3
MODEL II - D = 10 - THETA = 1.1
MODEL II - D = 10 - THETA = 1.15
MODEL II - D = 10 - THETA = 1.2
MODEL II - D = 10 - THETA = 1.25
MODEL II - D = 10 - THETA = 1.3
MODEL II - D = 15 - THETA = 1.1
MODEL II - D = 15 - THETA = 1.15
MODEL II - D = 15 - THETA = 1.2
MODEL II - D = 15 - THETA = 1.25
MODEL II - D = 15 - THETA = 1.3

Figure 6.3



AUTOCORRELATION of OUTPUT - ANNUAL
1.0000
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1
2
3
4
5
6
LAGS
GDP
MODEL I - D = 5 - THETA = 1.1
MODEL I - D = 5 - THETA = 1.15
MODEL I - D = 5 - THETA = 1.2
MODEL I - D = 5 - THETA = 1.25
MODEL I - D = 5 - THETA = 1.3
MODEL I - D = 10 - THETA = 1.1
MODEL I - D = 10 - THETA = 1.15
MODEL I - D = 10 - THETA = 1.2
MODEL I - D = 10 - THETA = 1.25
MODEL I - D = 10 - THETA = 1.3
MODEL I - D = 15 - THETA = 1.1
MODEL I - D = 15 - THETA = 1.15
MODEL I - D = 15 - THETA = 1.2
MODEL I - D = 15 - THETA = 1.25
MODEL I - D = 15 - THETA = 1.3

Figure 6.4

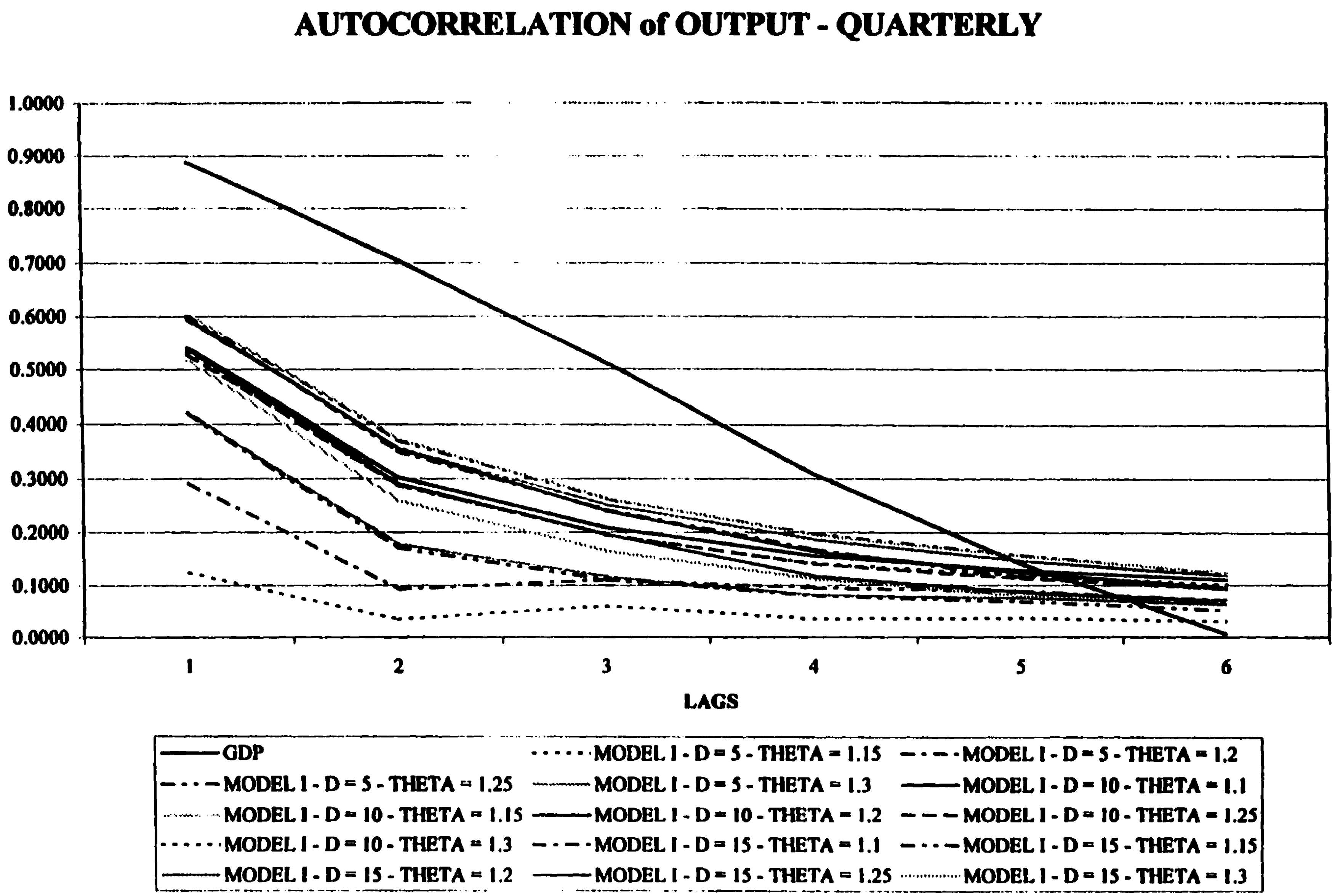

AUTOCORRELATION of OUTPUT - QUARTERLY
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
1
2
3
4
5
6
LAGS
GDP
MODEL 1 - D = 5 - THETA = 1.15
MODEL 1 - D = 5 - THETA = 1.2
MODEL 1 - D = 5 - THETA = 1.25
MODEL 1 - D = 5 - THETA = 1.3
MODEL 1 - D = 10 - THETA = 1.1
MODEL 1 - D = 10 - THETA = 1.15
MODEL 1 - D = 10 - THETA = 1.2
MODEL 1 - D = 10 - THETA = 1.25
MODEL 1 - D = 10 - THETA = 1.3
MODEL 1 - D = 15 - THETA = 1.1
MODEL 1 - D = 15 - THETA = 1.15
MODEL 1 - D = 15 - THETA = 1.2
MODEL 1 - D = 15 - THETA = 1.25
MODEL 1 - D = 15 - THETA = 1.3

Figure 6.5

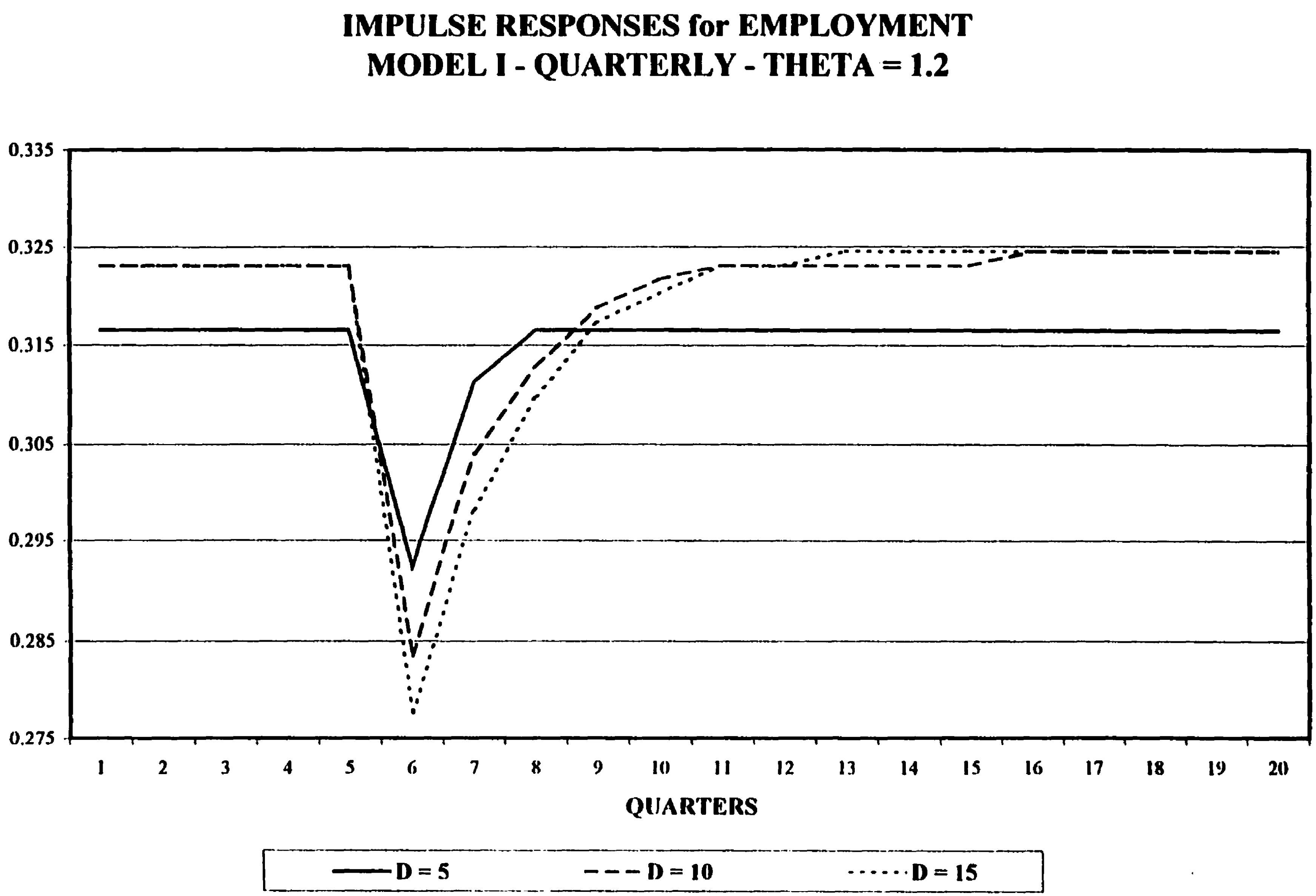

IMPULSE RESPONSES for EMPLOYMENT
MODEL I - QUARTERLY - THETA = 1.2
0.335
0.325
0.315
0.305
0.295
0.285
0.275
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
QUARTERS
D = 5
D = 10
D = 15

Figure 6.6

7

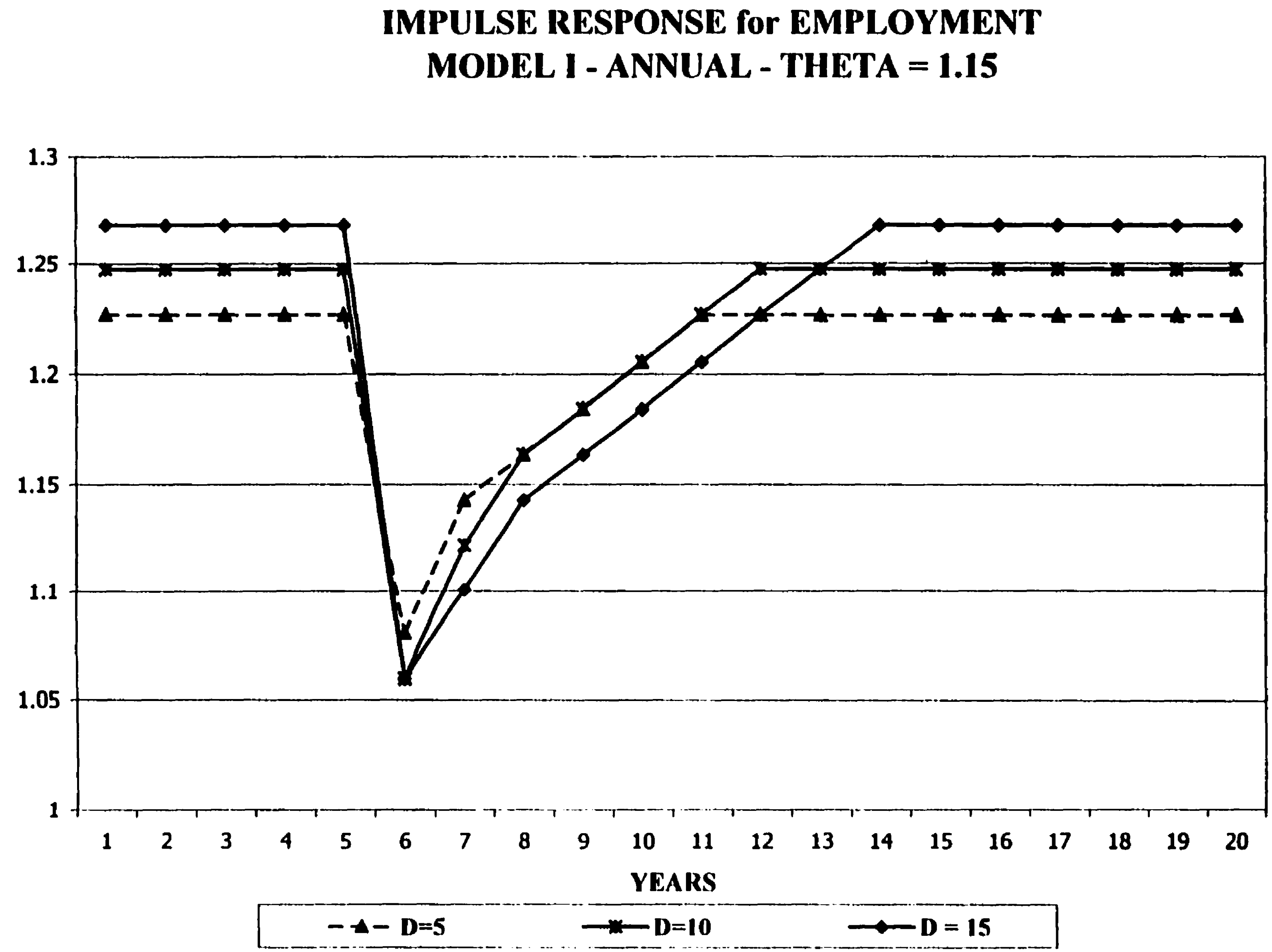

IMPULSE RESPONSE for EMPLOYMENT
MODEL I - ANNUAL - THETA = 1.15
1.3
1.25
1.2
1.15
1.1
1.05
1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
YEARS
D=5
D=10
D = 15

Figure 6.7

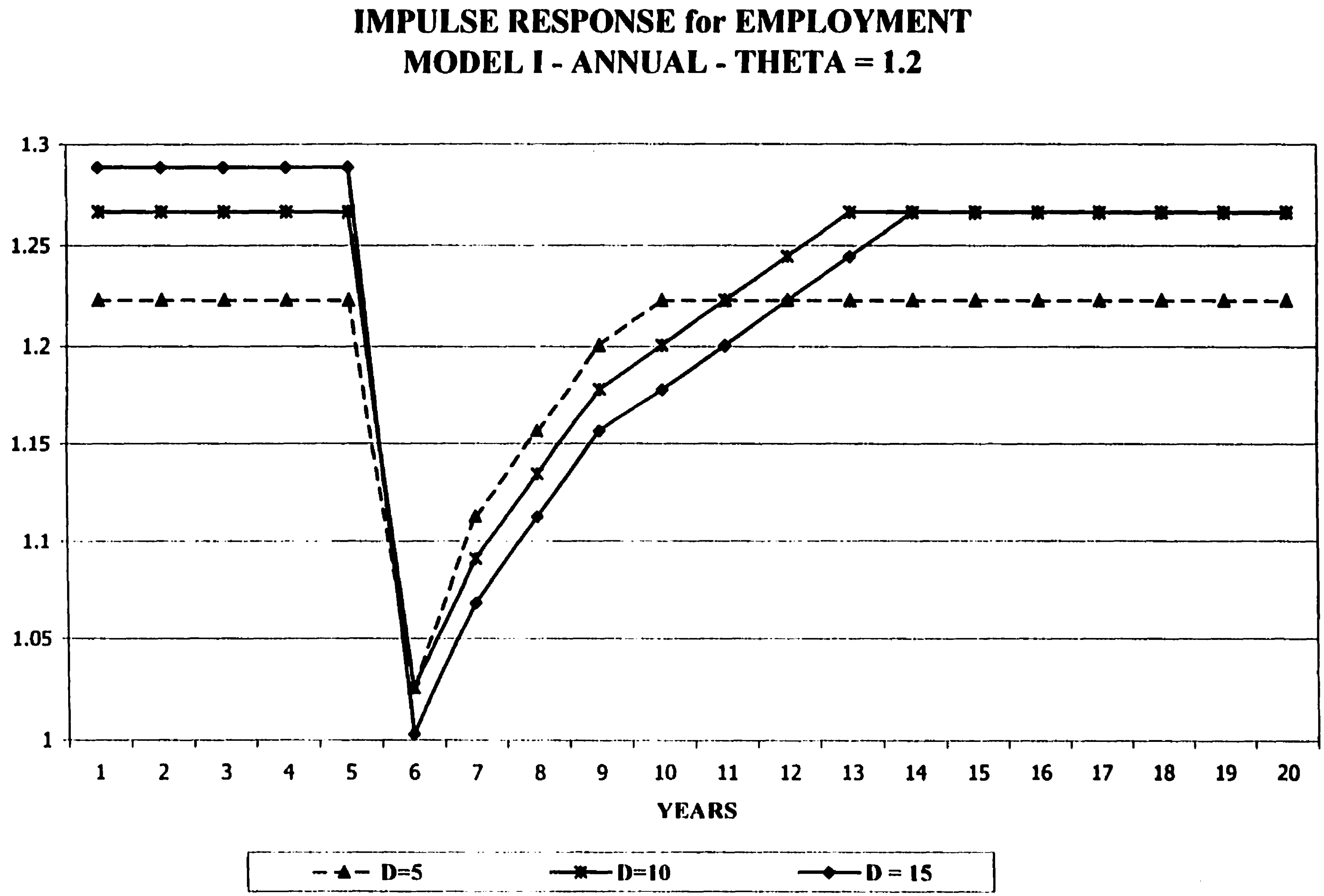

IMPULSE RESPONSE for EMPLOYMENT
MODEL I - ANNUAL - THETA = 1.2
1.3
1.25
1.2
1.15
1.1
1.05
1
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
YEARS
D=5
D=10
D = 15

Figure 6.8

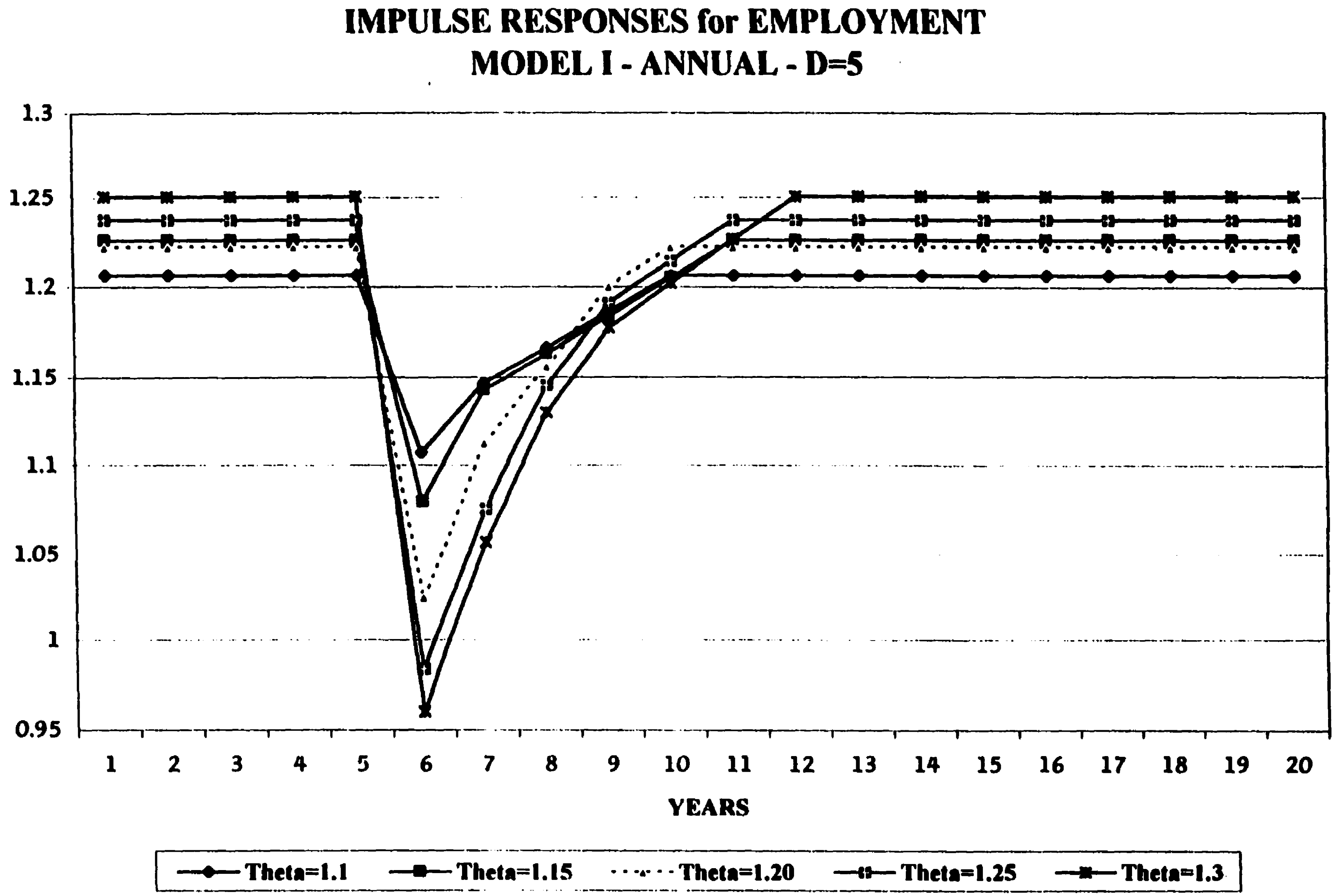

IMPULSE RESPONSES for EMPLOYMENT
MODEL I - ANNUAL - D=5
1.3
1.25
1.2
1.15
1.1
1.05
1
0.95
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
YEARS
Theta=1.1
Theta=1.15
Theta=1.20
Theta=1.25
Theta=1.3

Figure 6.9

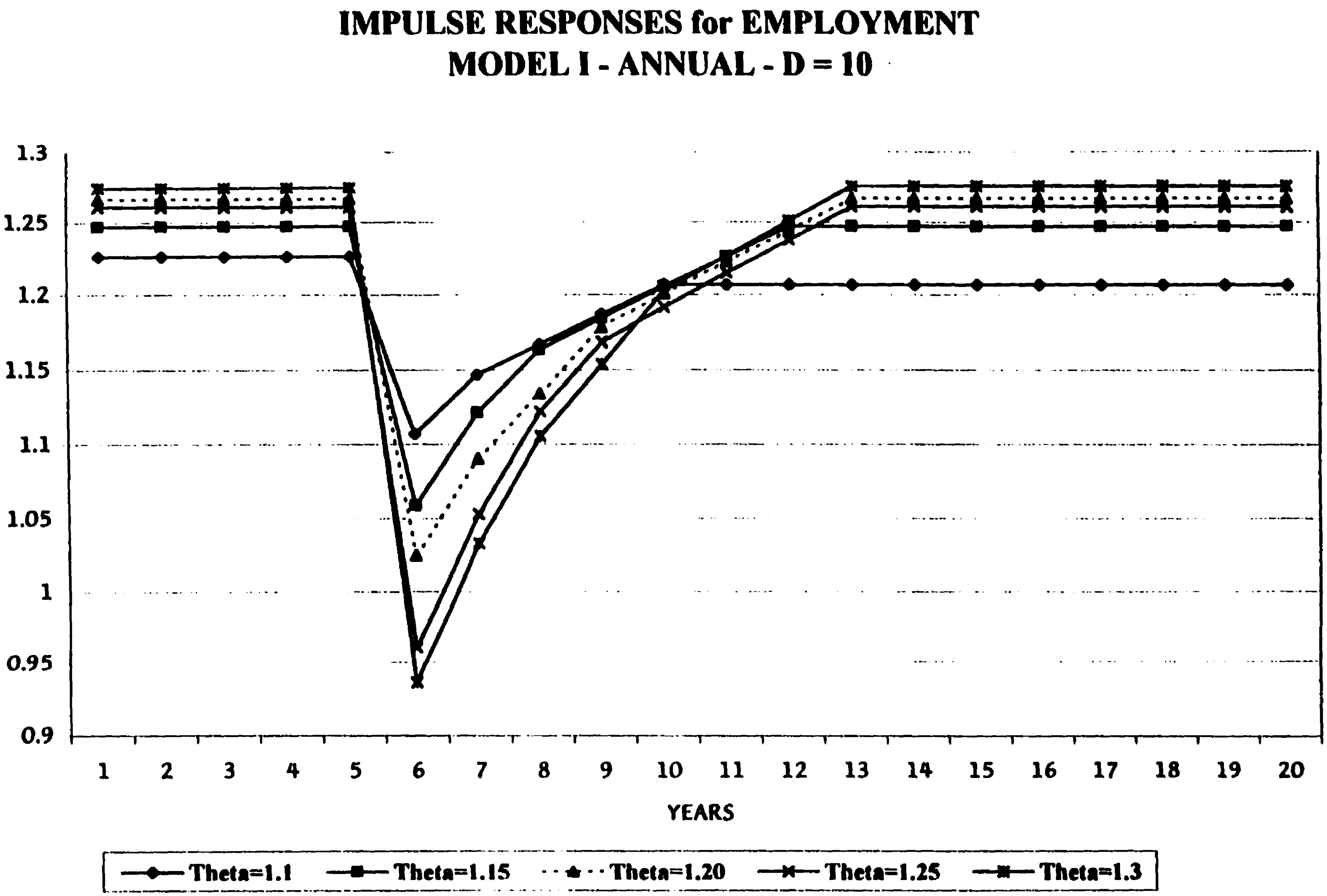

IMPULSE RESPONSES for EMPLOYMENT
MODEL I - ANNUAL - D = 10
1.3
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
YEARS
Theta=1.1
Theta=1.15
Theta=1.20
Theta=1.25
Theta=1.3

Figure 6.10

11

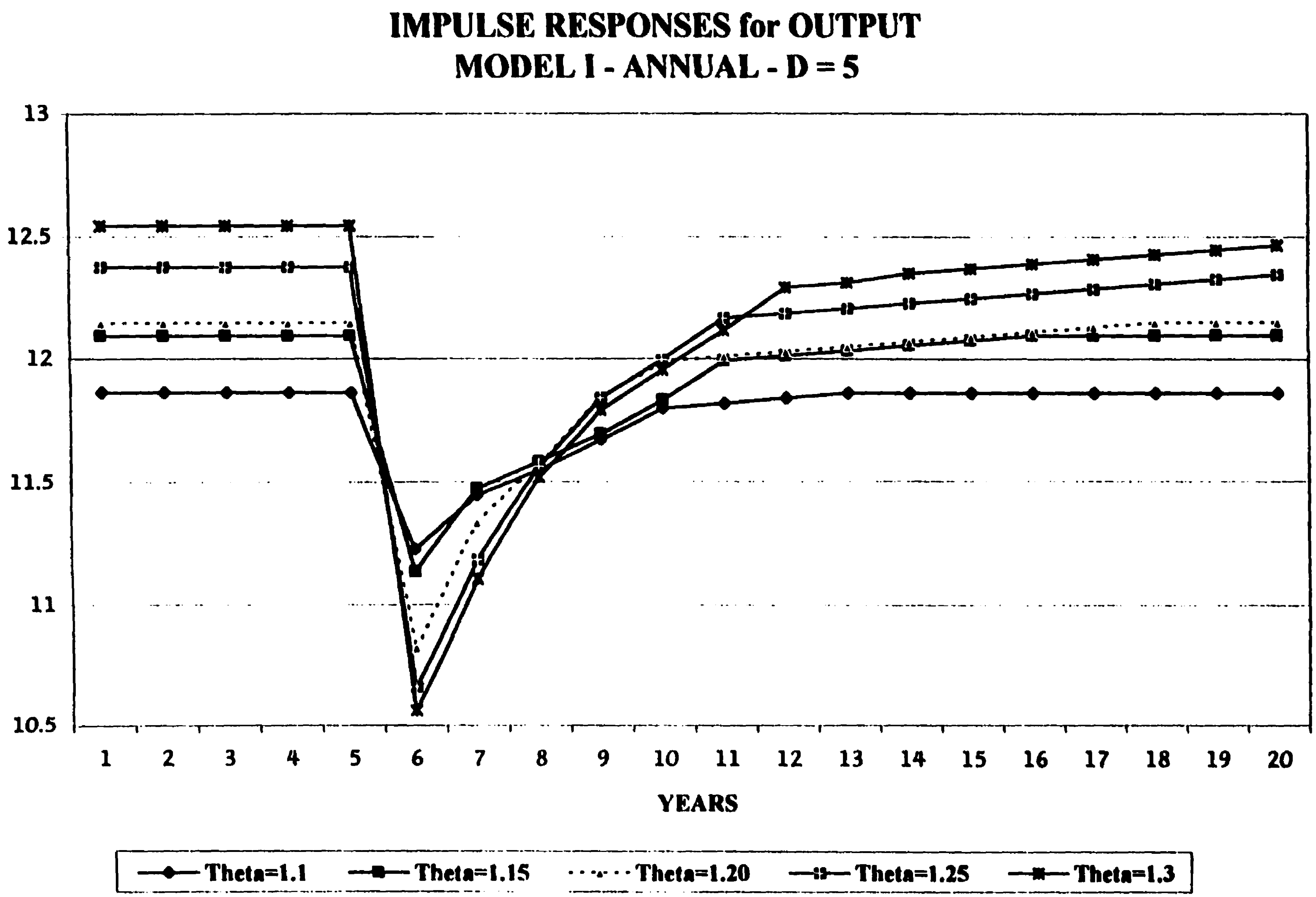


Figure 6.11

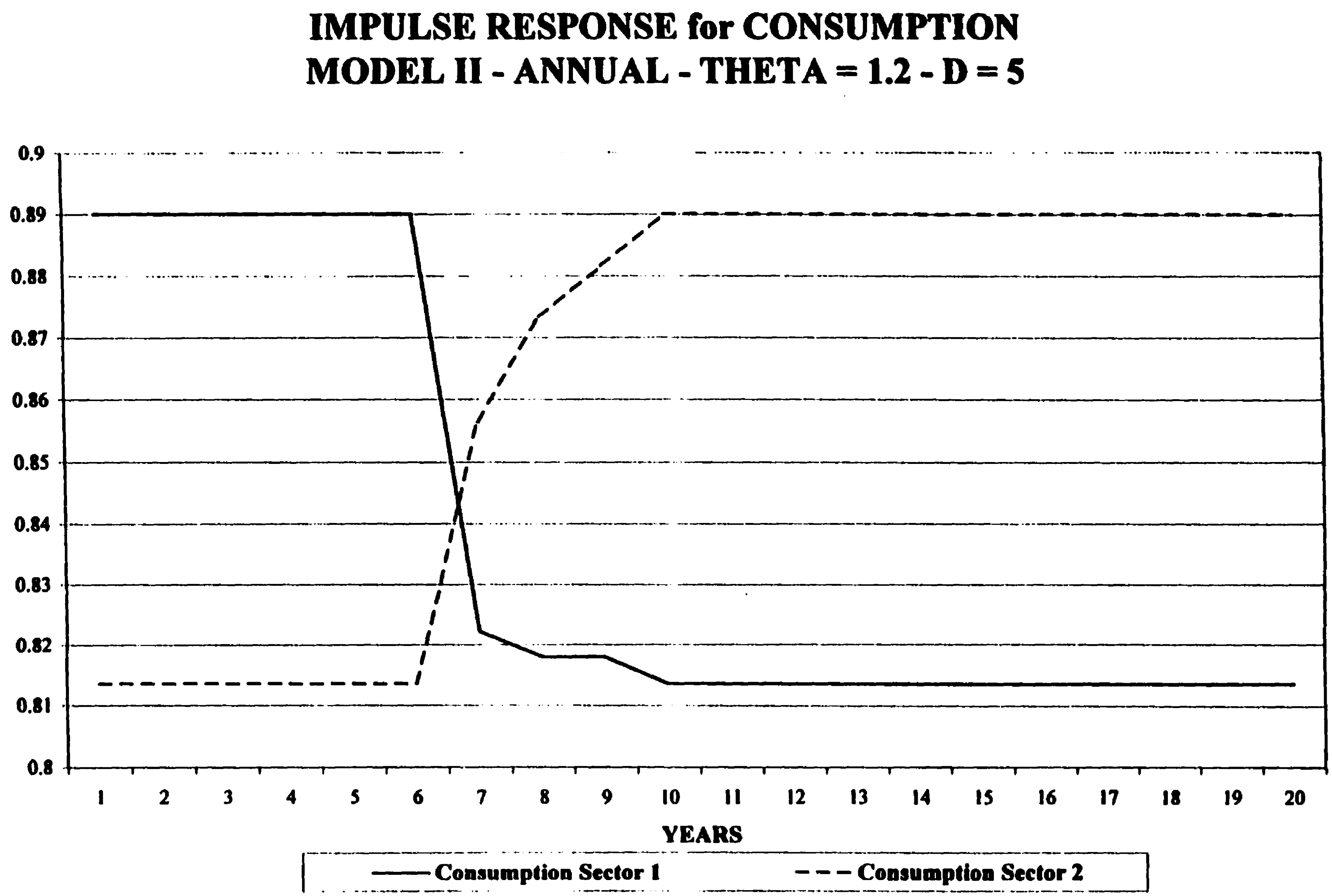

IMPULSE RESPONSE for CONSUMPTION
MODEL II - ANNUAL - THETA = 1.2 - D = 5
0.9
0.89
0.88
0.87
0.86
0.85
0.84
0.83
0.82
0.81
0.8
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
YEARS
Consumption Sector 1
Consumption Sector 2

Figure 6.12

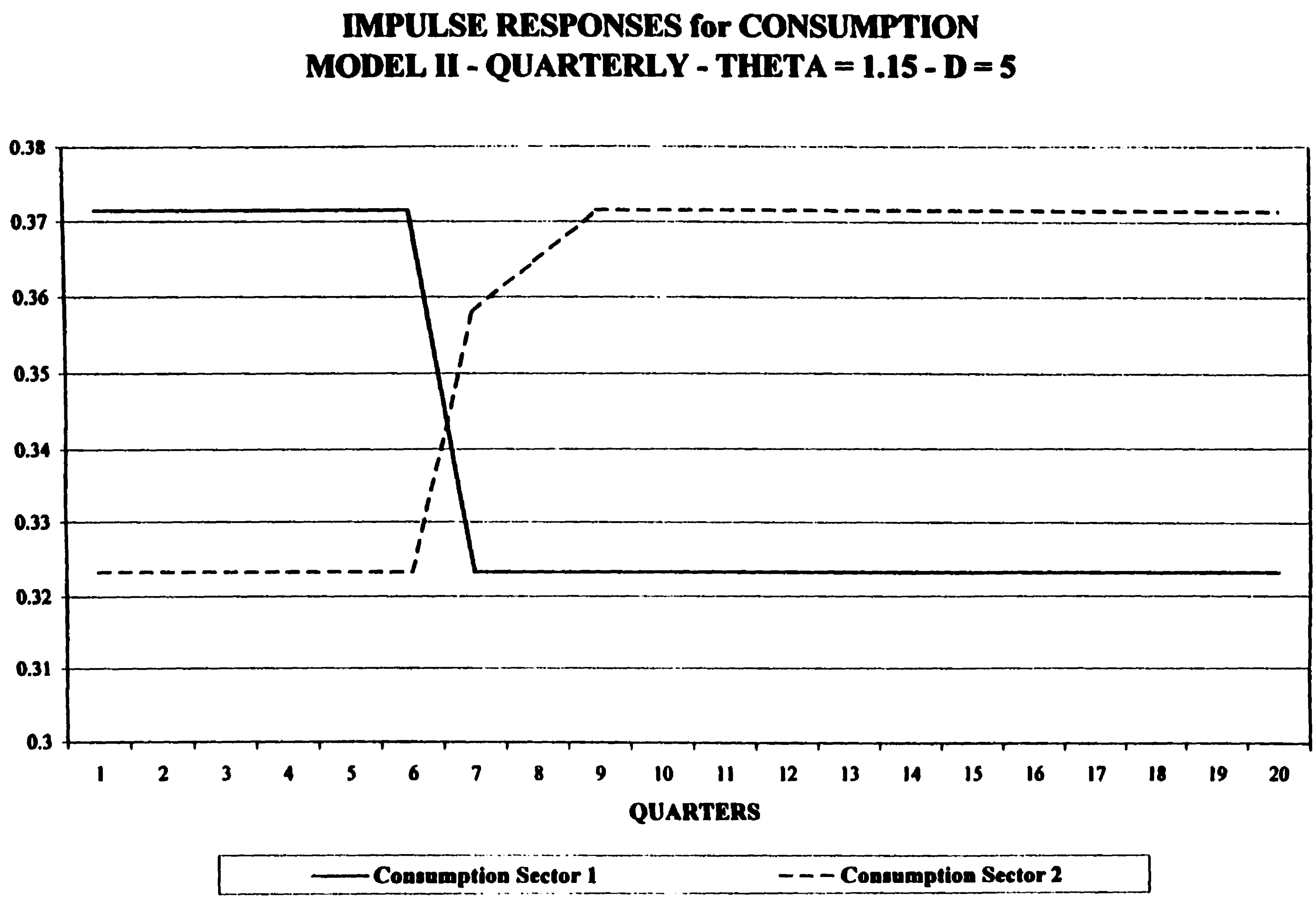

IMPULSE RESPONSES for CONSUMPTION
MODEL II - QUARTERLY - THETA = 1.15 - D = 5
0.38
0.37
0.36
0.35
0.34
0.33
0.32
0.31
0.3
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
QUARTERS
Consumption Sector 1
Consumption Sector 2

Figure 6.13

14

IMPULSE RESPONSES for CONSUMPTION (Sector 2)
MODEL II - QUARTERLY - THETA = 1.2

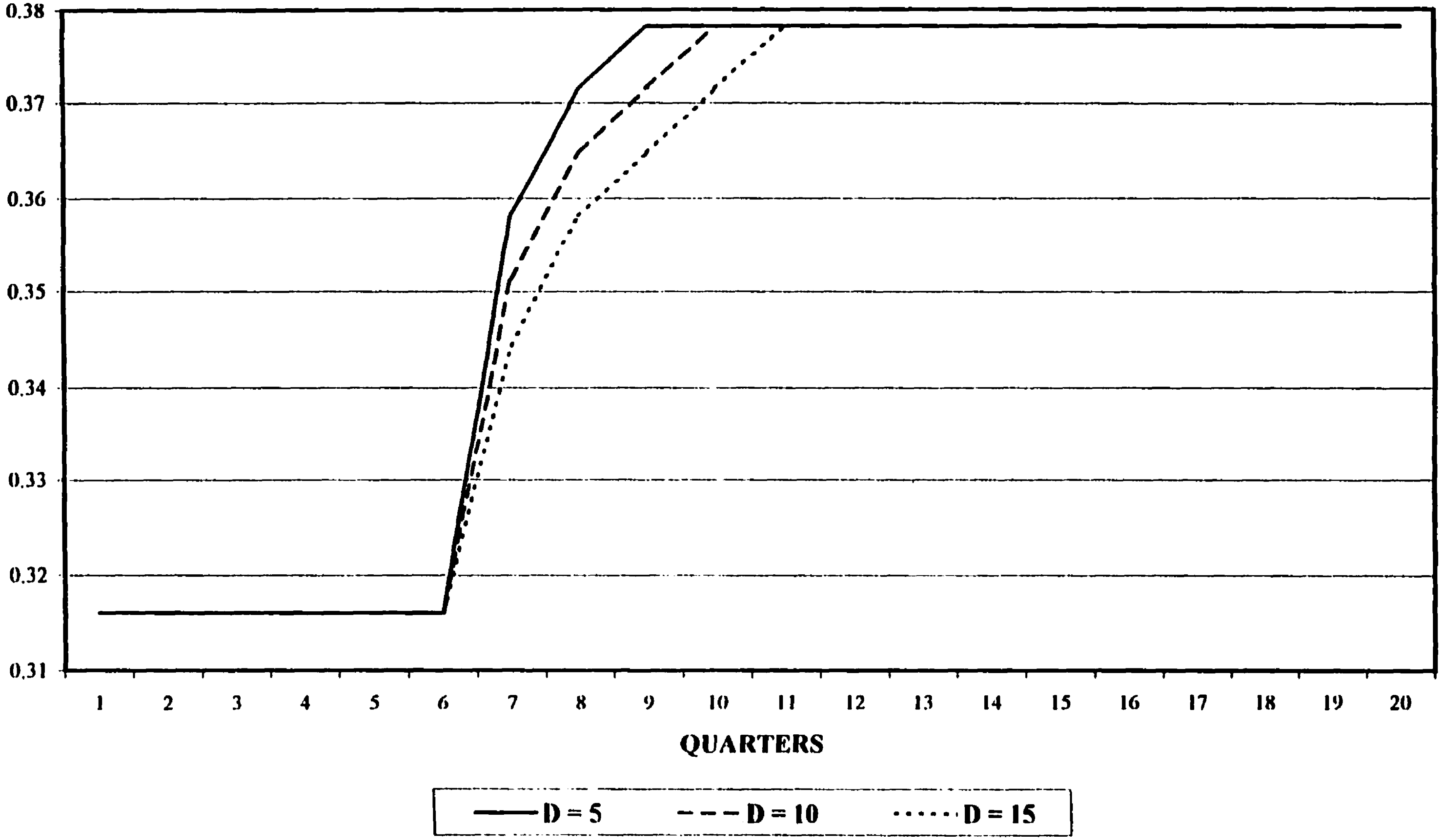


Figure 6.14

15

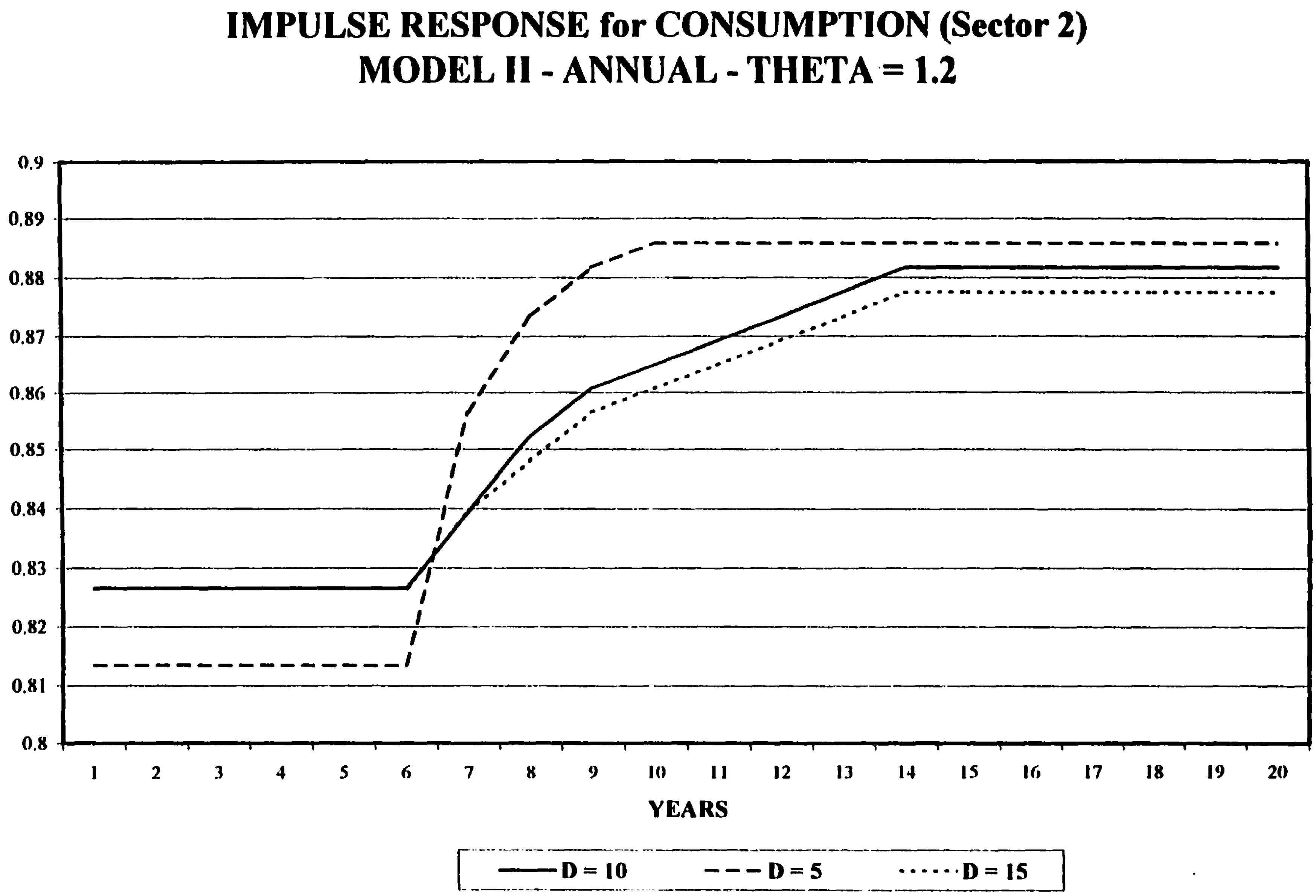


Figure 6.15

16

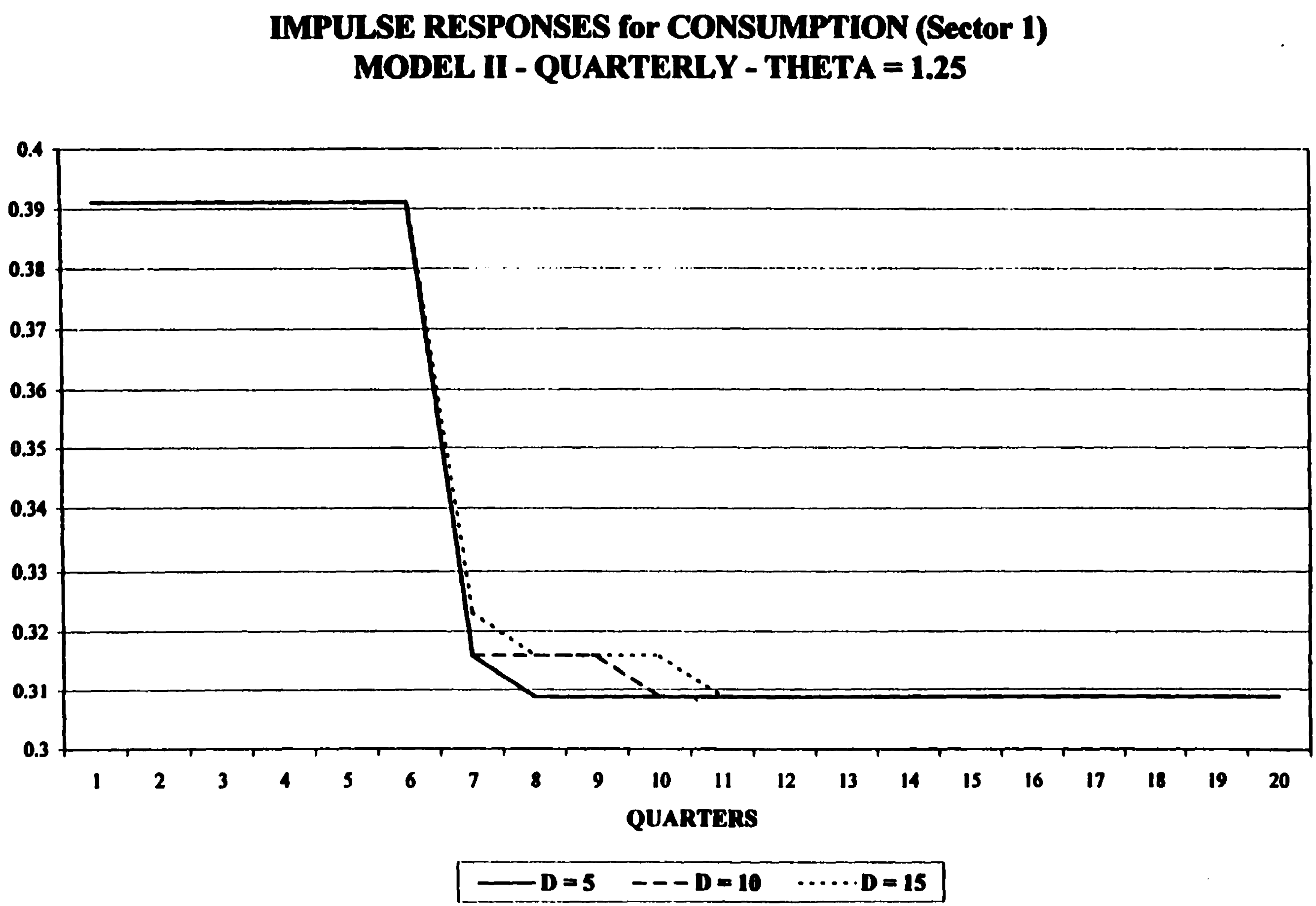


Figure 6.16

17

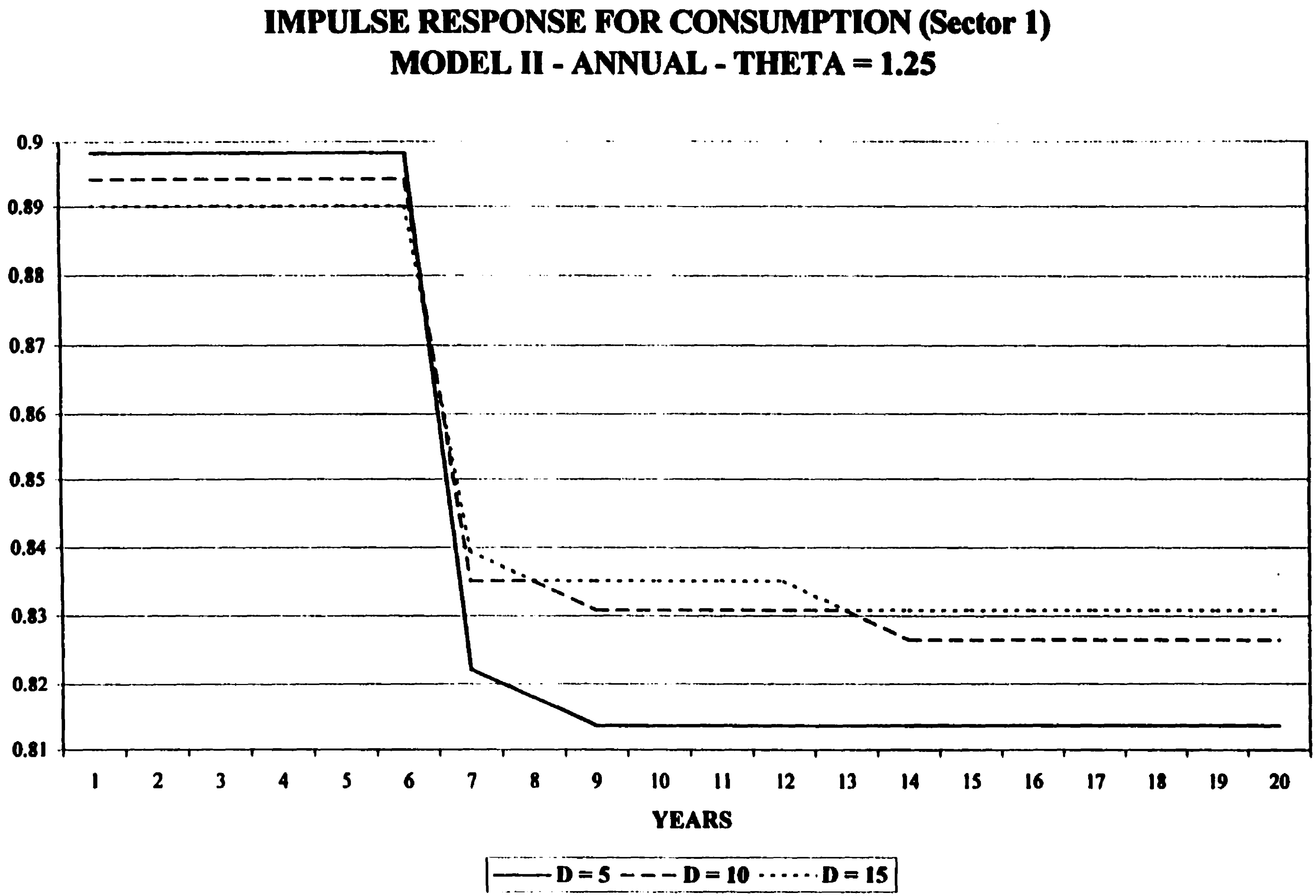


Figure 6.17

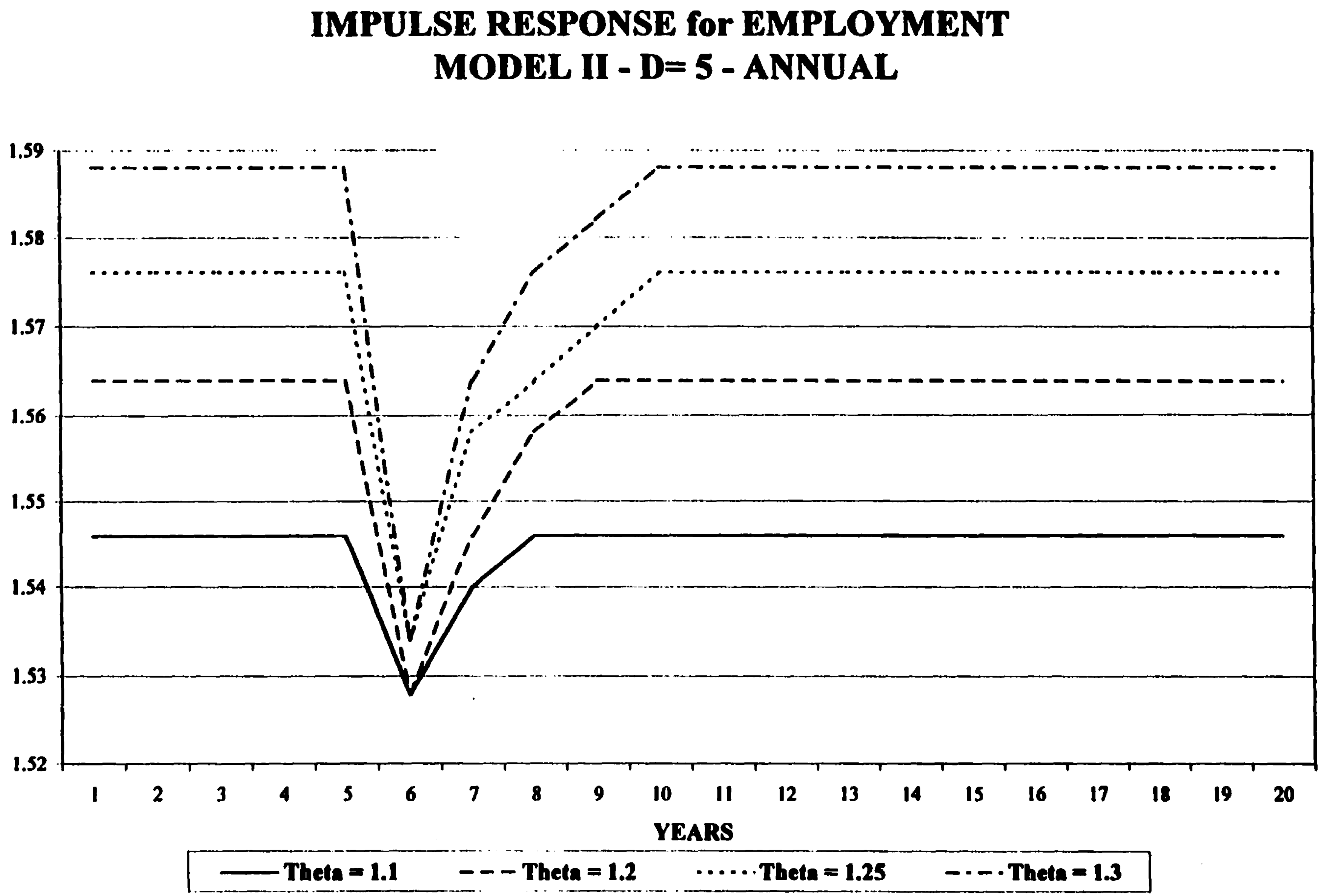

IMPULSE RESPONSE for EMPLOYMENT
MODEL II - D= 5 - ANNUAL
1.59
1.58
1.57
1.56
1.55
1.54
1.53
1.52
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
YEARS
Theta = 1.1
Theta = 1.2
Theta = 1.25
Theta = 1.3

Figure 6.18

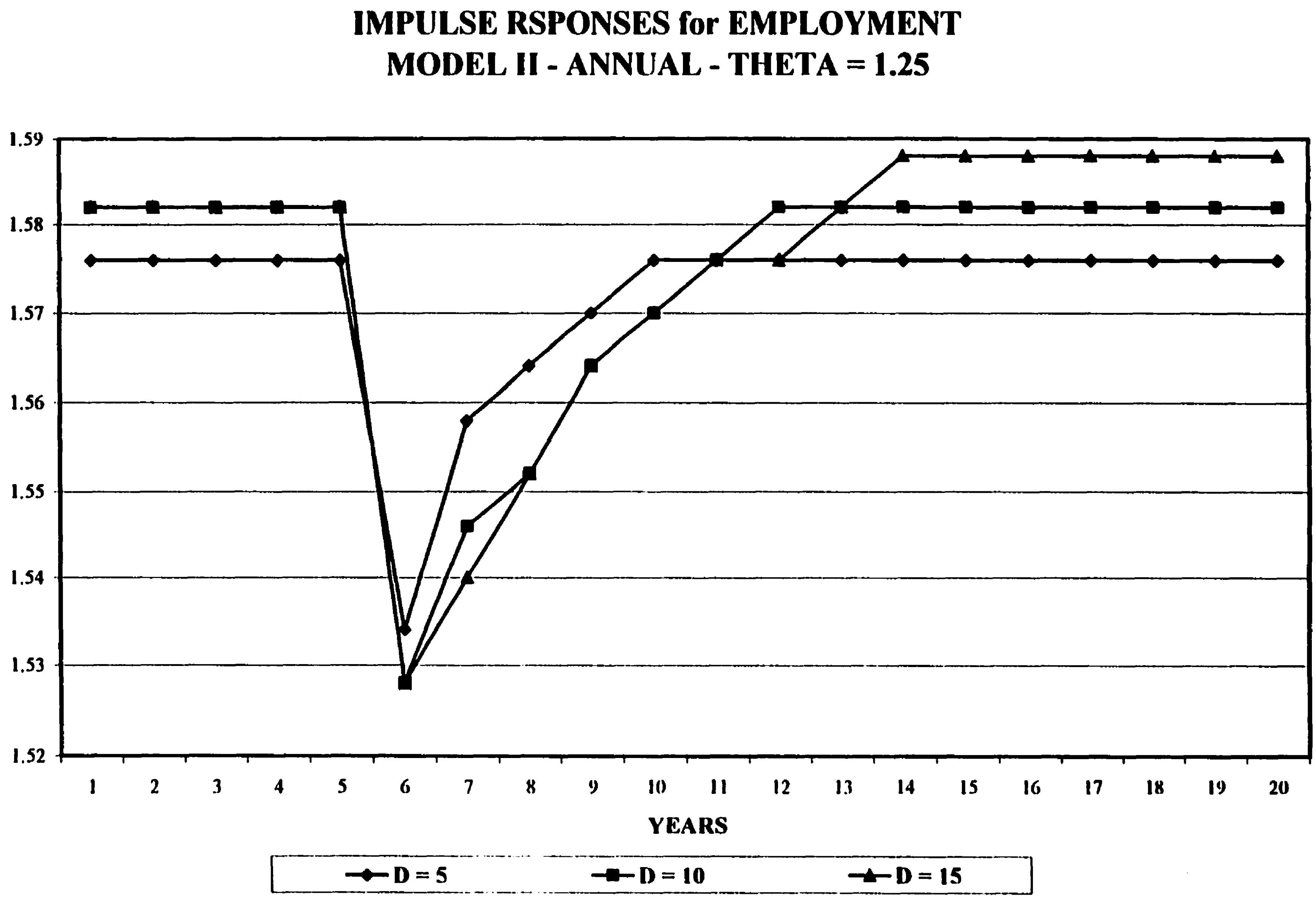

IMPULSE RSPONSES for EMPLOYMENT
MODEL II - ANNUAL - THETA = 1.25
1.59
1.58
1.57
1.56
1.55
1.54
1.53
1.52
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
YEARS
D = 5
D = 10
D = 15

Figure 6.19

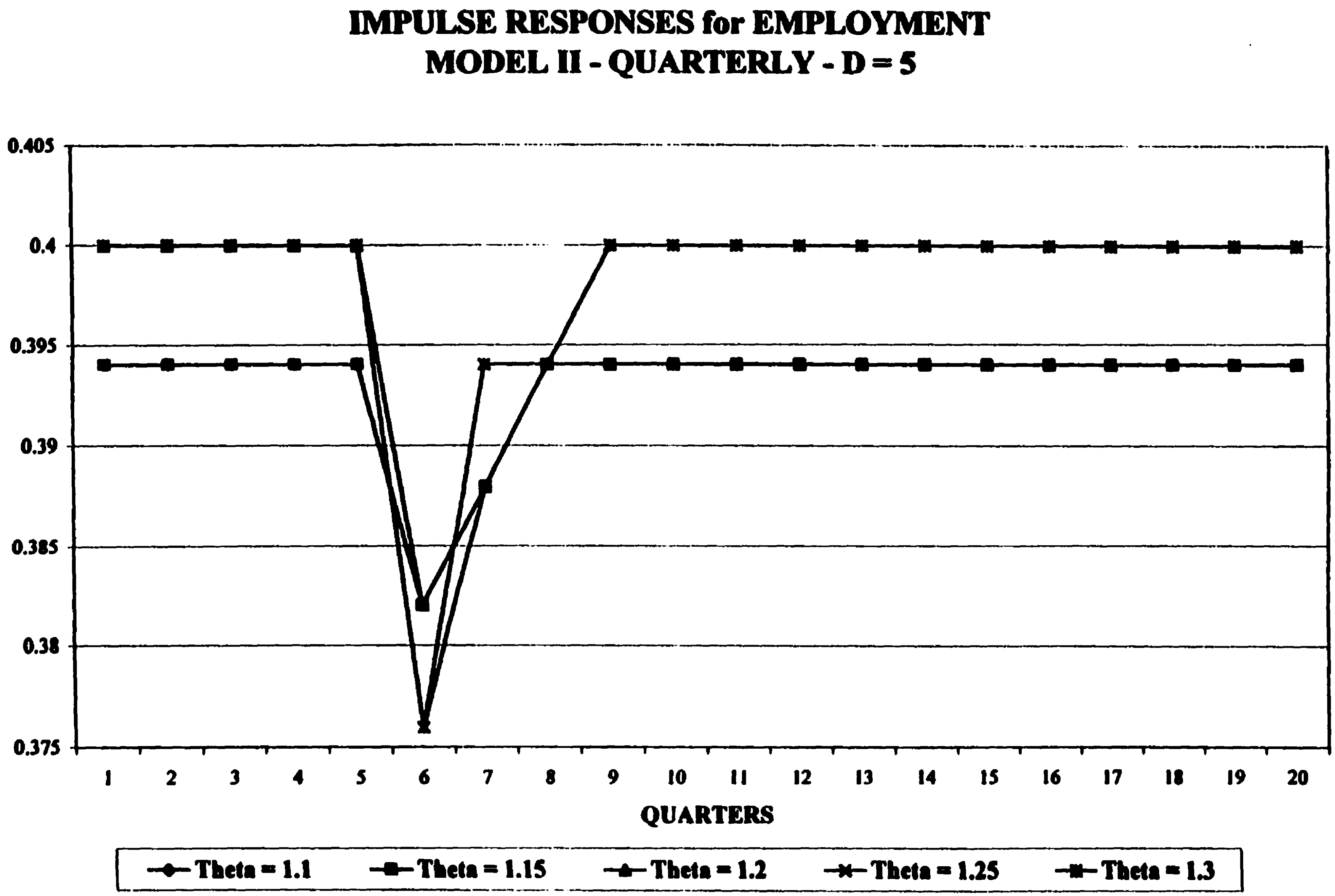

IMPULSE RESPONSES for EMPLOYMENT
MODEL II - QUARTERLY - D = 5
0.405
0.4
0.395
0.39
0.385
0.38
0.375
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
QUARTERS
Theta = 1.1
Theta = 1.15
Theta = 1.2
Theta = 1.25
Theta = 1.3

Figure 6.20

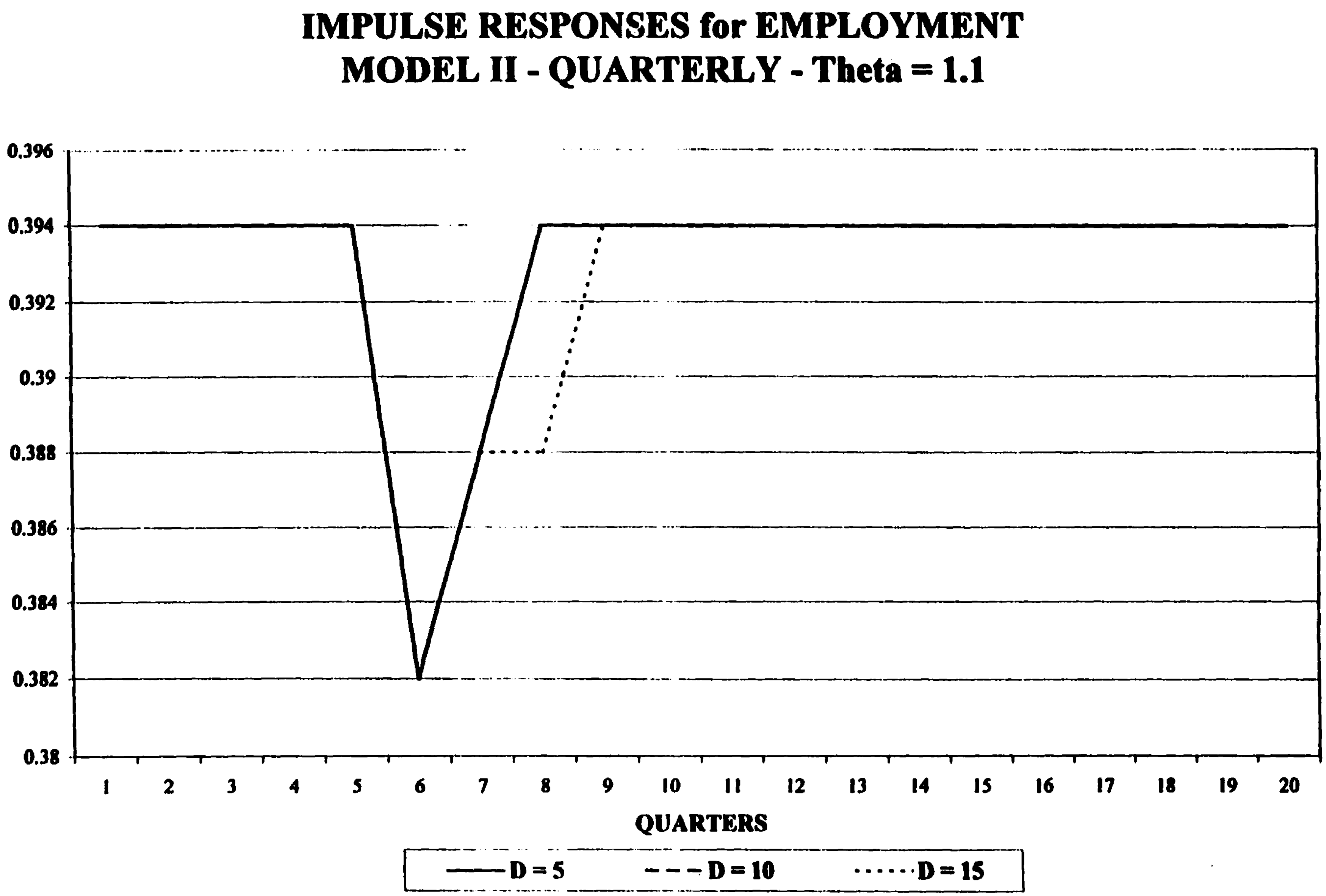

IMPULSE RESPONSES for EMPLOYMENT
MODEL II - QUARTERLY - Theta = 1.1
0.396
0.394
0.392
0.39
0.388
0.386
0.384
0.382
0.38
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
QUARTERS
D = 5
D = 10
D = 15

Figure 6.21

22

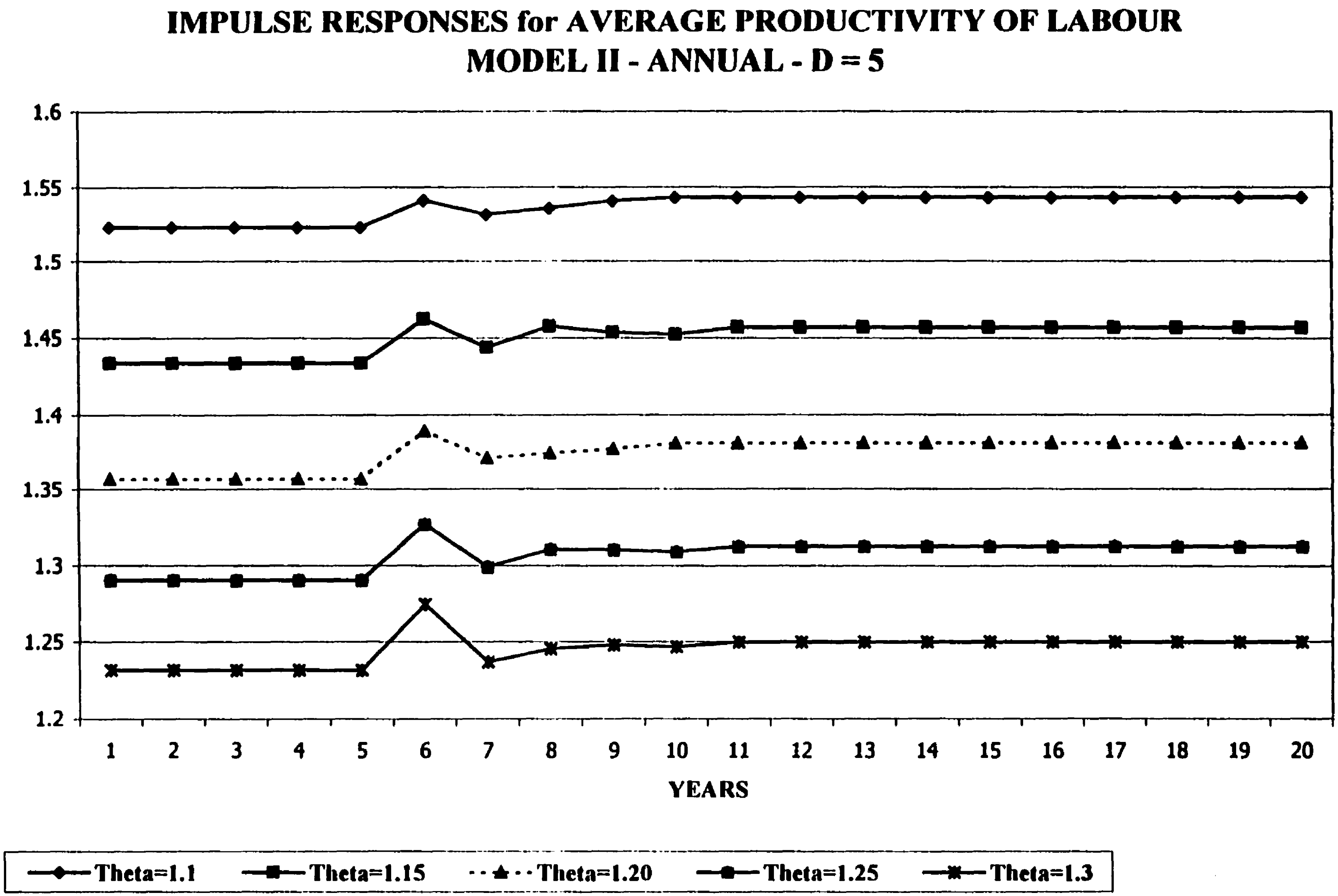


Figure 6.22

23

IMPULSE RESPONSES for AVERAGE PRODUCTIVITY OF LABOUR
MODEL II - ANNUAL - D=10

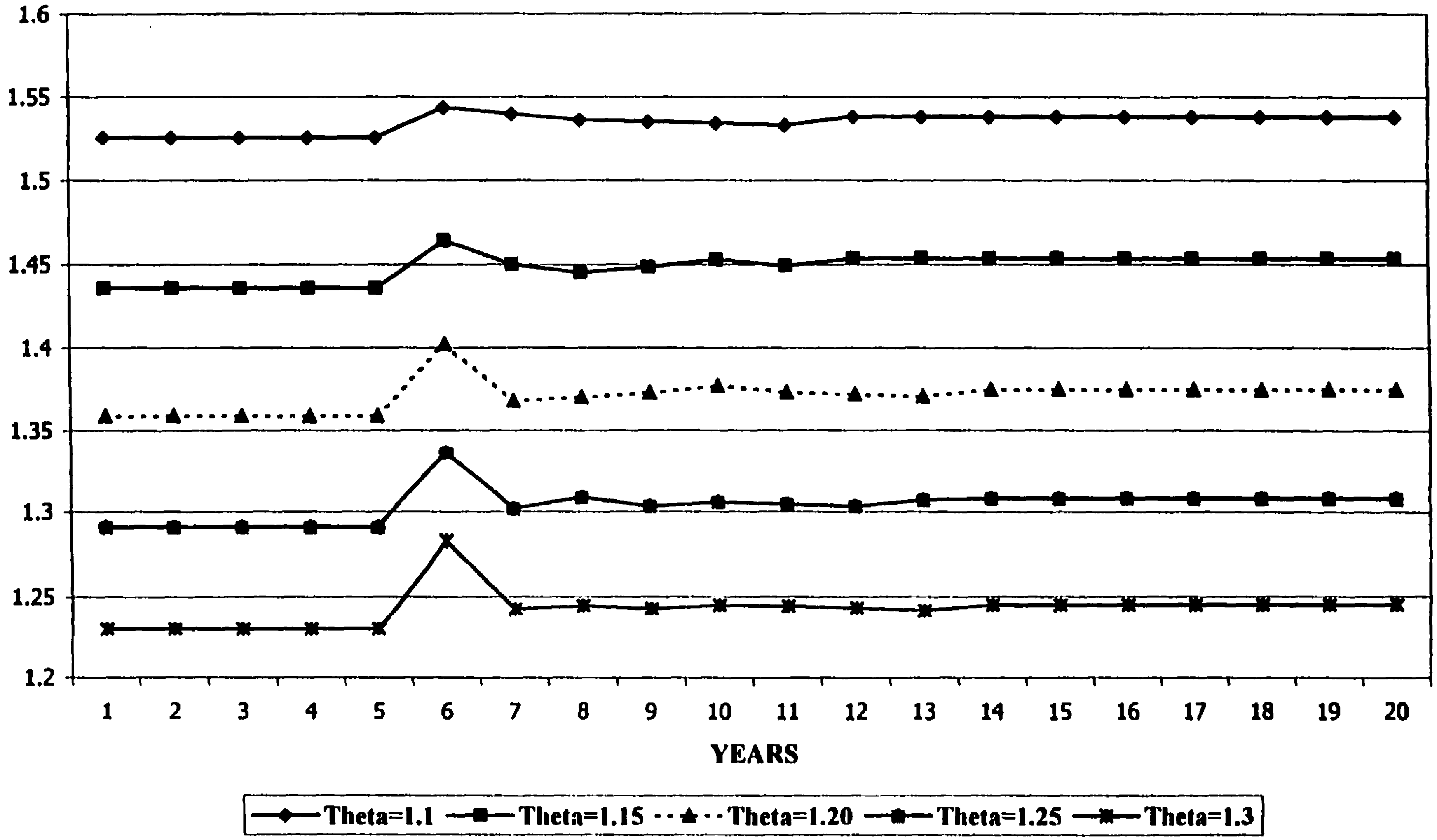


Figure 6.23

IMPULSE RESPONSES for AVERAGE LABOUR PRODUCTIVITY
MODEL I - QUARTERLY - THETA = 1.2

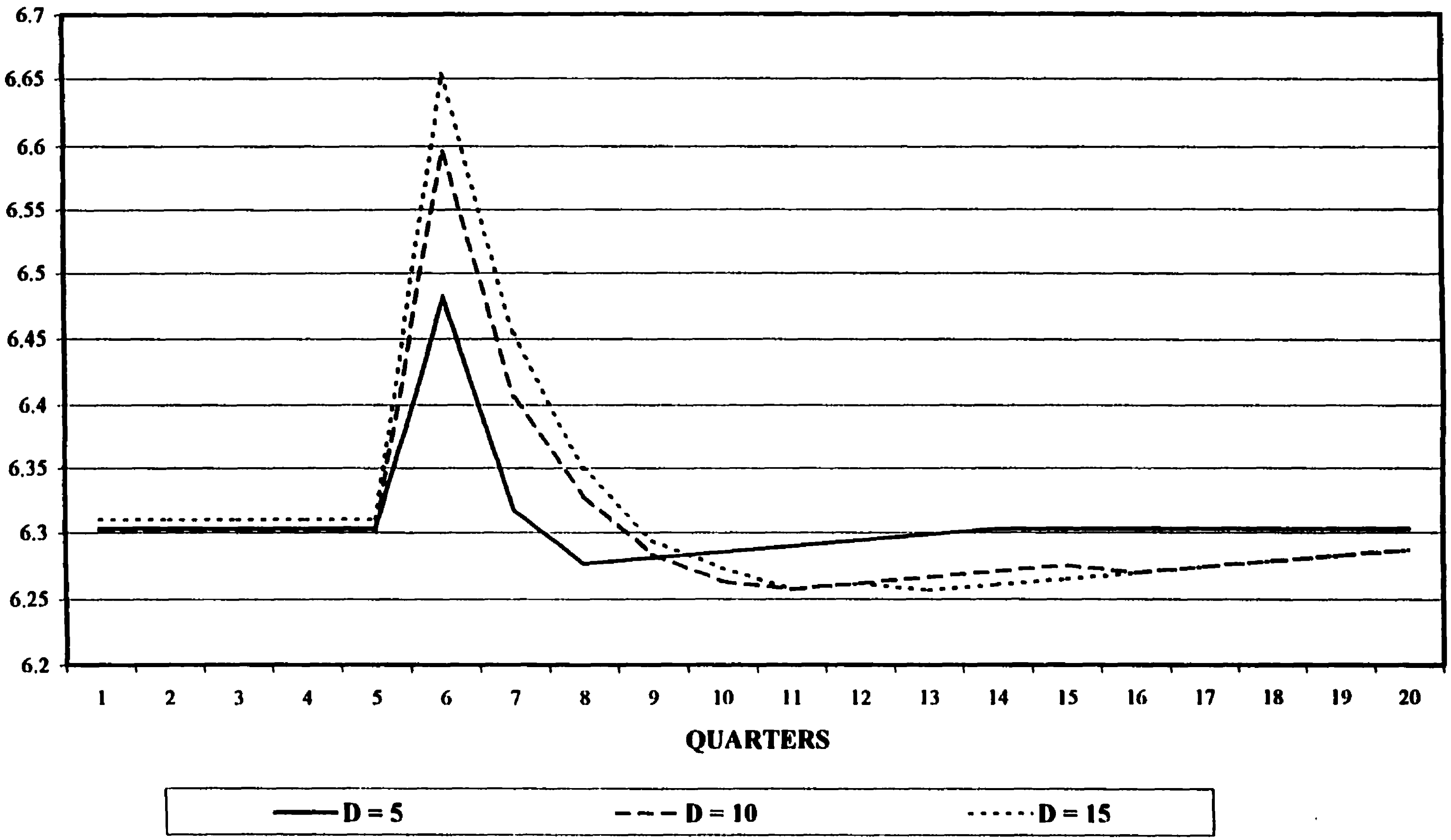


Figure 6.24

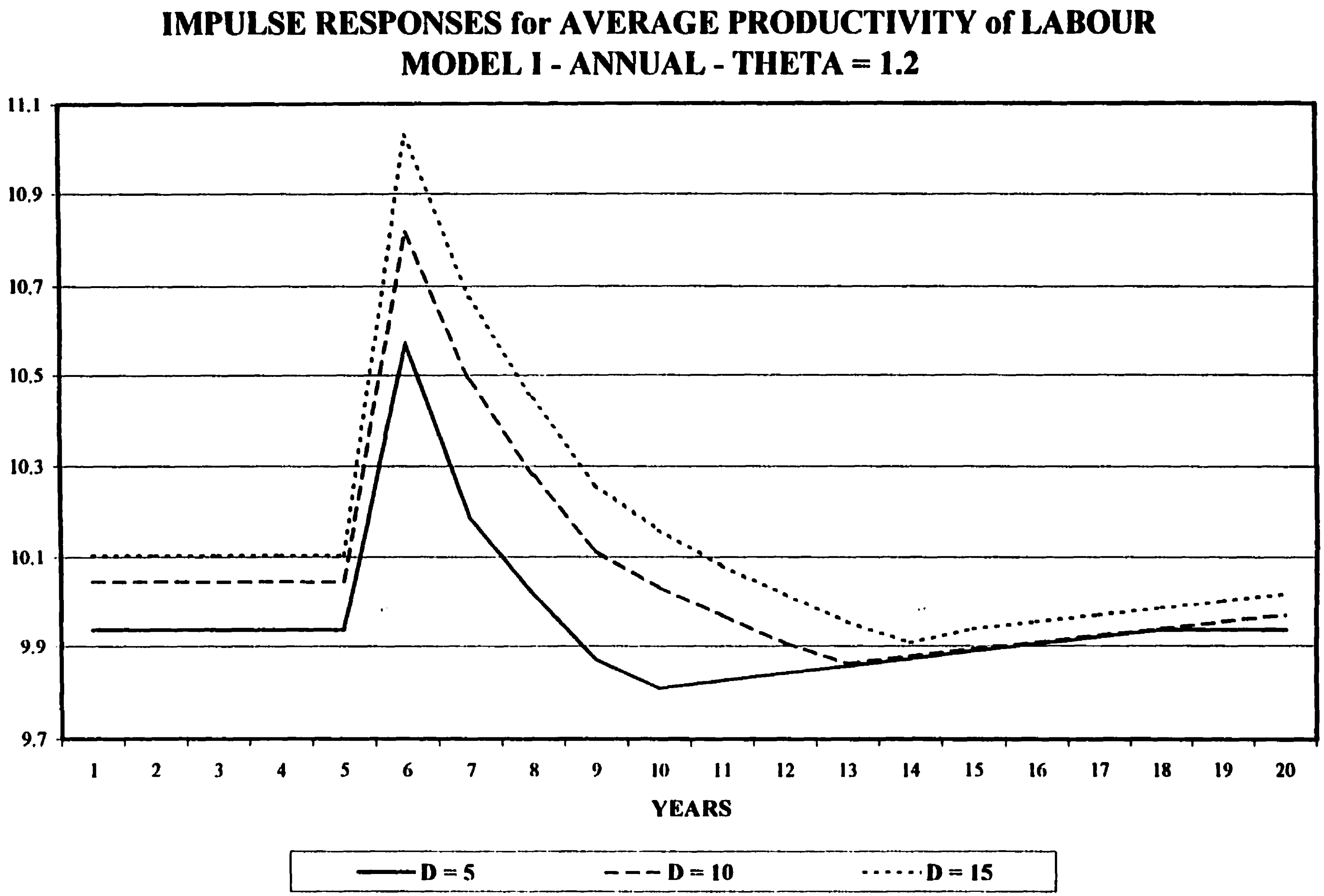

IMPULSE RESPONSES for AVERAGE PRODUCTIVITY of LABOUR
MODEL I - ANNUAL - THETA = 1.2
11.1
10.9
10.7
10.5
10.3
10.1
9.9
9.7
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
YEARS
D = 5
D = 10
D = 15

Figure 6.25

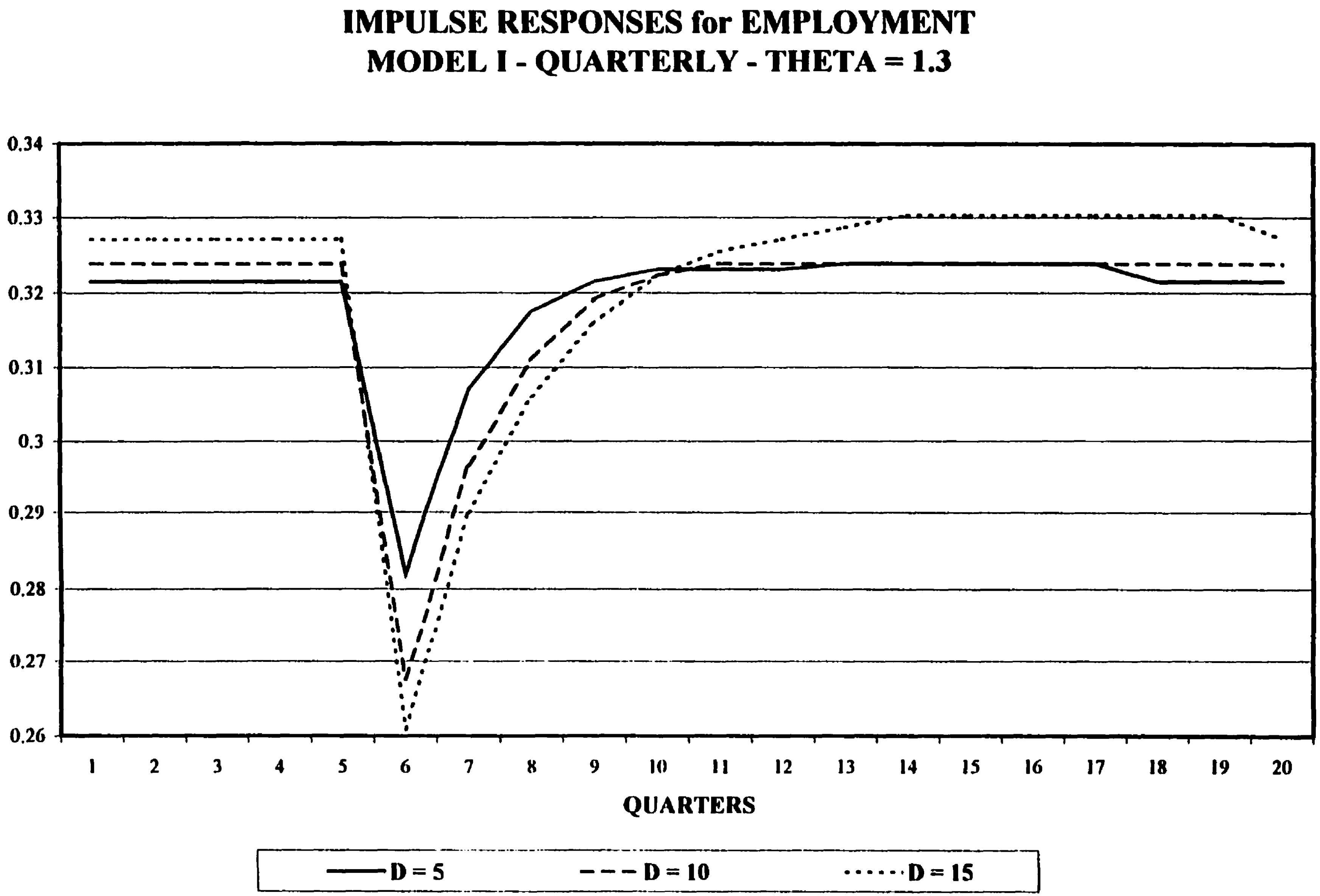

IMPULSE RESPONSES for EMPLOYMENT
MODEL I - QUARTERLY - THETA = 1.3
0.34
0.33
0.32
0.31
0.3
0.29
0.28
0.27
0.26
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
QUARTERS
D = 5
D = 10
D = 15

Figure 6.26

6.14 Appendix B: MathCAD Programs

This appendix presents results for a MathCAD[21] program to undertake a parameter sensitivity analysis for model I. As figure 1 shows, output and consumption are convex functions of the parameter θ. Both (output and consumption) reach a maximum at the point where $\theta = 1.2$. This is an implication of the calibration exercise. Figure 2 illustrates the effect of the capital depreciation parameter on consumption and output. A change in δ has greater impact on consumption than output. As capital depreciates, more work effort is put in place for the same level of production and consumption is lower. Figure 3 shows that labour supply is an increasing function of the size of the sectoral technology shock θ. As θ increases, unemployment increases and consequently the labour supply increases.

[21]Thanks to Stephen Millard for supplying the base code.

Representative Agent's Problem

Maximise $$E\left[\sum_{t=0}^{\infty}\left(\ln(c_t)+\gamma\cdot\ln\left(1-n1_t-n2_t-d\left(n1_{t+1}-n1_t\right)^2-d\left(n2_{t+1}-n2_t\right)^2\right)\right)\right]$$

Subject to $$c_t+k_{t+1}-(1+\delta)\cdot k_t=A\cdot\left(k_t\right)^{\alpha}\cdot\left(\min\left(\theta n1_t,\theta^{-1}n2_t\right)\right)^{1-\alpha}$$

$$n1_t-n2_t\le 1$$

Euler Equations - given the symmetry just solve for state 1

For n $$\frac{(1-\alpha)\cdot A\cdot\left(k_t\right)^{\alpha}\cdot\theta^{1-\alpha}\cdot\left(n_t\right)^{-\alpha}}{c_t}-\frac{\gamma\cdot\left(1+\theta^2\right)}{\left[1-\left(1+\theta^2\right)\cdot n_t\right]}=0$$

For k $$\frac{-1}{c_t}-\beta\cdot\frac{\alpha\cdot A\cdot\left(k_{t-1}\right)^{\alpha-1}\cdot\left(\theta\cdot n_{t-1}\right)^{1-\alpha}-\delta}{c_{t-1}}=0$$

Steady State

$$(1-\alpha)\cdot A\cdot(k)^{\alpha}\cdot\theta^{1-\alpha}\cdot n^{-\alpha}\cdot\left[1-\left(1-\theta^2\right)\cdot n\right]=\gamma\cdot\left(1-\theta^2\right)\cdot\left[A\cdot k^{\alpha}\cdot(\theta\cdot n)^{(1-\alpha)}-\delta\cdot k\right]$$

$$\alpha\cdot\beta\cdot A\cdot k^{\alpha-1}\cdot\theta^{1-\alpha}\cdot n^{1-\alpha}=1-\delta$$

Set Parameters:

$\alpha = 0.35$	Capital's Share of GDP	$A = 10$	Technology Aggregate
$\beta = 0.96$	Discount Factor	$\theta = 1.2$	Labour Shock
$\delta = 0.06$	Depreciation Rate	$\gamma = 2$	Weight of Leisure in U function

$\rho = \left(\frac{1}{\beta}\right)-1$ $\rho = 0.042$

Initialise Variables

$n = 0.5$ Labour

$k = 9$ Capital Stock

$$\text{Output}(\alpha,\beta,\theta,\delta,A,\gamma) := A\cdot\left[\left(\text{Capital}(\alpha,\beta,\theta,\delta,A,\gamma)^{\alpha}\right)\cdot(\theta\cdot\text{Labour}(\alpha,\beta,\theta,\delta,A,\gamma))^{1-\alpha}\right]$$

$$\text{Output}(\alpha,\beta,\theta,\delta,A,\gamma) = 9.608$$

$$\text{Investment}(\alpha,\beta,\theta,\delta,A,\gamma) := \delta\cdot\text{Capital}(\alpha,\beta,\theta,\delta,A,\gamma)$$

$$\text{Investment}(\alpha,\beta,\theta,\delta,A,\gamma) = 1.985$$

$$\text{Consumption}(\alpha,\beta,\theta,\delta,A,\gamma) := \text{Output}(\alpha,\beta,\theta,\delta,A,\gamma) - \text{Investment}(\alpha,\beta,\theta,\delta,A,\gamma)$$

$$\text{Consumption}(\alpha,\beta,\theta,\delta,A,\gamma) = 7.623$$

$$\text{LabourSupply}(\alpha,\beta,\theta,\delta,A,\gamma) := \left(1+\theta^{2}\right)\cdot\text{Labour}(\alpha,\beta,\theta,\delta,A,\gamma)$$

$$\text{LabourSupply}(\alpha,\beta,\theta,\delta,A,\gamma) = 0.291$$

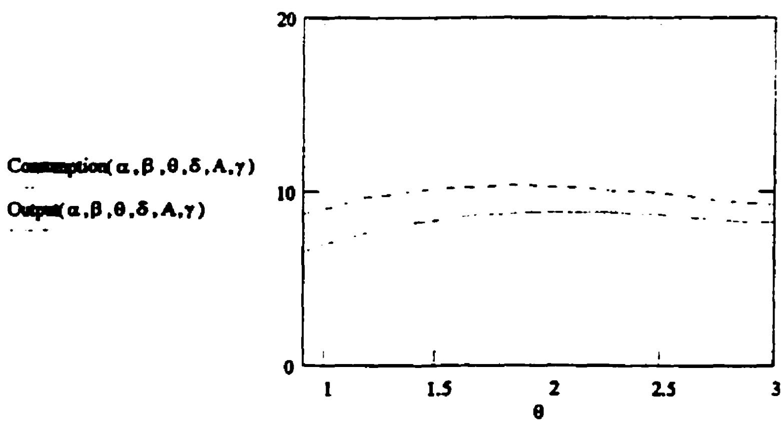
Create a range variable. This will be the variable whose value you are interested in changing.

As an example, let's look at the effect of varying the utility weight on leisure, *A*

$\theta := 0.9, 1 .. 3$

In the graphs below, the user should alter the x-axis label. The graphs will then be redrawn.

Graph of Effect of depreciation on Consumption, Investment, and Output



$$M := \left(\frac{\rho + \delta}{\alpha \cdot A \cdot \theta^{1-\alpha}}\right)^{\frac{1}{\alpha - 1}}$$

$M = 277.732$

$$co := \frac{\gamma \cdot \left(1 + \theta^2\right) \cdot \left(A \cdot \theta^{1-\alpha} - \delta \cdot M^{1-\alpha}\right)}{(1 - \alpha) \cdot A \cdot \theta^{1-\alpha}}$$

$co = 5.957$

Given

$$n = \frac{1}{co + \left(1 - \theta^2\right)}$$

$k = M \cdot n$

$$\mathrm{Find}(n, k) = \begin{bmatrix} 0.119 \\ 33.075 \end{bmatrix}$$

Steady State Analysis

Given

$$n = \frac{1}{co + \left(1 + \theta^2\right)}$$

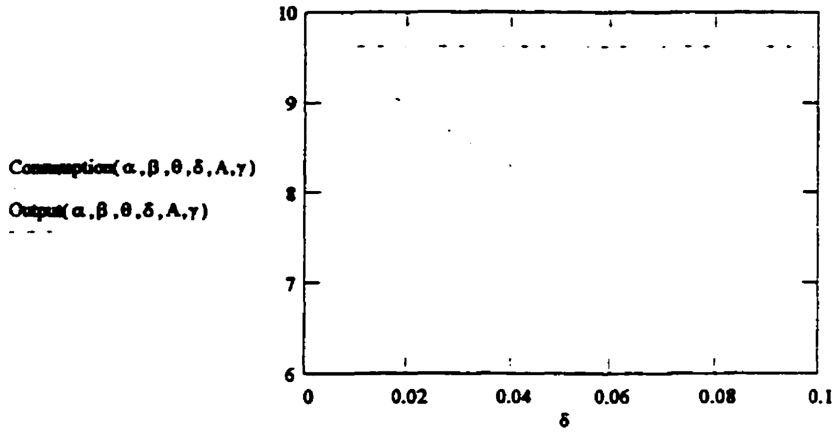
$k = M \cdot n$

$gl(\alpha, \beta, \theta, \delta, A, \gamma) := \mathrm{Find}(n, k)$ $\qquad$ $gl(\alpha, \beta, \theta, \delta, A, \gamma) = \begin{bmatrix} 0.119 \\ 33.075 \end{bmatrix}$

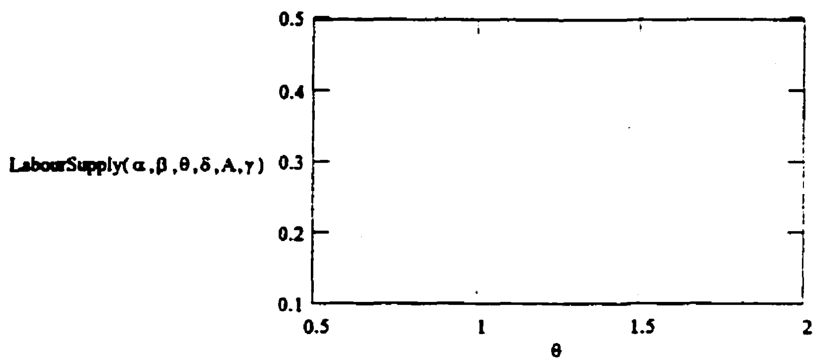
$\mathrm{Labour}(\alpha, \beta, \theta, \delta, A, \gamma) := gl(\alpha, \beta, \theta, \delta, A, \gamma)_0$ $\qquad$ $\mathrm{Labour}(\alpha, \beta, \theta, \delta, A, \gamma) = 0.119$

$\mathrm{Capital}(\alpha, \beta, \theta, \delta, A, \gamma) := gl(\alpha, \beta, \theta, \delta, A, \gamma)_1$ $\qquad$ $\mathrm{Capital}(\alpha, \beta, \theta, \delta, A, \gamma) = 33.075$

$\delta = 0.01, 0.02 .. 0.1$
$\theta = 1.2$



$\theta = 0.5, 0.6 .. 2 \quad \delta = 0.06$



6.15 Appendix C: Indices

This sections reviews index numbers. Indices are used to report total multi-factor productivity. In this thesis, the total multi-factor productivity in Canadian sectors and the calibration of the RBC models depend on.

Quantity indices - published by Statistics Canada - are: the Törnqvist, the Paasche, the Laspeyres and the Fisher ideal. All quantity (volume) indices are computed using a 'bottom-up' approach. They are initially estimated at the disaggregated industry level, then weighted according to their contribution to the industry, then summed together. For the properties of index numbers, see the comprehensive review by Diewert (1987).

The Törnqvist[22] volume index is a geometric weighted average of the ratios of the current and previous year's quantities.

$$T_Q = \prod_{i=1}^{n} \left(\frac{Q_{1i}}{Q_{0i}} \right)^{w_i} \tag{6.53}$$

similarly expressed as,

$$\ln T_Q = \sum_{i=1}^{n} w_i \bullet \ln \left(\frac{Q_{1i}}{Q_{0i}} \right) \tag{6.54}$$

where $i = 1, ..., n$ represents industries, and w_i denotes average value of the shares of the industries in total output at time 0 and 1. The Törnqvist index is used to estimate multi-factor productivity. It corresponds to the (general form) translog production function.

The Laspeyres volume index is an index of the growth in quantities valued at the

[22]Source: Statistics Canada (1994, p. 22).

previous year's prices,

$$L_Q = \frac{\sum_{i=1}^{n} P_{0i}Q_{1i}}{\sum_{i=1}^{n} P_{0i}Q_{0i}} \tag{6.55}$$

The Paasche volume index is an index of the growth in quantities valued at the current year's prices,

$$P_Q = \frac{\sum_{i=1}^{n} P_{1i}Q_{1i}}{\sum_{i=1}^{n} P_{1i}Q_{0i}} \tag{6.56}$$

The Fisher ideal volume index is a geometric mean of the Paasche and Laspeyres indexes,

$$F_Q = (L_Q \bullet P_Q)^{\frac{1}{2}} \tag{6.57}$$

Price indices are derived from quantity and value indices. Value (V), Volume (Q) and Price (P) indices are related as follows,

$$\frac{V_1}{V_0} = \frac{P_1}{P_0} \bullet \frac{Q_1}{Q_0} \tag{6.58}$$

Therefore, implicitly, one can compute the price index as,

$$\frac{P_1}{P_0} = \frac{V_1}{V_0(Q_1/Q_0)} \tag{6.59}$$

Indices emphasize relative changes in the time series as opposed to levels. However, one can re-construct the absolute level values[23] from the indices as in

$$\frac{Index}{100} \bullet 1986 \text{ base of the variable} \tag{6.60}$$

Note that the growth rate of the series is the same whether one calculates it from the index or from the absolute level data.

[23]For example, see the value in Statistics Canada (1996, p. 115) Table 1.

Chapter 7

Conclusions

This dissertation studied unemployment persistence and the influence of sectoral shocks on aggregate fluctuations in Canadian data. Among other hypotheses, it investigated the Lilien hypothesis using Canadian data. Chapter 4 documented the persistent nature of aggregate and sectoral Canadian unemployment. Chapter 5 explored the dynamic relation between sectoral and aggregate employment. Chapter 6 examined and proposed a theoretical framework wherein sectoral shocks generate observed aggregate persistence. We showed that the sectoral influence on aggregate variables is significant and relevant to policy decisions.

More specifically, this dissertation examined whether persistence in aggregate unemployment is a property of the impulses that impinge on the economy or a consequence of the structure of the sectoral interactions in the labour market. The objective was not to dismiss aggregate shocks and their influence, but to underline and quantify the relevance of sectoral shocks.

Throughout the dissertation, the results are conditioned on: the model, identification approach, variables de-trending procedures, variables transformations, functional specifications and other assumptions.

We addressed the robustness of the results. Relative to the assumptions made, we performed sensitivity analysis on the specific choice of prior distributions (Chapter 4), the specific transformation of the variables and the identification approach (Chapter 5), and the assumptions used to build the stochastic dynamic models (Chapter 6). We made reasonable modifications to the initial assumptions, recomputed quantities of interest and observed whether the modifications changed the conclusions. We investigated or used:

- The influence of the frequency of the data on the reported evidence of persistence by the Cochrane variance ratio in Chapter 4.
- The influence of the de-trending procedure on the reported evidence of persistence by the modified rescaled range test in Chapter 4.
- The number of fixed parameters in the Bayesian ARFIMA in Chapter 4, which led us to estimate 16 models.
- The prior used in the Bayesian ARFIMA (non-informative and informative) to compute the posterior probability of each model.
- Two identification approaches and variables transformations in Chapter 5 to estimate the Classical VAR models.
- Five different specifications in Chapter 5 to estimate the Bayesian VAR models, which led us to estimate 15 models.
- Three values for the adjustment cost parameter, the five values for the size of the shock and the two frequencies in Chapter 6, which led us to simulate 60 models.
- The method of the grid value function, which led us to evaluate the error bound for each model in Chapter 6.
- The calibrated parameters, which led us to compute elasticities as a measure for local sensitivity analysis in Chapter 6 and in Appendix B of Chapter 6.

In the VAR models, we used information criteria to select the lag length. We tested for lag exclusions and model over-identification in the Classical VAR. In the

Bayesian ARFIMA, we used the quadratic loss function to select the mean as the optimal point estimate.

We addressed model uncertainty throughout the thesis. We used Bayesian averaging to compute an overall model in Chapter 4. For the Classical VAR models in Chapter 5, we tested the residuals for misspecification signs. We also conducted Granger-causality tests. For the Bayesian VAR models in Chapter 5, we adopted the Theil U statistic as the criterion for model selection. For the RBC models, we adopted the comparison of the model generated impulse responses with the VAR one. We also used the informal moment matching approach.

Chapter 4 investigated persistence in Canadian unemployment data. Using the Cochrane variance ratio and the modified rescaled range test statistics, we reported significant evidence of persistence in total and manufacturing unemployment. Using a system of equations approach (SEA) to assess sectoral employment dynamics, Canadian employment data shows that Kaldor's first law holds for the period 1976 to 1998. Lilien's hypothesis does not hold in Canadian data. However, the results do suggest that a significant percentage of employment variability is due to sectoral shocks.

Adopting a statistical persistence measure as the fractional integration parameter in ARFIMA class of models, Chapter 4 estimated a range of low frequency models using a Bayesian approach. However, a commonly voiced concern with Bayesian methods is their reliance on sources of uncertainty such as the prior distribution and the precise parametric form of the likelihood function. Given the uncertainty over the models, we computed each model's posterior odds as a tool for model selection.

Our results showed that the first difference of the log of Canadian unemployment is stationary with intermediate memory. Posterior analysis of the impulse responses confirmed that the effect of a shock persists for at least 12 quarters. Chapter 5 examined the empirical dynamics between sectoral and aggregate Canadian employment data. The empirical investigations in Chapter 5 concluded with the following,

A Shock to:	Model	Variation in:	Persistence
		Employment Growth	
Manufacturing Reallocation	C-I	3 years: 13.58 %	2.5 years
Service Reallocation	C-II	3 years: 12.99 %	2.5 years
		Total Employment	
Manufacturing Employment	B-I	3 years: 14.3 %	3 years
Services Employment	B-II	3 years: 5.64 %	0.83 year

These results show that after 3 years, sectoral shocks are responsible for at most 14 percent of the variation in aggregate employment. In terms of persistence, all investigated models showed effects over 2.5 years, except for services employment shocks. In terms of employment variation, it is less than the 27 percent reported by Campbell and Kuttner (1996) and less than the 50 percent suggested by Lilien.

Chapter 6 presented two theoretical stochastic structural dynamic programming models to explain the effects of sectoral labour mobility on aggregate unemployment. We compared the impulse response results from the theoretical models with the empirical ones used in Chapter 5. We also used the Kydland-Prescott informal moment matching approach.

Is persistent unemployment a property of aggregate demand or aggregate supply fluctuations? Two RBC models were used to capture these two possibilities. In these models, relative sectoral technology shocks and taste shocks acted as impulse mechanisms. Sectoral reallocation and adjustment costs acted as propagation mechanisms and resulted in responses significantly greater than due to each one alone. Actual business cycle moments were employed as (pseudo) critical values to determine the merits of each model.

Comparing the RBC models' results with the unrestricted time series Bayesian VAR models showed that relative technology shocks generated higher employment volatility and longer unemployment persistence. This result held even for small adjustment costs incurred by the representative agent in terms of lost leisure. For higher adjustment costs, unemployment persistence was equally well generated in both models (relative technology shocks and relative taste shocks). Taste-shock models offered a good explanation[1] of non-technology driven procyclical labour productivity. They also allowed non-technology driven recessions. During recessions, one does not observe a large technological regress, as assumed by basic RBC models. Here, with a modest size shock to tastes, a recession was generated.

This thesis established that it took a smaller technology shock and a relatively larger taste shock to generate a similar decrease in employment. For both models, the adjustment mechanism was similar. The models differed in some aspects, e.g., model I included a capital stock whereas model II did not.

[1] While our simulations yield this result, many economists do not subscribe to changes in tastes as a significant cause of business cycles.

Our results showed that employment variance varied directly with adjustment costs and that a policy aimed at reducing these costs will result in significant reduction in employment variance. Our simulated results indicated that observed unemployment persistence could be the product of technology shocks or tastes shocks. Higher adjustment costs generated similar unemployment persistence regardless of the source of the shock. Smaller adjustment costs generated higher persistence for a technology shock than a taste shock. Given a shock of the same magnitude to both technology and to tastes, the former produced higher employment volatility, longer unemployment persistence and a deeper recession.

7.1 Contributions

This dissertation studied the effects of sector-specific shocks on aggregate fluctuations in unemployment. The plan was to find evidence of persistent unemployment and to integrate unemployment caused by sectoral shifts into a formal stochastic dynamic general equilibrium model.

We argued and concluded of the importance of sectoral reallocation in determining aggregate unemployment. We advanced the view that sectoral policies aimed at reducing unemployment are efficient and should be used. Sectoral policy solutions ought to be considered such as generating easier worker mobility between sectors.

Empirically and using a univariate analysis, we concluded that all monthly unemployment series exhibit slow autocorrelation decay. Using the Cochrane Variance Ratio and the Modified Rescaled Range Statistic, we significantly rejected the simple null hypothesis of i.i.d. process. Long-range dependence is evident in Canadian total, manufacturing and services unemployment. We estimated this persistence using Bayesian ARFIMA class of models to capture the omnipresent long memory. The results showed that Canadian aggregate unemployment is a long-memory process that exhibits the mean reversion property. In terms of persistence, the Effect of a shock persists for at least 12 quarters. Given the confusion regarding the definition of persistence in the literature, we proposed a new definition for 'economic persistence'.

Empirically and using a multivariate analysis, we estimated a Classical and a Bayesian VAR to assess the impact of a sectoral reallocation shock on employment. With a focus on identification issues, the Classical VAR concluded with the following observation. A reallocation shock of one standard deviation in manufacturing is responsible for 13.8 percent variation in the growth rate of employment after 4 years. The Bayesian VAR focused on the variance decomposition and the impulse responses. The results showed that Kaldor's first law holds in Canadian employment data over the period 1976 to 1998. Also, a shock in manufacturing employment of one percent is responsible for at most 20 percent of the variation in the rest of employment after one year.

Overall and empirically in terms of magnitude, sectoral shocks are less influential than reported in the literature but important.

Theoretically, we proposed and constructed two stochastic dynamic general equilibrium models to explain unemployment persistence, namely a relative technology shocks (model I) and a relative taste shocks (model II). For model I, a one percent technology shock induces at most a 0.7 percent increase in unemployment and 0.55 percent decrease in output. The effect of the shock persists for 4 to 6 periods depending on the difficulty of sectoral reallocation. For model II, a one-percent taste shock induces at most 0.2 percent increase in unemployment. The effect of the shock persists at most for 4 periods. Both models successfully generate unemployment persistence.

Among many, few important findings follow. It takes a smaller technology shock and a relatively larger taste shock to generate a similar decrease in employment. Technology shocks generate higher employment volatility and longer unemployment persistence. This result holds even for small adjustment costs. For higher adjustment costs, unemployment persistence could equally be generated from both models (technology shocks and taste shocks). Employment variance varies directly with the adjustment costs parameter. A policy aimed at reducing these costs will result in significant reduction of employment' variance.

Also, model II offers a good explanation of a non-technology driven procyclical labour productivity. It also presents a realistic view of a non-technology driven recession. During recessions, one does not observe a large technological regress as outlined by basic RBC models. Here, with a modest size shock to taste, a recession is generated. Also, model II is successful in generating the observed procyclical labour productivity.

Comparing the models, we showed that model I dominates model II on higher unemployment variance and that both models show partial success in matching empirical regularities. Given a shock with the same magnitude to both technology and to taste, the former produces higher employment volatility, longer unemployment persistence and a deeper recession. All models showed that employment variance varied directly with adjustment costs.

7.2 Future Research

Asymmetries in output movements over the business cycle are well documented. In general, there exist two types of asymmetries: first order and second order.[2] The former refers to the magnitude of the fluctuations around the mean: if the fluctuations around the mean are not symmetric, then the series is said to exhibit a first order asymmetry. The second order asymmetry refers to the length of the fluctuations: whenever the length of the cycles varies, the series is said to exhibit a second order asymmetry. The literature reports the asymmetry in output and unemployment to be of the second type.[3]

For further research, we suggest replacing symmetric by asymmetric costs of adjustment, so as to produce non-linear short-run fluctuations in stochastic dynamic general equilibrium models. This extension is important towards fully understanding the dynamics of the sectoral-shock effect on unemployment (see Pfann (1996) for a discussion).

Another extension would be to relate the adjustment costs to the state of the economy. For example, in booms, one expects some adjustment costs to be lower than in recessions. In such a setup, the adjustment cost parameter D should be stochastic and follow a transition probability matrix. Also, future research could apply the four steps outlined in Schorfheide (2000) to compute the posterior probabilities of each RBC model outlined here (model I and model II in Chapter 6), using as reference our estimated VAR in Chapter 5.

[2] These terms (first and second) are used in a non-mathematical sense.
[3] For direct and model based definitions of asymmetry, refer to Potter (1994, pp. 315-319) and Neftçi (1984).

Finally, extending the models to include more than two sectors is a definite must to understanding sectoral dynamics and their influence on aggregate behaviour (Swanson (1999b)). Allowing a multi-sector framework in which each sector is calibrated to its business cycle data should yield a better perspective on business cycles and sectoral policies. Sectoral theoretical modelling and empirical investigations offer promising avenues for future research.

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