ARE INNOVATIVE REGIONS MORE UNEQUAL? A CASE STUDY OF CANADIAN REGIONS, 1981-2016

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ABSTRACT: Since the 1980s, Canada, like many other OECD countries, has experienced a significant increase in income inequality. Persistent growth in disparities between the wealthy few and the rest has led to concerns over growing resentment and populist discontent. In this fraught era, understanding the drivers of growing inequality is more critical than ever. One such proposed driver, gaining increasing traction in the literature, has been innovation. Long touted as the key to economic growth, recent scholarly discussion has turned a critical eye to innovation-driven growth, highlighting the ways in which technological changes can displace or devalue certain workers whilst rewarding others, worsening income inequalities. Using high-resolution patent data from the United States Patents and Trademark Office in addition to microdata from Canada's Census of Population, this thesis empirically assesses the relationship between innovation and inequality at a pan-Canadian regional level using a series of spatial panel models. The descriptive results of the analysis reveal persistent divergent trends in both income inequality and innovation with urban regions both growing more unequal than rural regions and innovating at a faster pace than rural regions. The model results suggest that innovation is indeed positively and significantly correlated with inequality. This relationship appears to be further strengthened when innovation is restricted only to high-tech industries. While pro-creativity and innovation policies have been enormously popular in contemporary urban-economic discourse as a means to economic growth, the results suggest that such models need to be critically revisited and carefully implemented given the potential for innovation to induce inequality.

RÉSUMÉ: Depuis les années 1980, le Canada, comme de nombreux autres pays de l'OCDE, a connu une augmentation significative des inégalités de revenus. L'accroissement persistant des disparités entre les riches et les autres suscite davantage d'inquiétudes sur la montée possible d'un mécontentement populiste. Pendant ces temps difficiles, il est donc plus important que jamais de comprendre les facteurs qui sont responsables pour cet accroissement de l'inégalité. L'innovation est un facteur qui suscite beaucoup d'intérêt dans le discours académique. Longtemps considérée comme la clé de la croissance économique, la recherche a récemment jeté un regard plus critique sur le rôle de l'innovation dans la croissance, soulignant la manière dont les changements technologiques peuvent déplacer ou dévaloriser certains travailleurs tout en récompensant d'autres, aggravant ainsi les inégalités de revenus. En utilisant des données à haute résolution sur les brevets provenant du Bureau des brevets et des marques de commerce des États-Unis ainsi que des microdonnées du recensement de la population du Canada, cette thèse évalue de manière empirique la relation entre l'innovation et l'inégalité au niveau régional à l'aide d'une série de modèles de régressions spatiaux avec des données panel. Les résultats de l'analyse descriptive révèlent une tendance divergente de l'inégalité des revenus entre les régions. L'inégalité s'accroit plus rapidement dans les régions urbaines par rapport au régions rurales. Pareillement, l'innovation se concentre davantage dans les régions urbaines. Les résultats des modèles de régressions suggèrent que l'innovation est en effet positivement et significativement corrélée avec l'inégalité. Cette relation est encore plus forte lorsque la mesure d'innovation est limitée seulement aux industries de haute technologie. Les politiques en faveur de la créativité et de l'innovation comme moyen de croissance économique ont été énormément populaires dans les discours urbain-économique contemporains mais, les résultats de cette thèse démontrent la nécessité d'être prudent avec des modèles de croissances fondée uniquement sur l'innovation étant donné le potentiel de l'innovation à induire l'inégalité.

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CONTRIBUTION OF AUTHORS

The author confirms sole responsibility for the following study conception, data collection, analysis, interpretation, and manuscript preparation.

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Chapter 1

INTRODUCTION

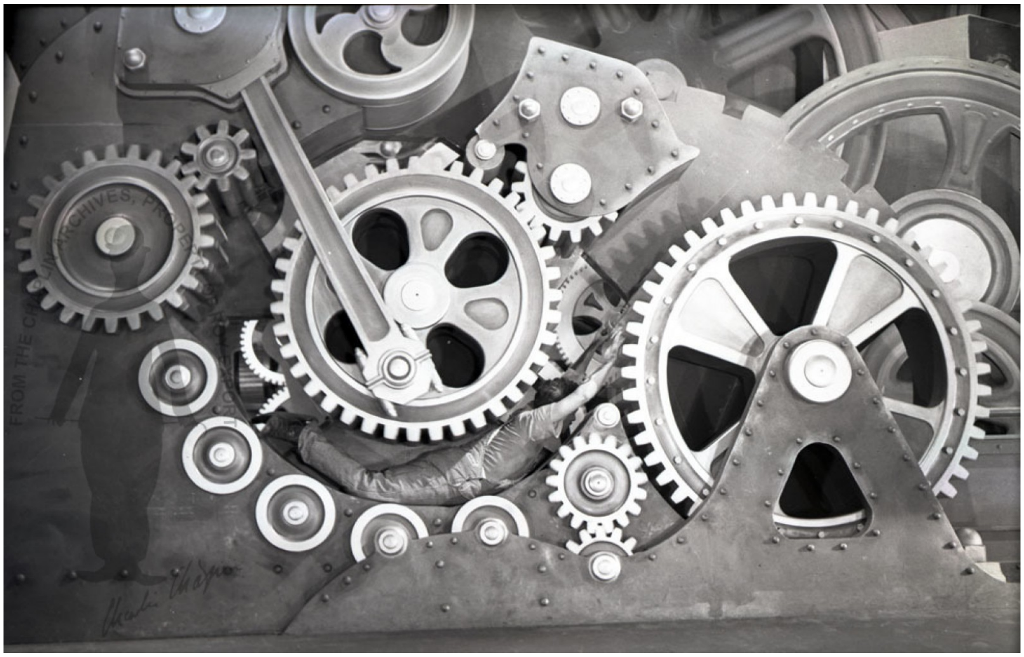
Charlie Chaplin's famous 1936 movie, *Modern Times,* begins with his beloved, re-occurring character 'The Tramp' working on a factory assembly line. From a faraway room, the company president, observing his workers from screens, orders the lines to be sped up. Thus, begins a series of classic Chaplin antics as The Tramp struggles hilariously to keep up with the breakneck pace and repetitive movements of his work, eventually suffering a nervous breakdown.

In another famous scene from the film, The Tramp is selected as the unfortunate test dummy for a new gadget, a feeding device, intended to mechanize the eating process and shorten workers lunch hours. Once again, hilarity ensues as the device malfunctions, spinning out of control, shoving nuts and bolts down The Tramp's throat, and smashing a cake in his face.

The films humorous yet obviously critical depiction of modern technology was an enormous box office success, resonating deeply with public anxieties surrounding their brave new world and its new steel-coated machinations. The film depicts the modern technologies (that make the eponymous modern times) as forebodingly large, dehumanizing, and dangerous (see Figure 1.1). Engaging with themes of surveillance (the factory boss observing employees from screens) and near-Foucauldian discipline of the body (workers subject to rapid repetitive movements on the assembly line), the films depicts the machines as the harbingers of the inequalities between the alienated, factory-floor workers and the wealthy factory owners (Puli, 2023).

In 1981, Chaplin's Tramp character resurfaced, this time, not as a production of Chaplin himself, but as part of an IBM advertising campaign for their first computer aimed for the mass market (Papson, 1990). The advertising campaign ran with the tagline "a tool for modern times" and featured The Tramp in a series of television commercials and print ads, usually comically struggling with an excess of paperwork or overwhelmed with other clerical tasks. These scenes were accompanied by a narrator touting the benefits of the IBM PC. The campaign was enormously successful, winning multiple advertising awards and boosting IBM's share of the personal computer market from 0 to 40% (Papson, 1990).

Figure 1.1. An infamous scene from *Modern Times* (1936). 'The Tramp' is swallowed by the factory machinery



Source: The Charlie Chaplin Archives

IBM's use of the Tramp was no small matter. In co-opting what was deliberately an Everyman figure, reckoning with the suffering and dislocations causes by modernization and a wave of new technologies, IBM effectively reframed the critical elements of *Modern Times,* presenting a new wave of technological change as the solution to the Everyman's woes, rather than a part of the problem.

A far cry from the 'dark satanic mills' of the factory assembly line, IBM promises the new era of the personal computer will be a comfortable one. As a beloved cultural character, the Tramp humanizes and makes palatable the unfamiliar intrusion of such a radical new technology into consumers' homes and private lives. No longer a symbol of worker dignity in the face of radical creative destruction, the Tramp is instead a willing and happy endorser of the PC, any woes he had soothed by the benefits of the new personal computer (Papson, 1990).

IBM's careful approach to the palatability of their new product was not unwarranted. Public pushback against disruptive new innovations is not new. The most famous such example is of course the Luddites, late 18th century and early 19th craftsmen who famously resisted the mechanization of the textile industry in England that was rendering their jobs and livelihoods obsolete.

Austrian economist Joseph Schumpeter was quick to recognize the growing pains associated with innovation and technological change, coining the term ‘creative destruction’ to refer to the constant demolition of products, processes, and ways of living, rendered obsolete by the relentless tide of new innovations. While ‘Luddite’ now carries a pejorative, techno-phobic, connotation, it is worth considering the very real pain that radical periods of technological upheaval can carry.

The IBM ad campaign came at the start of another era of radical change. The information communications technology (ICT) era ushered in mass computerization in workplaces and the home (as promised by the IBM PC). While some workers benefitted from the incorporation of this new technology, countless others were rendered obsolete putting whole labour sectors out of work. Notably, the 1980s is also when the major economies of the Global North (the US, UK and eventually Canada) began to experience a dramatic upswing in income inequality, following several decades of relative equality (Katz, 1999; Piketty, 2014).

There is a wealth of theory and discussion on the impacts of technological change on workers. Predominant labour economics theories have argued that new innovations will complement the work of highly-skilled labourers (e.g., an animator using computer animation software can produce output at a drastically faster pace than one working with traditional pen and paper methods), whilst lower-skilled labourers may find themselves replaced by technology that can do their jobs at lower cost (e.g., automation of grocery store checkout registers). The expected result is thus wage polarization and subsequently, rising inequality (Card and Dinardo, 2002).

The coincidence in the timing inequality growth following the proliferation of microcomputers (Katz, 1999) is paralleled with a similar spatial pattern: cities that are the most innovative also appear to be the most unequal (Florida, 2005). One need look no further than Silicon Valley, the poster child for innovation-driven growth, to question why such a seemingly prosperous place is plagued with inequality (Florida and Mellander, 2016).

However, despite the work and contributions of labour economists, studies offering a geographic perspective to the innovation-inequality relationship are scarce and relatively new. Only in the last decade have economic geographers (see for example Lee 2011, Lee and

Rodriguez-Pose, 2013, Breau et al., 2014) begun to explore the innovation-inequality relationship from a space-based perspective.

While much of the early research has been focused on Europe or the United States, so far Breau et al. (2014) are the only ones to have empirically examined the impact of innovation on income inequality in Canadian cities. And while the early results they offer are illuminating, the transferability of city-specific work, given the unique properties of cities, to wider scales is difficult. The broader Canadian space-economy is especially interesting given its vast size and historical intertwinement with the staples economy and all the unique challenges and opportunities this poses for the geographies of innovation (Watkins, 1963; Wolfe, 2014; Breau et al. 2018). This research intends to fill that gap by examining the innovation-inequality relationship across all regions in Canada, from coast to coast to coast, the first study – to the best of my knowledge – to do so.

Of course, technological changes are not the only reason for worsening income inequality. There has been significant discussion surrounding the shift towards free market economics (Harvey, 1989; Peck, 2001), manufacturing decline and changing geographies of production (Bluestone and Harrison, 1982; Massey, 1995) and union decline (Banting and Myles, 2013) that took place in the 1980s.

However, as the rise of generative Artificial Intelligence threatens another wave of worker redundancies (Acemoglu and Johnson, 2023), more and more researchers are investigating the so-called 'dark-side of innovation' and revisiting the legitimacy of an innovation-based growth paradigm (Shearmur, 2012; Pinheiro et al., 2022). Is innovation the quintessential mechanism through which growth and prosperity is generated? If so, is that growth being distributed equitably? Is such growth worth the inequality that arises or the personal hardships it may generate?

It is within this context that I situate my research questions for this thesis. There are three overarching sets of questions guiding the research undertaken:

1. What are the current trends in income inequality across Canadian regions? What regions are experiencing the fastest inequality growth?
2. What does the geography of innovation in Canada look like? Does innovation cluster primarily in urban areas? What is the rural dimension (if any) of Canadian innovation? What kind of innovation is occurring where?

3. Finally, what is the nature of the relationship (if any) between innovation and inequality in Canada? Does innovation play a role in worsening inequality across Canadian regions?

The first two sets of questions are intended to get a descriptive sense of both the inequality and innovation landscapes across Canada. Once this scene is set, I then turn my attention to the third question, which seeks to empirically investigate the connection (if any) between innovation and inequality across Canadian regions.

In order to address these questions, I develop a panel dataset measuring the intensity of innovation and inequality, along with other socio-economic variables across Canadian census division (CDs) for every census year between 1981 and 2016. Innovation is measured by proxy through patent data, acquired from the United States Patents and Trademark Office (USPTO) while inequality is measured using the Gini coefficient and Theil index, both calculated from the microdata files from the long-form Canadian census of population. The patent data are also cross-referenced with NAICS categories to determine the predominant industries in which innovation is occurring in each region. Finally, a series of spatial panel regression models are estimated to more formally explore the relationship between innovation and inequality. These models include a full set of covariates which measure the relative impact of innovation on inequality while also controlling for other inequality-influencing variables, such as local labour market characteristics, institutional characteristics (e.g., minimum wage, unionization rates) and local industrial mixes.

Spatially, I find that patterns of income inequality follow those initially observed by Breau (2015) and Marchand et al. (2020): first, urban regions are growing more unequal than rural ones, and this is especially true for the largest metropolitan areas. Second, there is also evidence of an east-west divide, whereby inequality is generally higher and growing faster in regions west of the Ottawa river, while those in the East, primarily Quebec and the Atlantic provinces, tend to have relatively lower levels of inequality.

Without surprise, gross innovation (measured by patent intensity) is highest in metropolitan regions, with per capita innovation highest in medium-sized cities which have large high-tech clusters (i.e., Ottawa-Carleton and Waterloo). Innovation rates are also growing at a significantly faster rate in large-metropolitan and medium-metropolitan regions. It is interesting to note that we also find evidence of some significant levels of innovation in certain rural regions.

Finally, the model results suggest that innovation is positively and significantly correlated with income inequality across Canadian regions, though this relationship appears to be weaker when using the Theil index as an alternate measure of inequality. Interestingly, when focusing the analysis on patent data that reflect high-tech innovation (i.e., 'cutting-edge' industries), the positive inequality-innovation relationship is stronger, suggesting that different types of innovative activities may have different levels of impact on the distribution of incomes.

The rest of the thesis is organized as follows. Chapter 2 provides a review of several bodies of literature related to the innovation-inequality nexus including long-run trends in inequality globally and within Canada as well as brief discussion of how and why innovation came to occupy such a seemingly indispensable position in economic growth discourse. Chapter 3 discusses the data and methodology used to conduct the analysis, including an overview of the strengths and weaknesses of patent data as a proxy for innovation. Chapter 4 begins by presenting descriptive results on the regional geographies of inequality and innovation across the country followed by findings derived from the spatial panel models estimated in the thesis. Finally, Chapter 5 concludes with a discussion of limitations, avenues for future research and what the insights gleaned mean for regional policymaking in Canada.

Chapter 2

LITERATURE REVIEW

This chapter presents an overview of the major bodies of literature related to innovation and inequality. The chapter is organized into four sections. The *first* situates the current era of increasing income inequality in Canada within the larger temporal and spatial context. This broad discussion includes a more specific exploration of the Canadian context and current trends in sub-national inequality, and also provides a brief overview of the consequences of increasing inequality.

The *second* section turns to innovation studies and how this body of work has become a key fixture of economic growth and policymaking in the neoliberal era. Here, I pay particular attention to the geographical literature on innovation and conceptual debates around the importance of cities and space in stimulating innovation.

In the *third* section, I offer an overview of the mechanisms through which innovation and inequality are thought to be related. While many theories have been put forth to explain a causal link between the two, there is yet to emerge a clear consensus on the specific nature of the innovation-inequality relationship. This discussion is followed by a brief review of empirical evidence on the innovation-inequality relationship.

The chapter's *final* section situates the innovation-inequality linkage within a larger conceptual framework that encapsulates the multifaceted factors contributing to growing income inequalities. Here, I review both the macro forces that have come to shape the socio-economic global structure since the 1980s as well as the more local, place-specific, micro forces that drive inequality in a given place. Innovation is integrated into this framework to build the conceptual basis for the methods I utilize to further examine the innovation-inequality relationship across Canadian regions.

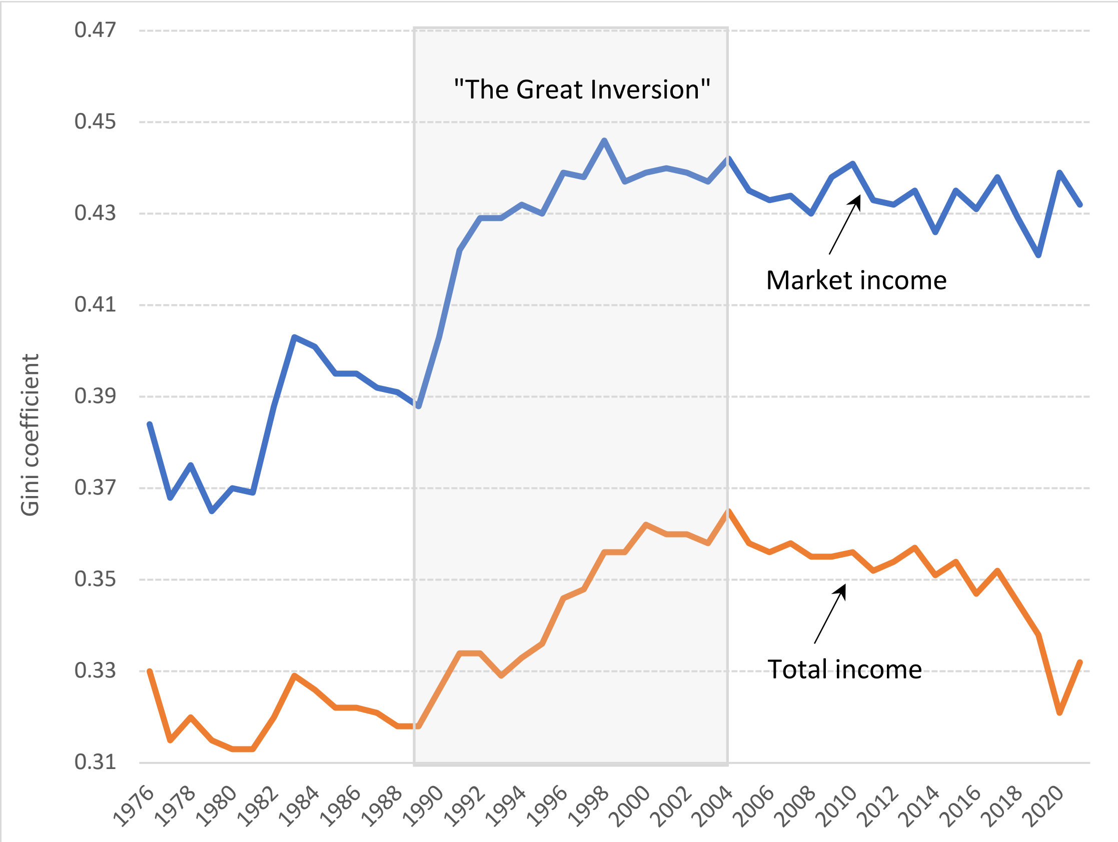
2.1. Inequality

2.1.1. Global and national trends

In the aftermath of the Great Depression and the second world war there existed, for a brief period, a time unlike any other in modern history. Across much of the Global North, the decades following the end of WWII through the 1970s were a time of unprecedented economic equality, a period often referred to as the "Great Compression" (Goldin and Margo, 1992). In the United States, the wage gap shrank significantly and the wealth share of the bottom 90% of Americans grew from 20% in the 1920s to a record-setting 35% by the mid-1980s (Goldin and Margo, 1992; Saez and Zucman, 2016). This period of relative equality proved to be short-lived as by the late 1970s and early-1980s, warning signs of a reversal of fortunes began to flash again with indicators pointing to a renewed uptick in both wealth and income inequality (Atkinson et al., 2011). Rising levels of inequality across most OECD countries would come to define much of the 1990s, a situation that largely has persisted to the present.

Canada is no exception to these trends. Until the late 1980s, Canadian national-level inequality remained steadfastly low (Figure 2.1). This changed, however, when Canada experienced some of the most rapid income inequality growth in the OECD from the early 1990s to the mid-2000s (Osberg, 2018; Davies and Matteo, 2021). This "Great Inversion" marked an abrupt reversal of post-war inequality trends. Top 10% income share capture increased from 28% in 1982 to 41% in 2021, whilst the bottom 50% declined from 22% to 16% in the same time period (Chancel et al., 2022). This increase is less than the US, but more considerable than many other OECD countries including Italy and France (Veall, 2012). Canadian income inequality peaked in mid-2000s when levels of inequality were 17% higher than they were in the 1980s (Fortin et al., 2012). Since then, national level inequality levels have remained consistently high despite the Great Recession (see Figure 2.1), with some small exceptions. The late 2010s saw a brief decline in total and market income inequality as the federal liberal party implemented policies aimed at strengthening the middle-class (Béland and Prince, 2019). 2020 saw an even steeper reduction in both total income inequality as the COVID-19 pandemic prompted the implementation of the Canadian Emergency Response Benefit (CERB) program which, among others, provided direct financial support to Canadians dealing with employment difficulties during the pandemic (Canada Revenue Agency, 2022). However, as pandemic-era redistributive policies were scaled-back, total inequality has once again begun to rise (Figure 2.1).

Figure 2.1. National-level inequality in Canada between 1976-2021



Source: Author generated using data from Statistics Canada Table 11-10-0134-01.

Within these broad patterns of national-level inequality, the gap between the top 1% and the rest of earners is growing at a particularly alarming rate. In 2021, the cut-off for total annual incomes for top 1% tax filers started at $579,100, a 9.4% increase from the previous year (Statistics Canada, 2023). Aggregate income share held by the top 1% peaked in 2007 when the 1% earners captured nearly 14% of the national income share - a 75% increase from just under 8% in 1978 (Veall, 2012). Between 1982 and 2014 the 1%, 0.1% and 0.01% saw their incomes grow 53%, 90% and 133% respectively, compared to a 28% loss in the bottom half of earners in the same time period (Statistics Canada, 2018). These shifts are a dramatic reversal of the declining 1% income capture between 1944 and 1978 (Statistics Canada, 2018).

In 2021, aggregate income earned by the top 1% has increased to 10.4%, the highest it has been since 2015, indicating a substantial inequality worsening in the midst of the COVID-19 pandemic (Statistics Canada, 2023).

2.1.2. Sub-national trends

Whilst the discussion so far has focused on national and global-scale trends in inequality over the last few decades, growing attention is now focusing on the increasingly divergent trajectories of inequality at the sub-national level. Canada's enormous topographic variation, complex regional histories, and unique dependence on the staples economy means there is considerable variation in economic fortunes across regions (Wellstead, 2007; Marchand et al. 2020).

In terms of how incomes are distributed, recent studies have documented two distinct spatial trends. First, regions West of the Ottawa river tend to have higher than average levels of inequality, whilst Eastern regions have lower than average inequality (Breau, 2015; Marchand et al., 2020). Accordingly, the top 1% earners are growing at a disproportionate rate in the Prairie provinces (i.e., Alberta, Saskatchewan, Manitoba) where the oil sands boom has been taking place (Breau, 2014). Significant inequality growth in the resource-rich western regions suggests some evidence of an inequality "resource-curse", whereby the expected benefits of a valuable local resource do not materialize for all individuals, though the local evidence of such a phenomenon is complicated and varies along boom-bust resource cycle dynamics (Dubé & Polèse, 2014; Marchand, 2015).

The second clear sub-national trend is the emergence of an urban-rural divide. Metropolitan regions consistently register much higher levels of inequality compared to the national average, whilst rural areas tend to have lower levels of inequality (Marchand et al., 2020). Furthermore, within Canada's metropolitan areas, larger cities show markedly higher levels of inequality growth compared to smaller ones (Bolton and Breau, 2012). These results remain significant even after controlling for the larger population size of metropolitan areas, suggesting a city-specific influence on inequality. As the work of Baum-Snow and Pavan (2013) demonstrates, city size-specific factors explain over 23% of the variance in income inequality in the US between 1979 and 2007. They attribute this rise to an interaction between the overrepresentation of higher-skilled, higher-paying jobs in larger cities and the agglomeration forces of cities, accentuating these wage disparities.

Such evidence of divergent regional patterns indicates the need to consider both local and macro-forces driving inequality. From the resource-rich regions in Canada's West, to former manufacturing strongholds of Southern Ontario, regional inequalities and their future trajectories are thus distinctly shaped by their regional complexities. Economic fortunes in western Canada appear closely shaped by its unique resource-boom based economies whereas eastern regions may be more shielded form economic inequality due to stronger provincial social assistance policies (e.g., Quebec) (Fortin and Lemieux, 2015).

Yet, if there is a considerable amount of research on inequality at the national-scale, as well as at the urban and neighbourhood-level scales, research at the meso-level (i.e., regional) is rather sparse. At the provincial scale, there is some work examining the causes of inequality (see: Breau, 2007 and Fortin and Lemieux, 2015). Below the provincial-scale, to date, the most comprehensive work on the regional dimensions of inequality in Canada comes from Breau (2015) and Marchand et al. (2020) who conduct a census-division wide analysis of the causes of income inequality in Canada. This research aims to complement the work of Breau (2015) and Marchand et al. (2020) by conducting a regional-scale analysis of inequality, incorporating the previously missing innovation angle to the discussion.

The discussion thus far, though primarily focused on income inequality, has considered wealth and income inequality somewhat interchangeably. It is worth pausing here to briefly consider the differences between the terms and establish a consistent lexicon before moving forward. Whilst income is driven by labour (i.e. wages and salaries), wealth refers to the sum of an individual's economic resources including labour derived income, capital gains, savings, and entrepreneurial income (Saez, 2017). For the bottom 90% of income earners, capital gains and other measures of wealth are negligible compared to labour income (Saez, 2017). In the US, the bottom 50% have essentially no wealth, and all income is derived from labour (Saez, 2017). In the case of both the United States and Canada, the rapid increase in wealth in the upper percentiles throughout the 1990s and early 2000s has been driven primarily by labour income (wages and salaries) as opposed to capital gains or entrepreneurial income (Breau, 2014; Saez and Zucman, 2016). Due partly to the larger impact of labour-derived income, combined with the methodological difficulties of measuring wealth, what follows in this thesis will focus specifically on income (labour) inequality and its causes. Further discussion on how income is measured (e.g., individual vs. household, workers vs. non-workers etc.) is provided in Section 3.2.4 below.

2.1.3. Consequences

Why should we care about inequality? By virtue of an intrinsic sense of fairness, individuals generally tend to have some concern for equality and redistribution (Saez, 2017). However, beyond an innate sense of humane compassion, inequality presents tangible and documented threats to both individual and societal health, well-being, and stability.

The 2011 Occupy movement, partially a response to the Great Recession of 2008-2009, was one of the first widespread public pushbacks against the ever-widening gap between the 1% and the rest (Breau, 2014). Since then, there have emerged a multitude of popular movements across the world, directly or indirectly citing frustration with the perceived state of inequality. As Rodríguez-Pose (2018) argues, we are expected to continue to see a distinctively geographically situated populist pushback as economically lagging regions experiencing decline contend with rising resentment towards the more prosperous cities and their inhabitants (Rodríguez-Pose, 2018). This 'revenge of places that don't matter' is making-itself felt in the polls with the election of populist politicians like Donald Trump in the US, polarizing movements like Brexit in the UK (Rodríguez-Pose, 2018), the 'yellow vests' in France (Bourdin and Torre, 2023) and the rise of right-wing populist political parties in Italy (Di Matteo and Mariotti, 2020). The winds of polarization and discontent are also increasingly apparent in Canada, where the populist surge can be seen in the political platforms of politicians like Doug Ford and parties like the People's Party of Canada (PPC) and the Coalition Avenir Quebec (CAQ) in Quebec (Erl, 2021). This discontent has not been limited to the polls and is increasingly spilling into the streets, most notably during the recent 2022 Freedom Convoy protest which converged in Ottawa amidst the COVID-19 pandemic (Gillies et al., 2023).

In addition to political unrest, inequality has demonstrable psycho-social and physical health consequences. Sustained inequality has been linked to poor physical health outcomes, mental health issues, public health problems (e.g., violence) and obesity amongst a range of other concerning health indicators (Pickett & Wilkinson, 2015). From a more psycho-social perspective, Stiglitz (2012) argues that wide-scale inequality can erode our collective societal sense of fair play and understanding of community. Similarly, using a biopsychosocial approach, Wilkinson (2006) demonstrates that health and longevity are worsened in unequal societies. In this model, the nature of the social environment has tangible biological outcomes: stress, resulting from precarious financial situations, lower social status, difficulty with social integration and adverse early life experiences, results in poorer health and reduced longevity (Wilkinson, 2006).

On the economic front, a growing number of studies have found that high levels of inequality tend to stifle economic growth. A global overview by Dabla-Norris et al. (2015) found that a higher Gini coefficient is associated with lower economic growth in the medium term. Similarly, they find that a 1% increase in the income shares of the top 20% lowers GDP growth by 0.08% in the following five years, whilst the same growth in the bottom 20% results in a 0.38% increase in GDP (Dabla-Norris et al., 2015). Within the Canadian context, Marchand et al. (2020) show that sustained inequality in the long run has net negative consequences for regional economic growth.

Global inequalities are also tightly related to ecological ones. Globally, higher earners make up the bulk of greenhouse gas emissions, both within and between countries (Chancel et al., 2022). Furthermore, emerging evidence has highlighted a link between high rates of inequality and increased biodiversity loss, as collective resources are eroded for the benefits of the wealthy few (Mikkelson et al., 2007; Holland et al., 2009). On a more local scale, economically disadvantaged and racialized communities tend to bear the brunt of environmental hazards. These communities are more likely to be located near dangerous pollutants (i.e. hazardous waste sites or heavy industries) and are more likely to suffer disproportionately from the effects of climate change, further exacerbating existing inequalities (Pastor et al. 2001; Islam, and Winkel, 2017; Boyce, 2018). Furthermore, even climate solution actions (e.g., 'green' transitions) are felt unequally. As Rodriguez-Pose and Bartalucci (2023) demonstrate, less-developed, rural, European regions are more likely to suffer adverse socio-economic consequences amidst a green transition.

Ultimately, given the well-documented consequences of inequality, understanding how it escalates and how it can be mitigated becomes an essential focus for societal well-being. The following sections (2.2-2.4) present a review of the literature on the drivers of income inequality in Canada and the Global North over the last forty years with a specific emphasis on the role played by innovation.

2.2. Innovation

This section introduces and examines the history and geography of innovation as a key variable of interest in understanding trends in income inequality. The discussion begins with a review of how and why innovation has come to be nearly synonymous with economic growth and prosperity, followed by some critiques of this hegemonic discourse. This section then covers a summary of academic discourse on the distinctive geographies of innovation. The following section (2.3) provides a detailed overview on the mechanisms through which innovation and inequality intersect.

2.2.1. Innovation and economic development

Innovation as a key economic process was first discussed at length by Joseph Schumpeter. According to the Schumpeterian view of economic growth, innovation, broadly defined as the creation and diffusion of new ways of doing things, is what fundamentally drives economic growth (Schumpeter 1942 as cited in Dicken, 2011). Using Kondratiev's wave-theory of economic growth, Schumpeter argued that innovation is the key to initiating a new cycle of growth (Dickens, 2011). More specifically, Schumpeter argued that breakthrough, radical innovations spur vast changes in techno-economic paradigms which subsequently trigger new Kondratiev waves of growth as a new set of techno-economic practices slowly replaces old ones (Dickens, 2011).

Schumpeter's pioneering work reached wider appeal following Solow's highly influential model of economic growth, which argued that the principal determinant of US growth over the first half of the twentieth century was technological change (Solow, 1957).

Despite these early insights, innovation did not become a major topic of academic research and policy until the 1980s with the emergence of endogenous growth theory which expanded Solow's model to conceptualize technological change as an internal process driving growth, reframing economic growth as a process that is primarily driven by harness-able internal forces as opposed to external ones (Lucas, 1988; Romer, 1990; Grossman and Helpman, 1991).

Endogenous growth theory was a helpful paradigm shift at a time when external forces of economic growth were increasingly uncertain. First, the 1970s and 1980s saw large-scale socio-economic shifts, a tumultuous era of economic restructuring referred to as the "Great U-Turn" (Bluestone & Harrison, 1988) or the shift from Fordism to neoliberalism (Harvey, 2007). The result of which was a complete departure from the post-war period of relative economic equality, towards rapid increases in income inequality across many countries of the Global North. Part of this restructuring included the development of a new regime of “flexible accumulation” (Jessop et al. 1994; Gertler, 1988) which came about as a response to the crises of Keynesian capitalism in the 1970s including stagflation, market saturation and rigidly fixed capital and labour (Gertler, 1988; Harvey, 2005). A critical feature of this new paradigm is the emphasis on individualistic economic growth characterized by innovation, competition, and flexibility of production and labour (Gertler, 1988; Harvey, 1989; Shearmur, 2012). The political economist Bob Jessop describes this turn towards a post-Fordist macro-economic model of growth as “flexible and *permanently innovative*” (Jessop, 1994 p. 19), requiring a new state form to stimulate supply-side innovation and maintain flexibility in labour markets. This gave rise to what he dubs the ‘Schumpeterian workfare state’ (SWS) (Jessop, 1994) who’s objectives are “to promote product, process, organizational, and market innovation in open economies” (Jessop, 1994 p. 24).

The 1970s and 1980s also saw a period of mass deindustrialization in the Global North (Bluestone and Harrison, 1988; Norcliffe, 1994). Manufacturing jobs that were once the backbone of Canada’s middle class were lost as corporations shifted their production overseas (Held et al. 1999; Dicken 2011). As Shearmur (2012) argues, this rise of production in the Global South inspired fear in nations of the Global North who could not compete with the lower production costs of the Global South. Therefore, government policy in the Global North shifted towards stimulating innovation-based knowledge economies to maintain their dominance of international markets (Shearmur, 2012).

From an urban-economic geographic perspective, neoliberal fiscal cutbacks and the reduced role of central government in the 1980s forced cities to become increasingly entrepreneurial in their efforts to assure their economic futures (Harvey, 1989). Cities, accordingly, became key sites of the new innovation-growth paradigm, forced to embrace the need for local innovators to drive local economic growth, and simultaneously forced to become innovators themselves in the quest to stay afloat amidst inter-urban competition for scarce resources (Harvey, 1989). One of the most widely-read and influential theories in the urban-policy domain has been the work of Richard Florida. His 2002 book *The Rise of the Creative Class*, argued that human capital and human creativity are the key engines that shape the growth and economic prosperity of cities. Florida introduces the concept of a creative class, a new class of workers distinguished by others in that they are paid to use “the full scope of their cognitive and social skills” (Florida, 2002: 9). In Florida’s framework, the most effective method for cities to attract firms and stimulate growth is by designing cities that attract members of this creative class. While this vision presented an appealing way forward to urban policymakers its effectiveness has since been widely criticized (more on this in the following section).

2.2.2. Geographies of innovation

Amidst the age of globalization and the information and communications technology (ICT) revolution, many academics initially predicted a decline in the importance of geography as the cost of the transfer of information, ideas and goods plummeted (Cairncross, 2001). However, growing evidence from the past thirty years has demonstrated that the importance of the local, far from declining, is increasing (Leamer and Storper, 2001; Morgan, 2004). There is an enormous body of literature dedicated to the importance of cities as critical nuclei of ideas and innovation (see, for example Glaeser, 2011) that make them the key to innovation and subsequently growth. This sub-section provides an overview of the literature of cities and their role as ‘Schumpeterian’ hubs of innovation, some critiques, and a discussion of the potentially neglected non-urban angle to innovation.

While the spatiality of manufacturing was determined by access to waterways, railways and other forms of transport, the new knowledge-based economy, characterized by intangible assets like innovation and ideas has been overwhelmingly linked to cities (Gertler, 2001; Wolfe, 2016). Cities, as dense agglomerations of people, institutions and infrastructure provide an ideal location for knowledge-exchange and specialization, along with providing access to a large and diverse pool of labour. From a firm-level perspective, cities offer several advantages. First, proximity to other firms, institutions and individuals engaged in similar or interrelated activities, highly specialized industries mean access to a local skilled labour force with the required skill sets for a given industry (Wolfe, 2016). Firms also benefit from knowledge spillovers between interrelated actors. Knowledge spillovers refer to the externalities of R&D activities used by one firm or industry being claimed by other industries or firms. These externalities can stimulate creativity and productivity across firms with less initial input, therefore stimulating productivity and economic growth (Griliches, 1992; Jaffe et al., 1993). Having firms localized near one another in space provides an opportunity for these spillovers to occur. Local specialization means firms also benefit from access to providers of specialized intermediate inputs and services (Krugman, 1991 as cited in Wolfe, 2016).

Another strand of the literature emphasizes the cross-fertilization of ideas between different and diverse industries as driving new innovations by applying methods, and knowledge from one industry to solve problems and push advancements in another (Jacobs, 1969; Feldman and Audretsch, 1999). Here, the city, as an agglomeration of multiple and diverse industries, serves as the proverbial melting pot that provides the built environment for cross-fertilization between these industries to occur. In Canada, Toronto and Montreal, as the largest and most industrially diversified, Canadian cities, should benefit the most from cross-industry knowledge spillovers (Wolfe, 2009). In contrast, cities like Ottawa and Calgary, are less diversified and more specialized (Ottawa in telecommunications and public administration and Calgary in oil and gas) (Wolfe, 2009). In Ottawa, cooperative relationships and knowledge sharing between interrelated actors in the same industry drive innovation whilst Calgary has benefitted instead from the emergence of new knowledge platforms related to the resource economy (Wolfe, 2009).

Despite the rationality of spillover-related arguments for the innovation-stimulating effect of cities, one would assume that rapid advancements in ICT technologies would somewhat offset the need for physical proximity for the exchange of ideas between economic actors. However, innovation continues to occur primarily in large urban areas. Why then, does spatial proximity continue to matter? Academics have largely attributed this to the high spatial cost of knowledge and learning (Morgan, 2004; McCann, 2007; Christopherson et al., 2008). Despite the radically decreased cost of physical distance (Dicken, 2011), the information and exchanges required for knowledge and learning remain highly context specific (Gertler, 2003) and require integration in high-trust local networks (Gordon and MacCann, 2005). These more complex, 'tacit' forms of knowledge are intrinsically place-based. They require "being there" (Gertler, 1995) and cannot be easily transferred over distance unlike codified forms of knowledge (Polanyi, 1962; Hall and Vodden, 2019).

The work of Saskia Sassen has also highlighted the importance of cities in the increasingly globalized world as coordinators of global flows of finance (Sassen, 2001). These global cities have become the main hubs of innovation in the financial sector. That said, lower-tier cities can also act as innovation hubs for their respective national and regional economies (Simmie 2003; Wolfe, 2016) as they house business and political leaders, a proximity which can accelerate investment and decision-making creating a dynamic environment for innovation (Simmie 2002; Wolfe, 2016).

Another branch of the literature is dedicated to the individuals that drive innovation and their relationship to the city. As previously discussed, Florida's (2002) "creative class" thesis sees creative individuals as the drivers of innovation. These individuals, drawn to the cultural opportunities, authenticity, entertainment, social diversity, and tolerance of places, tend to cluster in certain cities (Florida, 2002; Glaeser and Gottlieb, 2006). Florida argues that firms are subsequently drawn to cities where these creative individuals tend to cluster (Florida, 2002). However, critics of Florida have also been quick to point out issues with this thesis citing evidence that high-skilled workers are more likely to choose to live in certain places based on the availability of jobs that fit their skills, as opposed to the other way around (Peck, 2005; Scott, 2006; Storper and Manville, 2006).

Finally, Shearmur et al. (2016) argue that cities themselves exert a certain power over innovation. *First*, by attracting creative people to the city, seeking employment opportunities or to develop their market, and *second*, by housing 'innovation gatekeepers', journalists, major universities, and trend-setters which hold considerable influence over what is considered creative and innovative (Shearmur et al., 2016).

However, the fixation on cities as sites of innovation may belie other important non-urban contributors to innovation. As Shearmur (2012) argues, policymakers and academics alike have largely internalized cities and innovation as intrinsically linked, omitting non-urban spaces, "non-creative classes" and the different forms of dynamism, creativity, and innovation that they encompass.

Many have pointed out that cities are not isolated, independent entities but rather part of a global system of flows. Sassen (2001) and Castells (1996) both acknowledge cities as nodes amongst a vast and tightly connected global network of interconnected flows. Conceptualized in this way, a city's innovative potential comes from a combination of local, endogenous impacts as well as their access to international pipelines of new knowledge and ideas (Simmie, 2003; Bathelt et al., 2004).

A related area of research argues that temporary geographic proximity (e.g., conferences) suffices in generating the face-to-face interaction required to transfer tacit knowledge without the need for related actors to be permanently co-located (Torre, 2008). The concept of proximity itself has also been critiqued, most notably by Boschma (2005) who argues that the focus on geographic proximity conceals other forms of proximity that lend themselves equally to fostering innovative exchanges, namely cognitive proximity, organisational proximity, social proximity, and institutional proximity (Boschma, 2005).

Several researchers have also pointed out that different firms, and different stages of innovation require different inputs to stimulating innovation. Gordon and McCann (2005) demonstrate that firms where customer contact is critical or are working with short life cycles benefit more from the tacit knowledge exchange of city-related cluster dynamics whilst firms dealing with products of long life-cycles do not benefit as much from cluster interactions. The high real-estate costs of cities create a cost-benefit decision for firms, suggesting firms locate in a gradient outward from cities based on the importance of face-to-face contact to their innovation process (McCann, 2007). Asheim and Hansen (2009) argue that different knowledge bases (analytic, synthetic and symbolic) have different innovation-driving requirements, with symbolic knowledge (i.e., the creation of cultural meaning) benefiting the most from city dynamics. Similarly, Duranton and Puga (2001) suggest that diversified cities are beneficial for stimulating innovation at the early stages of a product's life cycle whilst smaller cities with a more specialized industry are better suited for the later stages of product innovation. In Quebec, Shearmur (2011) finds that major product innovations, most likely to result in patents, occur close to cities whilst minor process (incremental) innovations take place in smaller metropolitan areas, consistent with Duranton and Puga's (2001) nursery city hypothesis.

Empirical research on non-urban innovation has been so-far limited but is slowly growing. Many have pointed out that traditional methods of measuring innovation (e.g., patents) are not properly suited to rural regions (Vodden et al., 2013). Isaksen and Karlsen (2010) argue that innovation for rural regions is centered around "doing-using-interacting", which involves localized problem-solving and more incremental results, as opposed to the "science, technology, innovation" of cities. Hall and Vodden's (2019) mixed-methods research on innovation in Canadian regions found that peripheral innovation involved new or improved programs and services within local organizations as opposed to the technological intensive innovations of city-regions. Many of these innovations involve creative ways of utilizing existing community resources to address local needs such as the St. Anthony Basin Resources Incorporated (SABRI) social enterprise in the Northern Peninsula of Newfoundland and Labrador that utilized profits from a commercial mussel operation to reinvest in the community's art scene (Hall and Vodden, 2019). While Hall and Donald (2009) acknowledge peripheral innovation remains limited by some geographic realities (e.g., infrastructure constraints, remoteness, and youth out-migration), their work highlights the need for better measures of innovation that can capture the unique innovative processes of rural regions.

Finally, suburbs are often explicitly excluded from the creativity and innovation narrative. Given their relatively newly built, and cookie-cutter nature, they are the opposite of the unique, diverse, and "authentic" urban spaces that have been touted for their creativity-stimulating nature (Bain, 2013). Suburbs also tend to lack much of the urban infrastructure that Florida argues is needed to attract creative individuals and stimulate innovation (e.g., bike friendly infrastructure, café culture etc.). However, as Bain (2013) argues, suburbs are host to their own dynamic creativity, mobilized both by local spatial interaction as well as through engagement in the cyberspace.

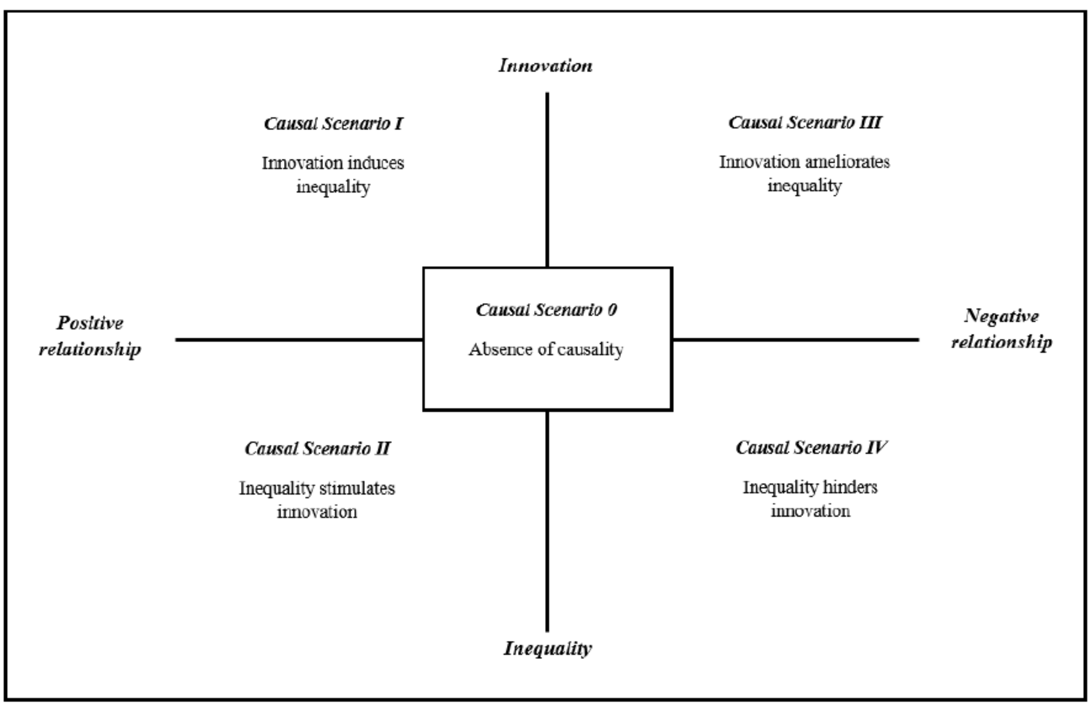
Overall, whilst cities and their agglomerative forces do appear to provide a stimulating environment for innovation, innovation is not limited to, nor does it originate exclusively within cities. By considering the regional scale in this analysis I hope to encapsulate both urban and non-urban innovation. As will be discussed later, however, measuring innovation in different geographic milieus requires slightly different approaches.

2.3. Innovation as a driver of income inequality?

In the current globalized, post-Fordist era, technology, creativity, and innovation have been synonymous with growth and prosperity. However, from its earliest conceptualizations innovation has also been described as a force of "creative destruction", necessarily tearing up old structures, systems, institutions, and ways of life in order for new structures to take their place (Schumpeter, 1942). On the path to 'progress' innovation has and continues to drastically alter labour markets. From automation increasingly replacing low-skilled, repetitive labour (Autor et al., 2003; Autor, 2015) to new artificial intelligence programs threatening to replace writers, artists and other forms of creative employment and expression, there is increasing merit in asking 'progress' for whom? As Shearmur points out, the uncritical acceptance of innovation as the de-facto engine for growth "legitimizes the social dislocation and individual hardship that innovation can cause" (Shearmur, 2012: 11). In this sub-section we explore the intersection of our previous discussions of innovation and inequality, two phenomena that have increased drastically since the 1980s, to examine how these variables may be causally related.

Using a systematic literature review framework, Fragkandreas (2022) develops a five-pronged causal scenario categorization system of the innovation-inequality relationship. Causal scenarios are categorized as follows: (Scenario 0) the absence of causality between the two variables, (Scenario 1) innovation induces inequality, (Scenario II) inequality stimulates innovation, (Scenario III) innovation ameliorates inequality and finally, (Scenario IV) inequality hinders innovation (see Figure 2.2). The results of Fragkandreas' (2022) review find that of studies conducted on the subject between 1990 and 2019, 71.1% provide evidence for causal scenario I (i.e. innovation induces inequality) with this share having increased from 58.3% amongst studies conducted between 1990-1999 to 73.1% for the 2010 to 2019 period.

Figure 2.2. Causal scenarios for the relationship between innovation and inequality



Source: Fragkandreas (2022)

The question of how innovation may induce inequality is what I turn my attention to next. As we will see, multiple theories drawing from a range of disciplines have attempted to offer an explanation. In what follows, I provide an overview of these different mechanisms, along with some supporting evidence and a brief discussion of their drawbacks.

2.3.1. Innovation as a driver of inequality: Proposed explanations

By far the predominant theoretical approach to explaining how innovation may affect the distribution of wages comes from mainstream labour economics (Fragkandreas, 2022). Known as the skill-biased technological change (SBTC) hypothesis, it emerged to explain the pattern of increasing income inequality first observed in the 1980s (Fragkandreas, 2022). Under the SBTC hypothesis, innovation, such as the adoption of microcomputers in the manufacturing process, or the broader proliferation of computers in the workplace, drives income inequality by intensifying the skills premiums (Card and DiNardo, 2002). New advancements in the workplace requires skilled labour to operate, manage, and further develop said technologies. Consequently, such skills increase in their value, as do theoretically, the wages of the skilled workers. Conversely, new technologies depress the relative value of goods developed by less-skilled labour, consequently depressing the wages of less-skilled labourers (Card and DiNardo, 2002).

In the longer run of American history, Goldin and Katz (2010) have argued that technological change, education, and inequality have been locked in an arms race. Revolutionary changes to the American education system in the 20th century permitted a massive up-skilling of the labour force, allowing skilled labourers to surpass the market demand throughout the 1960s, initially lowering inequality. However, the technological revolution of the 1980s generated increasing skills premiums that, as Goldin and Katz argue, the educational system has yet to meet, increasing inequality by rewarding the highly-skilled few (Goldin and Katz, 2010).

In a similar vein, Levy and Murnane (2004) argue that whilst the computerization wave of the 1980s made many fields of labour redundant, it has also generated enormous growth in positions like managers, doctors, lawyers and engineers, highly-skilled and complex industries that are complemented by computerization. These positions, requiring complex intellectual and emotional abilities are expected to resist computerization (Levy and Murnane, 2004).

However, the SBTC hypothesis is not without its limitations. Card and Dinardo (2002) point to several key problems with the SBTC hypothesis. Firstly, they argue that evidence for the SBTC hypothesis is largely based on timing: the concurrent rise inequality and technology in the 1980s (Card and Dinardo, 2002). Given that wage inequality stabilized across many countries in the late 1990s, despite the continued advancement of computer technology, a temporal link between innovation and inequality is not sufficiently robust evidence (Card and Dinardo, 2002). Additionally, Card and Dinardo (2002) demonstrate that the SBTC hypothesis fails to explain the continued growth in the wage gaps between gender and racial groups. Overall, the authors argue a need for a more multifaceted framework of understanding which including political factors like stagnating minimum wages in the United States (Card and Dinardo, 2002).

Furthermore, contrary to what would be expected from the SBTC hypothesis, Autor and Dorn (2009) observed surprising employment growth in *both* the highest-skilled and lowest skilled quartile of occupations in the United States between 1980 and 2005, a pattern also seen in 16 European countries with similar industrialized economies (Goos and Manning, 2007). While growth in highly skilled jobs is consistent with the SBTC hypothesis it does not account for rapid growth in low-skilled service occupations like food service workers, janitors, gardeners, home health aides, and beauticians (Autor and Dorn, 2009). To address this apparent bifurcation, Autor et al. (2003) and Levy and Murnane (2004) suggest that skill-biased technological change will favour employment growth in not just the highly-skilled labour but for the opposite of the spectrum as well. Now commonly referred to as the Autor-Levy-Murnane (ALM) or the task-biased technological change hypothesis, this model suggests computerization remains limited to work that is repetitive or routine, following precise, well-defined procedures that are easy to automate (Autor et al., 2003). Tasks requiring creative problem solving or complex coordination are more difficult to computerize, thus driving demand for highly-educated, highly-skilled and subsequently, highly-paid workers, able to meet these demands. At the other end of spectrum, low-skilled labour requiring physical dexterity, flexible interpersonal communication, and physical proximity (e.g., beauticians, janitors, home health aides etc.) are also non-routine and similarly resist computerization, leading to employment growth at the highest and lowest ends of skill and education levels (Autor et al., 2003).

Autor et al. (2003) argue that polarizing employment demand will result in wage growth in both highly skilled occupations but also service occupations. However, evidence from the UK and Canada demonstrates that despite strong evidence supporting the ALM hypothesis of polarizing labour growth in the lowest and highest ends of the wage distribution, growing demand has not been matched by wage increases at the bottom of the distribution (Goos and Manning, 2007; Green and Sand, 2015). Green and Sand (2015) attribute persistently low wages in the bottom percentile of Canadian wages to a supply shift, as declining demand for middle-skilled, manufacturing jobs, means labourers shift to working in the service sector. As such, Green and Sand (2015) argue that the ALM task-biased model of wage change is only partly attributable to the Canadian context as employment growth in the bottom of the skills distribution is not matched by wage growth. The expected outcome of such a polarization in the labour distribution, combined with wage growth only for highly-skilled labourers, is an increase in inequality.

Whilst the most popular explanations for changes in inequality related to innovation has come from the field of labour economics, there have been some alternatives put forward by sociologists and economists.

Kristal & Cohen (2017) demonstrate that worker disempowerment (i.e. declining union power and declining minimum wage) is a larger causal factor than market forces like computerization in explaining increasing wage inequality in the US. Kristal (2013) argues that increasing wages for high-skilled workers (as proposed by the SBTC and ALM hypotheses) does not explain why workers share of aggregate industry income has declined over the last 30 years. They propose instead a *class-based* technological change model, demonstrating that capitalist owners yielded a larger profit increase from computerization gains than the highly-skilled workers benefiting from skills-premiums did (Kristal, 2013).

Avent-Holt and Tomaskovic-Devey (2014) propose an alternative sociology-informed relational theory of earnings inequality. Their model focuses on how concepts like productivity and skills are *defined* (and subsequently valued) within a workspace, and how these definitions change with the integration of new technologies, thus creating new relations of production (Avent-Holt and Tomaskovic-Devey, 2014; Hanley, 2014). Hanley (2014) apply this model to General Electric's (GE) large-scale adoption of new technology in the 1950s. Their findings demonstrate that the integration of new technologies in the workplace restructured internal conceptions of productivity, placing increased value on managers, and creating harsher distinctions between managerial and clerical roles (Hanley, 2014). The result was the creation of new relations of production that legitimized increasingly unequal pay relations, over-rewarding managers at the expense of production workers (Hanley, 2014).

Finally, in contrast to the labour-focused SBTC and ALM hypotheses which suggest investment in educating the workforce will help in reducing inequalities, Lazonick and Mazzucato (2013) propose a Risk-Reward Nexus (RRN) framework to demonstrate that inequality is generated by unequal capture of the value created in the innovation process by strategically placed individual actors. The authors argue that despite the collective exertions of the workers in the firm who generate innovations, the gains are not distributed equally, with certain actors (i.e. top executives, venture capitalists, hedge fund managers etc.) positioning themselves to extract more value than they create (Lazonick & Mazzucato, 2013). They describe this as an organizational failure that "occurs when certain economic actors gain control over the allocation of substantial business organizations that generate, value, and then use product or financial markets on which the enterprise does business to extract value for themselves" (Lazonick and Mazzucatto, 2013: 1096). Unequal individual capture of capital gains means efforts to up-skill the workforce will not address the root of the inequality issue as "…we do not as a rule see PhDs running corporations" (Lazonick and Mazzucatto, 2013 p.1120).

There have also been a number of geographically grounded perspectives put forth to complement the economic and sociological innovation-inequality theories. The so-called "Silicon Valley Paradox" (Simmonds, 2017) made major headlines for highlighting the shocking wealth disparities in one of the most successful innovation hubs of the world. Echeverri-Carrol and Ayala (2009) observe that skilled-workers in US cities with high levels of tech-employment earn a 4.6% wage premium suggesting a place-based dimension to the innovation-inequality relationship. Similarly, Winters (2014) finds that employees in STEM fields earn more in cities with a higher proportion of STEM graduates. This is attributed either to agglomeration forces or self-selected relocation of STEM workers to higher-paying regions (Winters, 2014).

Much attention has also been paid to the costs of the creative class (Lee, 2016). Florida himself has noted that the cities ranked highest in creativity are also the ones where inequality is highest (Florida and Mellander, 2016). Florida's creative class thesis acknowledges the simultaneous existence of the highly-paid creative class and the low-paid 'service class' that makes their coffee-loving, entertainment and consumption-driven, lifestyles possible. Florida's argument for resolving these inequalities was to "make all jobs creative jobs" (Florida, 2012:

xiv). However, as Peck (2005) suggests “who will launder the shirts in this creative paradise?” (Peck, 2005: 756-757).

From an inter-regional perspective, Kemeny et al. (2022) and Connor et al. (2023) investigate regional inequality trajectories at radical innovation frontiers and their ‘seedbed’ geographies in the United States. This recent research demonstrates first the strong tendency for radical new technologies to geographically concentrate, and second, that this spatial sorting results in persistent long-term spatial inequalities. For example, the second industrial revolution of the 20th century saw a major geographic concentration of frontier workers in the US northeast whilst the digital technological revolution of the late 20th century was primarily clustered on the west coast (Kemeny et al., 2022). The establishment of these new technological frontiers results in strong localized increases in regional prosperity that persist over time (Connor et al., 2023). However, as highly skilled, highly paid workers flock to these seedbed regions, the long-term result is strong inter-regional inequality (Kemeny et al., 2022; Connor et al., 2023). This effect is particularly pronounced in the technology and finance revolution of the 1960s-1980s, partly because frontier workers are concentrated in a more limited set of regions and second and furthermore because the high-tech industries have failed to create as many jobs for less-skilled workers as the previous manufacturing revolution had (Connor et al., 2023). The results of Connor et al. (2023) and Kemeny et al. (2022) provide long-run historical evidence for a relationship between radical innovation shifts and spatial income inequality.

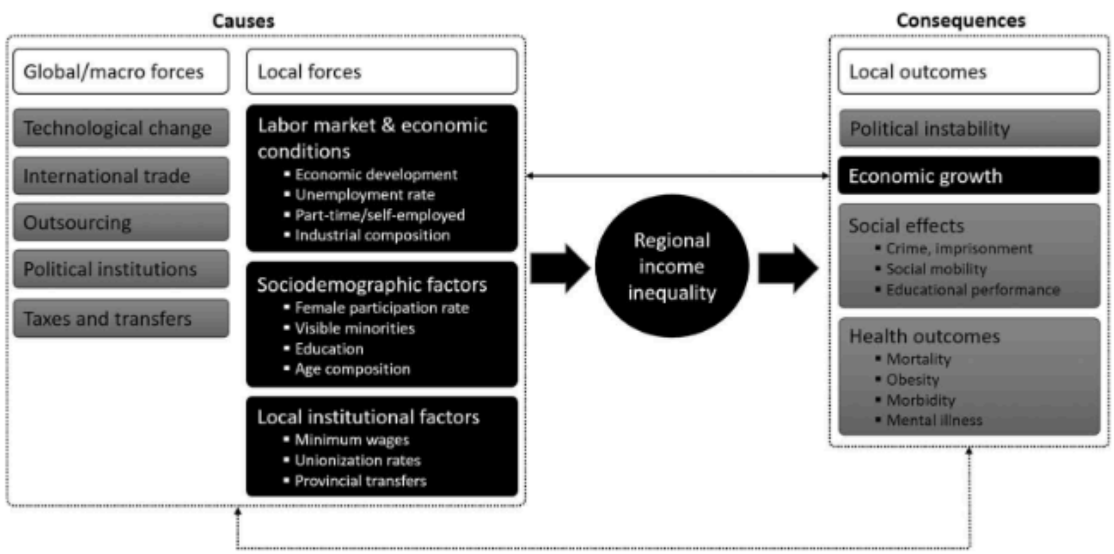
On the empirical side, there are a growing number of empirical studies examining the intra-regional impact of innovation on income inequality. Donegan and Lowe (2008) conducted a literature review of papers on earnings inequality in the United States, combined with a statistical analysis between creative class presence and inequality in US cities. They find that creative class presence is indeed correlated with higher inequality (Donegan & Lowe, 2008). This was followed by Lee (2011), who was the first to more formally model the relationship between innovation and wage inequality. Using the European Community Household Panel and the Eurostat Regio database, Lee (2011) finds a positive relationship between regional innovation (measured by patenting) and inequality in Europe between 1996 and 2001. However, when the model was repeated using employment in knowledge-based industries as a proxy for innovation, this correlation was not present (Lee, 2011). In a follow-up study, Lee and Rodriguez-Pose (2013) conducted a comparative study of the innovation-inequality link between

European regions and US cities. Echoing the earlier work by Lee (2011), they found strong linkages between innovation and inequality in European regions but not in the US (Lee & Rodríguez-Pose, 2013). However, as the authors acknowledge, the study is limited to a relatively short time period. Breau et al. (2014) remains the only research to focus on the innovation-inequality link at the sub-national level for Canada. The results of this analysis find that cities with higher levels of innovation typically have higher levels of earnings inequality (Breau et al., 2014). More recently, Aghion et al. (2019) find that the increase in income share held by the top 1% of earners in a given US state is significantly positively correlated with the state-wide rate of innovation. In a study of the innovation-inequality link across Chinese cities between 2004 and 2012, Guo (2019) observes a rise and then subsequent fall in inequality as innovation levels increase. In a long-run analysis of the influence of R&D expenditure and income inequality in G7 countries between 1870 and 2016, Churchill et al. (2021), find that on average, R&D expenditures are negatively associated with income inequality over this time period. Meanwhile, Consoli et al., (2023) find that across European regions, digitization of labour worsens inequality for less affluent groups but mitigates inequality across higher income groups. Overall, the empirical evidence remains mixed with no clear consensus emerging on the innovation-inequality relationship.

2.4. What other drivers may affect income inequality?

The discussion thus far has been focused on innovation and its potential role in exacerbating inequality, specifically since the 1980s. However, the story is not so simple. As we have gleaned from some of the issues raised above, inequality is a multi-faceted phenomenon linked to everything from globalization to demographic changes in the local labour force. In order to investigate the impact of innovation on income inequality, I first identify and later control for other variables related to inequality. This sub-section provides an overview of the other variables that have been linked to regional income inequality. It begins first by describing macro-level forces including variables related to globalization, political institutions and policy. Innovation is one such macro factor but as it has already been discussed in length in the previous section, it is not revisited here. This is followed by a discussion of the local or micro forces related to inequality, including economic growth, labour market conditions, local institutional factors and sociodemographic factors (see Figure 2.3 for a summary of macro and micro variables related to inequality). This section borrows heavily from the work of Marchand et al. (2020) and Breau (2015) who, to my knowledge, have conducted the most comprehensive studies on regional inequality in the Canadian context.

Figure 2.3. The causes and consequences of regional income inequality



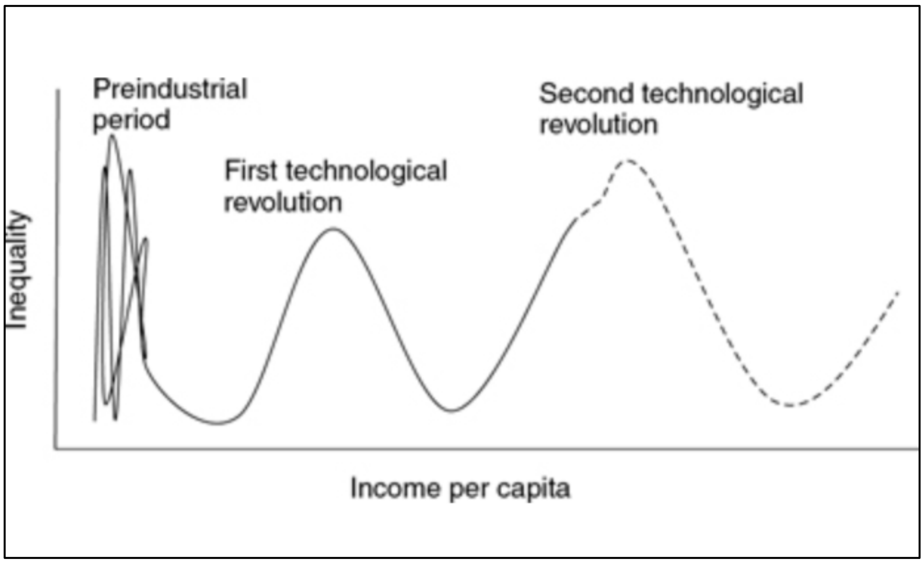
Source: Marchand et al. (2020)

2.4.1. Macro forces

In the 1950s, Simon Kuznets famously hypothesized a relationship between economic growth and income inequality arguing that as countries progressively industrialize, inequality will increase at first, but then ultimately decline, following an upside-down U-shaped curve (Kuznets, 1955). Kuznets hypothesis was well-suited to the post-war period which saw massive gains in equality in the Global North, a period of time economists generally referred to as the "Great Compression" (Goldin and Margo, 1992; Atkinson et al., 2011). However rising inequality in the world's most developed countries in the 1980s threw askew Kuznets hypothesis (Breau and Lee, 2023).

To explain this upswing, Milanovic (2016) suggests instead a wave-like pattern of inequality with peaks corresponding to periods of large technological upheaval (see Figure 2.4). Milanovic's theory proposes a cyclical pattern to inequality levels that has existed for the long-run of world-history. In contrast, Piketty's (2014) seminal work argued that increasing inequality is the natural state of global capitalism. According to Piketty, the post-war period of relative equality was a unique blip driven mainly by war-time taxation, economic convergence, and socialist movements. The inequality increase observed since the 1980s can thus be seen as a return to the natural state of global capitalism, unencumbered by welfare-based institutional systems and the Keynesian economics of the post-war period (Piketty, 2014).

Figure 2.4. Kuznets waves of inequality according to periods of technological upheaval



Source: Milanovic (2016)

The effect of the institutional changes that took place in the 1980s cannot be understated and they are perhaps one of the most widely discussed macro-shifts in the literature (Harvey, 2005). The neoliberal, or post-Fordist, turn was initially spearheaded in the United States and the United Kingdom by politicians like Thatcher and Reagan, who oversaw a period of political-economic restructuring typified by an emphasis on the free market, individual competition, and fiscal austerity (Peck, 2001). In Canada, the transition came slightly later (1990s) and was shaped considerably by its unique hinterland-heartland geography, a point which will be returned to shortly (Norcliffe, 1994). Neoliberal policies included cuts to income support programs, reduced taxes and government redistribution policies, and hostility towards unions which had significant consequences for inequality by reducing the social safety net and bargaining power of workers (Banting and Myles, 2013). However, as Harvey (2007) argues, the neoliberal project cannot be understood simply as a neutral effort to restructure international capitalism in response to crises of capital accumulation. Rather, neoliberalism is a political project operating with the deliberate aim to restore class power in the wake of a period of relative equality and reduced class disparity between the 1% and the rest (Harvey, 2007).

In addition to the scaling back of state interventionist policies, much of this period's economic restructuring was facilitated by paradigm-shifting technological developments, particularly the growing use of microchips in production activities of all kinds, which allowed for dynamic automation of assembly lines and the rapid growth in global logistics (Norcliffe, 1994). These innovations allowed a reconfiguration of the production process away from the mass-production of the Fordist era and towards a new era of 'production flexibilization' (Norcliffe, 1994). This production flexibilization, coupled with the general deindustrialization that took place in the Global North in much of the 1970s and 1980s (see Bluestone and Harrison, 1982), resulted in a large decline in manufacturing activities (and with it the middle class). Between 1967-1988 period, Canada's manufacturing sector shrank from 24% to 17% of the workforce (Economic Council of Canada, 1990 as cited in Norcliffe, 1994). The rise of production in the Global South further shifted labour demand away from middle-class, manufacturing jobs, which were replaced by growth in high-skilled managerial, scientific, and professional jobs as well as lower-paid service sector jobs, resulting in labour polarization (Norcliffe, 1994). These changes took on a distinct geography with highly skilled, highly paid job growth being concentrated in large metropolitan areas. Major metropolitan areas, consistent with Sassen's Global Cities hypothesis, saw an influx of foreign capital investment from multinational companies entering the Canadian market, generating growth and labour demand (Norcliffe, 1994, Sassen, 2001). Meanwhile, the periphery was left with unstable, short-term, part-time service jobs often performed disproportionately by women (Norcliffe, 1994), though more recent shifts have observed more nuanced changes in peripheral-region gender dynamics in the workforce (see for example Bye, 2019).

2.4.2. Local forces

Amidst the global-scale macro-shifts like globalization and technological upheaval are an equally important set of local forces at play in driving income inequality. As Marchand et al. (2020) demonstrate, income inequality is not growing at the same pace across the country, and regions are becoming increasingly divergent in their inequality. Therefore, local, place-specific forces appear to be playing just as important of a role as macro-scale forces. Local forces can be broadly categorized as factors related to local labour market conditions, socio-demographic factors, and institutional factors.

The local labour market conditions of a region can have a significant impact on inequalities within a given region. For example, a high degree of local economic development can at times mitigate inequality; however, this effect does not persist over time likely because overall wage gains fail to trickle down to lower earners (Bolton and Breau, 2012). A high rate of precarious or unsteady labour (i.e., high rates of part-time workers, self-employed workers or a high unemployment rate) are unsurprisingly, correlated with income inequality (Norcliffe, 1994; Marchand et al., 2020). The industrial composition of a given region also has demonstrable impacts on income inequality. As Fortin and Lemieux (2015) observe, the extractive resource sector pays significantly higher wages compared to other sectors. They attribute a boom in employment in this sector, and its spillover effects, for driving wage growth in Newfoundland, Saskatchewan and Alberta. In these provinces, the extractive resource sector has grown by 50% between 1999 and 2013 (Fortin and Lemieux, 2015). Interestingly, the authors observe a decrease in inequality following the growth of the extractive resource sector, indicating that less-skilled workers at the bottom of the wage distribution have made large relative gains in wage growth (Fortin & Lemieux, 2015). Similarly, Marchand (2015) found that the Western Canada energy boom showed a U-shape pattern in the gains it produced with individuals at the lowest and highest ends of the income distribution seeing income gains, but not those in the middle. When disaggregated by industry, the results showed overall inequality increase within the directly impacted energy sector and a moderate inequality increase in the indirectly impacted construction and retail trade industries. In contrast, a small inequality reduction was observed in the indirectly impacted service sector, suggesting spillovers from the extractive resource industry into the service sector may have helped income growth at the bottom of the wage distribution (Marchand, 2015).

Many industries have also been associated with lower levels of local inequality. Manufacturing industry employment has traditionally made up the bulk of the middle-class (Bluestone & Harrison, 1988; Levernier et al., 1998), and high rates of manufacturing employment have accordingly been linked to lower income inequality (Marchand et al., 2020).

Similarly, high employment in the public sector, another heavily unionized labour force, has also been linked to lower income inequality (Card et al. 2020).

Institutional factors such as minimum wage, unionization rates and government transfers also have significant influence on local income inequality. The decline of unions has repeatedly been associated with the erosion of bargaining power for workers. Accordingly, decreasing unionization rates in major OECD nations (including Canada) have been linked to rising earning inequality (Card et al., 2020; Lemieux, 2008).

Strong minimum wage policies have also been shown to relieve inequality by raising wages for the bottom percentiles. Empirical evidence in the Canadian context finds that closing the gap in wage distribution is significantly influenced by provincial minimum wage standards (Fortin & Lemieux, 2015). Frenette et al. (2009) also demonstrate the ability of government transfers to mitigate income inequality, arguing that historically progressive tax and transfer systems, instituted at both federal and provincial levels, have helped mitigate inequality growth. The reversal of those same institutions in the 1990s has contributed significantly to rising inequality rates (Frenette et al., 2009).

Finally, local socio-demographics have important supply-side impacts on employment and wages. Educational achievement is highly correlated with wages, where highly-educated, highly skilled workers tend to receive higher renumeration compared to less-educated workers. In the Canadian context, wage differentials between educated and less educated workers have increased sharply since the 1990s (Boudarbat et al., 2006) and have been demonstrably linked to growing inequality in Canada (Breau, 2015; Marchand et al., 2020). The proportion of visible minorities in a given region has also been positively linked with income inequality as ethnic minorities experience earning disparities compared to their white counterparts (Pendakur and Pendakur, 2007). The percentage of dependents in a population (i.e., young and senior individuals) also has an influence on inequality. In regions where the age composition includes a high ratio of dependants relative to working-age individuals there tends to be a greater level of pressure placed on the active workforce to directly or indirectly support the dependent population. Women's increased role in the labour force outside of the home also has an impact on the distribution of income as they are able to achieve greater financial independence (Orloff, 2002). However, in practice, the impact of women's emergence into the workforce has been multidimensional. From persistent pay disparities between women and men in the workforce, different rates of union membership for men and women, and disparities in employment between women of colour and other intersectionality's, there is no clear-cut direction of impact on inequality (Florida, 2002; Pelletier et al., 2019; Card et al., 2020). Whilst in Canada, women have begun to outnumber men in number of university degrees completed (Ferguson, 2016), this does not necessarily translate to greater equality in pay, especially as earnings for graduates from female-dominated fields are generally lower than those in male-dominated fields (Ferguson, 2016). Econometric evidence on the influence of women's participation in the workforce on inequality in Canada is mixed. Breau et al. (2014) find that at the urban-scale, women's participation in the workforce does not make a significant difference in inequality. In contrast, Marchand et al. (2020) found a significant, positive association between women in the workforce and inequality, likely due to regional differences in the timing of women joining the workforce, their skill sets and their full-time or part-time status (Marchand et al., 2020). Finally, at an international level, Cohen and Ladaique (2018) find that high rates of women employment in the OECD appear to be lowering wage inequality. While the effect of women's labour force participation appears to vary significantly by scale and the measure of inequality used (i.e., individual or household-level inequality), more research is needed to better understand how women's role in the labour force affects inequality. Finally, given their occupational profiles, Canadian women also appear to be at greater risk of losing their jobs to automation compared to men (Breau and Marchand, forthcoming), making it likely women will see greater wage depreciation than men in the coming years.

Ultimately, it is clear that income inequality growth cannot be explained by one simple factor but rather a multi-faceted combination of macro and local forces. Amidst these factors, technological change has been repeatedly emphasized as a macro-level force driving wage polarizations and creating new relations of production. However, empirical studies on the local effects of innovation in driving income inequality have yet to be examined at the pan-Canadian scale.

The regional scale is of particular interest in Canada, a country whose vast size, low population density and subsequent remoteness of certain regions does not appear conducive to innovation based on popular cluster theories of innovation. However, as researchers are beginning to point out, there may be a neglected non-urban dimension to innovation, that has been overlooked by city-specific innovation research.

The aims of this research are thus two-fold. First, to take a comprehensive look at the *where* of Canadian innovation. Is Canadian innovation occurring primarily in cities or does it also have a more rural element as well? Furthermore, what kind of innovation is occurring where? The second and overarching goal of the research is to then ask whether innovation worsens local income inequality, after taking into account all of the other variables driving local income inequality. The next chapter provides more details on the data and methodology used to conduct the analysis.

Chapter 3

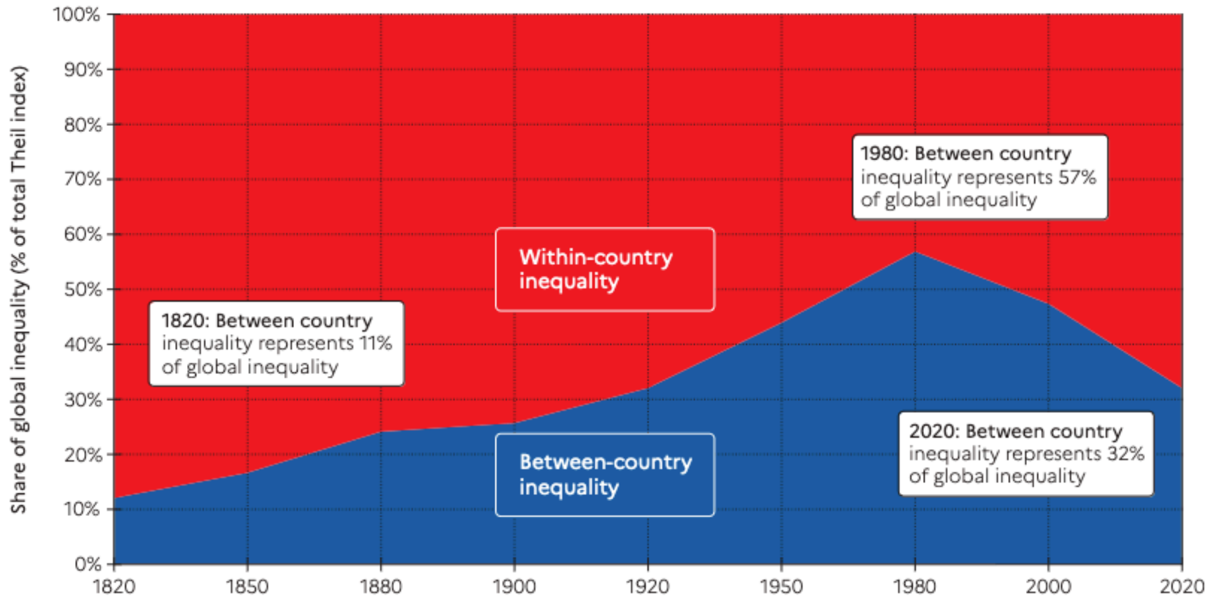
DATA AND METHODOLOGY

This chapter discusses the data and methods used to model the relationship between innovation and income inequality across regions in Canada. It is organized in three main sections. I begin by providing a summary discussion of the geographic scale of analysis used in the thesis. Having done so, I then go over the data sources and methods used to measure both innovation and inequality. This includes a brief review of the benefits and drawbacks of each method. In the final section of the chapter, I focus on the development of the spatial panel model approach adopted to estimate the relationship between innovation and income inequality.

3.1. Geography: Regions as key units of analysis

As previously discussed, the current literature suffers from a lack of regional analysis in both innovation and inequality research (Shearmur, 2012; Hall and Vodden, 2019; Marchand et al., 2020). Inequality research has traditionally been carried out at the national scale, with emphasis on comparing coefficients of inequality between countries. However, as research has increasingly demonstrated growing within-country disparities (see Figure 3.1), there has been renewed effort to diversify the scale of analysis. Here, the main focal point, however, has been studies of inequality at the city-level. Similarly, the innovation literature suffers from a significant "urban bias" (Shearmur, 2012) where a disproportionate amount of weight is placed on the importance of cities to processes of innovation and creativity. This overemphasis on cities tends to eclipse a potentially important non-urban dimensions to innovation (Boschma, 2005). In the Canadian context, to the best of my knowledge, study of the innovation-inequality relationship has been so far limited to the city-scale (Breau et al., 2014).

Figure 3.1. Total global inequality by relative share of within-country vs. between-country inequality, measured by the Theil Index (1920-2020)



Note: Before the 1980s, the share of between-country inequality was increasing peaking at just under 60% of the total global inequality share. By 2020, within-country inequality has increased its share to about two-thirds of total global inequality.

Source: Chancel et al. (2022)

To address the need for more diversified scales of analysis, the research undertaken in this thesis is based on a regional scale of analysis. One of the key advantages of using such a scale is the full coverage of the Canadian landscape, with new insights on the inequality-innovation relationship for non-urban regions. For this project, regions are defined as census divisions (CD). A census division refers to a “group of neighboring municipalities” that have been amalgamated for regional planning and management of common services that are more effective at a larger scale than a municipality (Statistics Canada, 2022). From a more practical point of view, census divisions provide a standard, intermediate geographic scale: larger than municipalities or census sub-divisions, but much more detailed than a provincial scale. In many provinces, census divisions exist under provincial law, while in provinces and territories without an equivalent regional classification system Statistics Canada has developed census boundaries for statistical reporting (Statistics Canada, 2022). Census divisions are highly useful for longitudinal research as they remain relatively constant over time, making them a highly stable geographic division.

That said, from one census to the next, there are a certain number of inevitable boundary changes in how CDs are defined given that some are annexed over time, others dissolved, or new ones created (based on changes to their building blocks, Census sub-divisions). Between 1981 and 2011, Marchand (2017) estimated that 42% of all census divisions experienced some change across censuses (see table 3.1 for a summary of census changes over the period of study). To account for delineation changes over time, I employ the methods developed by Marchand (2017) who tracked boundary changes over time to create a new set of 284 census divisions with reconfigured borders. Using these re-configured borders, the number of census divisions is standardized to 284 across the entire study period (1981-2016), permitting robust longitudinal geographic analysis and comparisons.

Table 3.1. Total number of census divisions for each iteration of the Canadian census (1981-2016)

Year	1981	1986	1991	1996	2001	2006	2011	2016
Census Divisions	266	266	290	288	288	288	293	293

Source: Statistics Canada, n.d

For the purposes of providing summary descriptive statistics, I also employ the use of a regional classification system developed by the OECD. This method classifies regions (i.e., Census divisions) based on their access to metropolitan areas (Fadic et al., 2019). Regions are grouped as 'metropolitan' or 'non-metropolitan' with further breakdowns based on metropolitan population size, and degree of remoteness for non-metropolitan regions (Fadic et al., 2019). A metropolitan area is defined as a functional urban area with a population of 250 000 inhabitants and a large metropolitan area is one with over 1.5 million inhabitants (Fadic et al., 2019). Non-metropolitan areas are classified based on access to either a metropolitan area or a small/medium city (details on classification thresholds are provided in table 3.2 below). If a region is close to neither it is classified as remote. 'Access' is calculated according to a driving threshold of 60 minutes by car. Based on these delineations, the largest share of Canadians (43.4%) live in large-metropolitan areas (Fadic et al., 2019). The second largest category are remote regions (24.1%) which also makes up the largest category in total area (Fadic et al. 2019). Figure 3.2 illustrates the breakdown of the standardized 284 Canadian census divisions according to the OECD classification system.

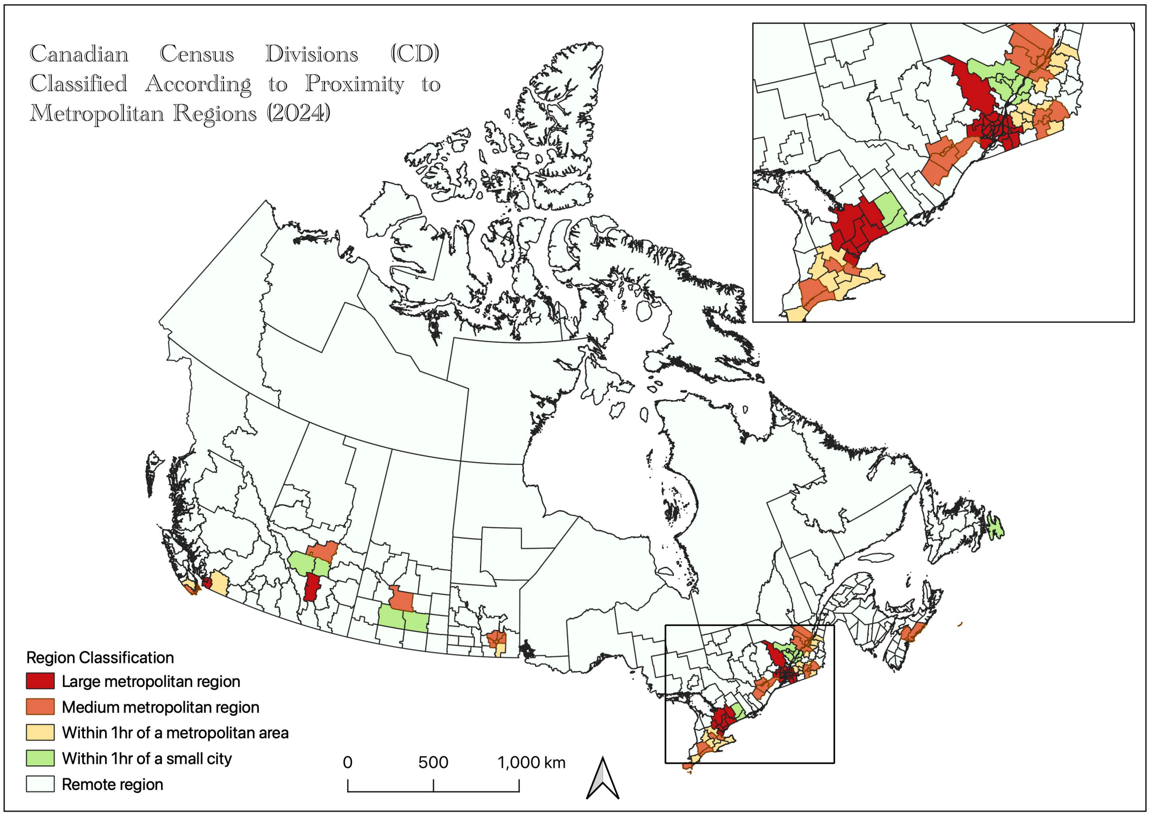
While every region is fundamentally unique, employing a classification system that groups characteristically similar regions (i.e. rural regions, or urban regions) allows for a more macro-level comparative analysis of the urban-rural divide.

Table 3.2. OECD Regional classification guidelines and descriptive statistics for Canadian regions

	Metropolitan Regions		Non-Metropolitan Regions		
Classification	Large (MR-L)	Metro (MR-M)	Metro (NM-M)	Small/Medium (NM-S)	Remote (NM-R)
Definition	50% or more of the population in the region lives in a large metro area (1.5mil+ inhabitants).	50% or more of the population in the region lives in a large metro area (250k+ inhabitants).	50% or more of the population in the region are within a 60min. drive from a metro.	50% or more of the population in the region are within a 60min. drive from a small or medium city.	50% or more of the population in the region is not within a 60min drive of a functional urban area (FUA).
Number of regions (CDs)	30	31	20	13	190
Population (%) (2016)	43.9	22.4	6.0	3.8	23.9

Source: Adopted from Fadic et al. (2019) with author's calculations

Figure 3.2. Distribution of Canadian regions according to the OECD metropolitan/non-metropolitan classification system



Source. Adapted from Fadic et al. (2019).

3.2. Data sources and development

3.2.1. Patent data

Quantifying innovation is no easy feat. The first difficulty in its encapsulation is its definition and the second is how to measure such a process on a large-scale in a way that is practical yet tangible. Schumpeter famously defined innovation as "new combinations of new or existing knowledge, resources, equipment, and other factors" (Schumpeter 1934). While this definition is enormously inclusive, it is limited in its practicality when looking to quantify the innovative process.

In a review of the innovation literature, Edison et al. (2013) summarizes 41 definitions of innovation from the literature into five broad categories. First, those that define innovation based on its impact: incremental, market breakthrough, technological breakthrough, or radical/disruptive innovations (Edison et al., 2013). The second, separate innovation by type:

product (new or improved products), process (new or improved design, analysis, or development method), market innovations (new marketing strategies) or organization innovation (related to the organizational structure of a firm and their practices) (Edison et al., 2013). A third category measures innovation by degree of novelty (i.e. whether an innovation is new to the firm, market, industry, or the world) (Edison et al., 2013). The fourth and fifth categories are focused on the nature of the creative process and its commercialization which, whilst important, are not the focus of this thesis and therefore are not discussed further.

For the purposes of this study, I employ the use of the OECD Oslo manual, which defines innovation as: "*a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)* (Oslo Manual, 2018). The purpose of the Oslo manual definition is to provide a standardized definition that is functional for data collection, reporting and comparison across countries. It should be noted that this definition, whilst a helpful framework, has its limitations. Most notably, it is focused only on product or process innovations (omitting market or organizational innovation) and does not differentiate on the basis of impact (i.e., incremental vs. breakthrough). However, the Oslo definition is inclusive of all degrees of novelty, the only requirement being novelty at the baseline firm level.

Within this definition there is still no perfect way to quantify all new or improved products or processes therefore, measuring innovation requires the use of imperfect proxies (Crosby, 2000). A vast aray of proxies have been used in the innovation literature and can generally be divided into either *input* or *output*-based measures of innovation, the limitations and benefits of which are briefly discussed below.

The most-used input-based proxy for innovation is R&D expenditure (Crosby, 2000). However, whilst R&D related proxies provide a measure of the financial input towards innovation, financial input does not necessarily guarantee innovation, nor does it represent a 1:1 reflection of innovative output (Griliches, 1987). Furthermore, the time between the input and output is riddled with uncertain lags, with no guaranteed linear relationship between R&D and innovation (Griliches, 1987; Crosby, 2000). Similarly, many studies have also used employment in knowledge-intensive industries as a proxy for innovation (see, for example Hope and Martelli, 2019). Such an approach has the benefit of potentially capturing a broader set of activities involved in the advent of innovation that are not captured by output-based innovation proxies

(Lee, 2011). However, high employment in creative fields does not necessarily guarantee commercially successful innovative output. Furthermore, restricting a measure of innovation to a specific industry sector neglects the possibility for innovation in other sectors.

Since the objectives of my research are to measure the consequences of innovation, rather than the conditions related to stimulating innovation, I opt for an output-based innovation proxy that circumvents the input uncertainties associated with R&D expenditure or employment-based measures. The most used output-based proxy, and the one ultimately employed in this research, is patent data. Patents, though a noisy measure, have been commonly used as an innovation proxy for over 50 years (Schmookler, 1966). A patent consists of a property right to commercial use of a product or process (Kogler 2010) and provides a reliable measure of innovation output (Griliches, 1990). Patents have been a popular choice for researchers since they became widely available and more easily accessible to researchers in the 1980s (Kogler, 2010). Patent data are historically extensive, providing a rich time series for analysis over longer time periods (Hinze & Schmoch, 2004). Patents also cover all fields of technologies and offer near-complete geographic coverage making them a good choice for analysis interested in certain technologies or analysis across large geographic scales (Kogler, 2010). Jaffe and Trajtenberg (2002) have suggested that patents are the most comprehensive measure of technology, with each patent providing a wealth of information from the innovation itself, its field of application and the geographical location of its inventors to information on the firm(s) involved. Furthermore, due to the time and money associated with patent-filing, a patent indicates that an invention has serious market potential, making it an excellent measure of innovation from a Schumpeterian perspective.

However, patent data are not without their limitations. The most glaring issue is that not all innovations are patented as different inventors and industries may benefit from other intellectual property defense mechanisms (Pakes and Griliches, 1980). For example, inventions with revenue streams expected to exceed the 20-year USPTO protection may rely on secrecy instead of patenting (Kogler, 2010). Furthermore, patent filing and defense is costly, creating a bias towards large firms who can afford the cost of specialists and patent lawyers. Some firms have been known to exploit this flaw, employing a defensive patent strategy, filing superfluously to strengthen a firm's defense against intellectual property rights (IPR) disputes (see Entezarkheir, 2017 for more details). Excessive patenting highlights another issue with patent data. Simple patent counts do not distinguish between high and low impact innovations (Crosby, 2000). Of the hundreds of thousands of patents filed every year, some are more radical in their impact, having a more drastic impact on existing products and processes while most others are more small-scale or incremental progressions (Crosby, 2000; Dickens, 2011). Therefore, when examining the disruptive impact of innovation, raw patent counts are limited due to their inability to give an indication of the scale of impact of a given innovation. Finally, patents skew towards larger ‘new to world’ innovations which is limited in its application to rural contexts which require a ‘new to region’ approach (Vodden et al., 2013). Whilst an innovation may not be new to the world, it is its novelty in a given area that produces local consequences of interest (Vodden et al., 2013). Whilst patent data are limited in their ability to explain rural innovation, the lack of other indicators available with the same temporal and spatial scale means it is the most feasible option for the purposes of this study. However, I acknowledge the limitations of this proxy in capturing the full extent of rural innovation.

From a broader perspective, there are some pitfalls to the mainstream approach of limiting discussions of innovation to specifically technological innovation or treating these concepts as nearly synonymous (see for example Rosenberg, 1974 or Dicken, 2011). Typical innovation measures focused on product or process innovation favour technological innovation and exclude other forms of innovations such as organisational innovation (e.g., changes in internal management structures) (OECD, 2018) or social innovations (Gibson-Graham and Roelvink, 2009).

In this thesis, the main source of data for patents is the United States Patents and Trademarks Office (USPTO). Due to the relative size and strength of the US market, Canadian inventions are typically filed first, and often only, in the United States (Trajtenberg 1999; Kogler 2010), providing them with IP protection in the much larger US market. Patent data from the United States therefore provide a strong measure of Canadian innovation.

The data were originally extracted and cleaned by Dieter Kogler and members of his Spatial Dynamics Lab at University College Dublin[1] and contains all patents filed with at least one Canadian inventor between 1976 and 2021.

Since most patents have multiple inventors (the average patent in this dataset had 4 inventors, with a maximum of 65 inventors on one patent), I develop a fractional weighting system when calculating patenting intensity by geography drawing on the methods of Moreno et al. (2005),

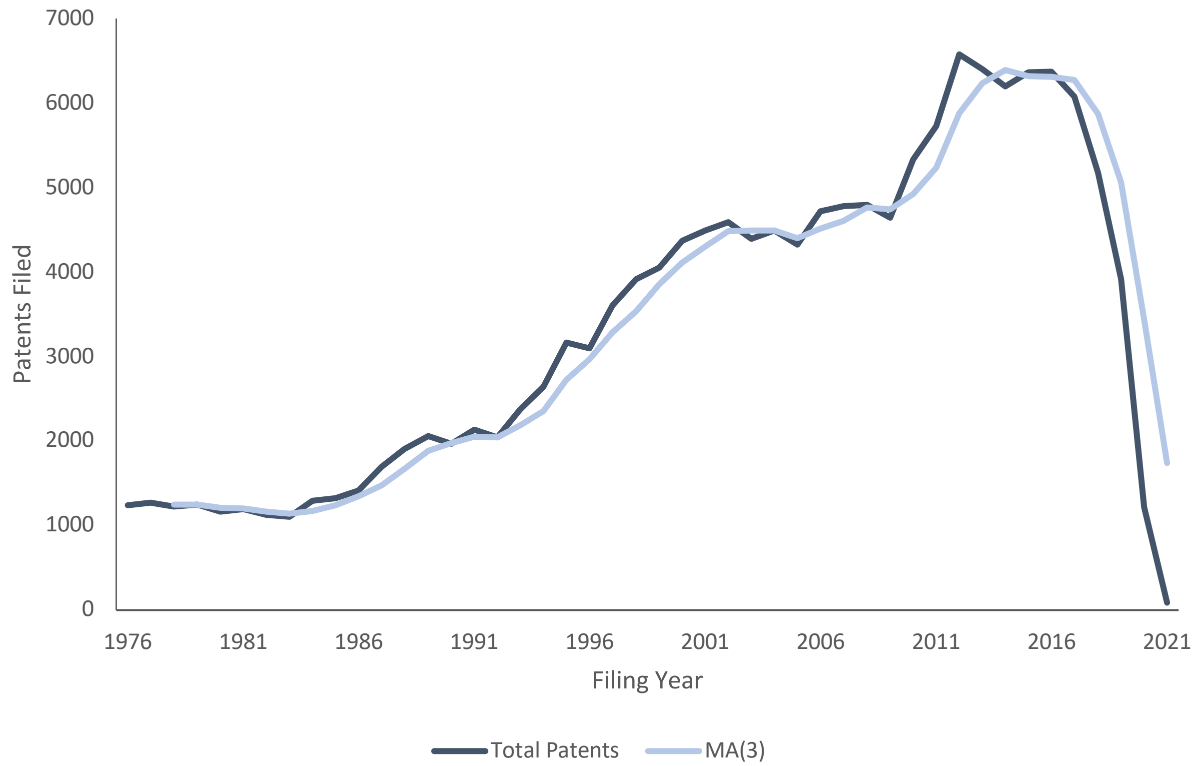
[1] My sincere thanks for his help in acquiring this data.

Sonn and Storper (2008) and Breau et al. (2014). Consider a patent with four inventors, two of whom are located in Toronto, one in Ottawa, and another in Peel. According to the fractional weighting system, the Toronto census division is given ½ a patent, whilst Ottawa and Peel each receive 1/4 patent count. Thus, the patent dataset used here is developed by calculating the sum of all patents in a given region for each given time period.

Due to the high variability of patents filed per year, patent counts are also calculated (or smoothed) based on a three-year moving average. Dates are based on the patent application year, as opposed to the year granted, in order to avoid distortions based on patent-granting delays. There is approximately a 2-year lag in this process, with about 85% of patents being granted after two years, though this number can vary over time (Hall et al., 2001). To account for such variability, Hall et al. (2001) recommend using a 3-year moving average (MA-3) as a "safety lag" when working with patents based on application year or to include time variables to account for truncation.

Figure 3.3 shows the number of patents per year in the dataset. While there is noticeable year-to-year fluctuations throughout, there is also a clear trend of strong patenting activity throughout most of the 1990s and early 2000s, coinciding with the largest period of Canadian inequality growth, after which point things flatten out. This trend is also evident in the 3-year moving average curve also shown in Figure 3.3. After the Great Recession of 2008-09, there is strong rebound in patenting activity in Canada for a period of approximately three years before stalling again around 2012 and 2013. The noticeable decline in data from 2018 onwards reflects the lag mentioned above in terms of how the USPTO data are collected. Many patents applied for after 2017 have yet be granted, resulting in the sharp decline visible in Figure 3.3. This data lag restricts the upper bound of the study period to 2016, or the year of second-to-last Canadian census. Census data will be discussed in greater detail in the next sub-section.

Figure 3.3. Total patents, and a smoothed three-year moving average (MA-3) of total patents filed by Canadian inventors per year (1976-2021)



Note: Data drops off significantly after 2018 corresponding to an approximate 3-year lag in data availability based on patent-granting delays.

Source: Author generated using data from the USPTO, 2023

One concern with studying the innovation-income inequality relationship is the potential for reverse causality. According to the neoclassical economics perspective, it is inequality that stimulates innovation (Falkinger and Zweimüller, 1997). In Fragkandreas' (2022) review, a small, but not insignificant 6% of studies find that inequality induces innovation and an additional 8.4% conclude that inequality hampers innovation (Fragkandreas, 2022). To limit the potential for reverse causality in this investigation, the 3-year moving average (MA-3) described above is based on the patent averages for the *t*-2 years of each time point in the panel dataset (i.e., MA-3) $=\frac{(t-2)+(t-1)+t}{3}$. Therefore, for every census year (1981, 1986…2021), patent values are calculated for the census year and the two-years prior (e.g., patent values for 1981 are an average of 1979, 1980 and 1981). This helps prevent the possibility of reverse causality by adding a temporal lag between the independent (innovation) and dependent (inequality) variables (more on this later).

Patent data contain not only rich geographic and temporal information but also extensive information about the nature and expected use of each patent. Patents are filed according to the Cooperative Patent Classification (CPC) system, which was developed to facilitate harmonization between classification systems used by the USPTO and the European Patent Office (EPO). The CPC contains nine broad patent classes, each divided into various sections and sub-sections with a total of over 250 000 patent classifications. Despite its comprehensiveness, patent categories do not provide a practical or particularly legible classification system for discussing innovation in the context of different economic industries. Therefore, to fully exploit the potential of patent data in economic analysis, it is necessary to link technological categories to economic activity. To do so, I apply the concordance developed by Lybbert and Zolas (2014) which matches the CPC classifications to NAICS categories. Lybbert and Zolas constructed the algorithmic concordance by mining patent abstracts and titles for descriptive keywords drawn from industry classification descriptions (ISIC or NAICS). Because patents do not fit cleanly into one industry class, they utilize a probabilistic method that applies a weighted distribution of one patent across multiple industry classes. These matches were reweighted to reduce noise, placing more emphasis on technologies specific to each industry. An arbitrary cut-off weight of 2% was also applied to reduce Type I errors (Lybbert and Zolas, 2014). This classification system is used in the descriptive analysis to explore the top patenting industries in geographic regions of interest, giving a snapshot of the different types of innovation across geographies.

3.2.2. Census data

The second major data source for this thesis comes from the confidential micro-data files of the Canadian Census of Population. Census micro-data provide a uniquely powerful dataset for research. Protected under the Statistics Act, the Canadian Census of Population is mandatory and response rates are accordingly extremely high (90%+) though with certain exceptions (i.e., highly remote areas with unique collection challenges) (Statistics Canada, 2020)**.** The modern form of the census has been administered every five years since 1981 (with the exception of 2011 when it was replaced by the National Household Survey) (Statistics Canada, 2020) thus providing exceptional data continuity. For every census cycle, both short- and long-from questionnaires are administered. The short-form questionnaire consists of baseline questions on number of household inhabitants and spoken languages, whilst the long-form questionnaire collects more exhaustive sociodemographic, labour and income data. The latter is administered to a representative 20% sample of the population (25% as of 2016).

Due to the highly confidential nature of the data, the long-form census data are only available to researchers through two avenues. The first are public-use micro-data filed (PUMFs), a 1% sample of the population available for download available with institutional access. The second is the entire 20% (or 25%) sample, which is highly confidential and only available for access to researchers through designated Statistics Canada Research Data Centres (RDC). The RDC's are a network of university or government-based secure research facilities for researchers wishing to work with confidential Statistics Canada data. The advantage of working with the long-form sample include data availability at finer geographic scales, data availability in more remote regions, and more accurate results derived from the significantly larger sample size. That said, access to these centres is subject to several layers of security including the approval of a request for data access, a Government of Canada security clearance, and the signing of a contract with Statistics Canada. Upon passing these security requirements, I was able to access the data through the McGill-Concordia RDC, which is itself part of the Quebec Inter-University Centre for Social Statistics (QICSS). Per the RDC guidelines, all results disclosed from this dataset were subject to vetting by a Statistics Canada analyst before release to ensure the confidentiality of respondents was protected.

3.2.3. Sample size

I make use of the 20% (25%) micro-data from the 1981, 1986, 1991, 2001, 2006 and 2016 Census of Population as well as the National Household Survey (NHS) for 2011 when it replaced the mandatory census. The 2021 census data was made available during the course of my research; however, due to the lag in the patent data (discussed in the previous section), the patent data are of limited quality for 2021. Therefore, the timeframe for this analysis is restricted to 2016 as the most recent year with fully available, high-quality census and patent data.

From the 20% (25%) long-form, the sample size used was limited to Canadian aged 20-64, currently employed and making more than $2600 per year in 2002 dollars, adjusted with inflation to each census year using the Consumer Price Index (CPI). The purpose of these limitations was to avoid inflating measures of income inequality by excluding individuals that do not have a concrete or active attachment to the labour force (e.g., retirees, students, children etc.). Since this study is interested in understanding income inequality changes between *workers,* it is essential to limit the sample-size to only individuals that are actively tied to the labour force and whose livelihood is primarily tied to work. Including individuals beyond workers (ex: children, retirees, people who are unemployed) will artificially inflate measures of income inequality in a way that is not representative of real-world inequality dynamics. Furthermore, bottom-coding income (i.e., setting the minimum income threshold of $2600 per year) ensures that only individuals with a steady attachment to the labour force are included, again reducing the possibility of overestimating inequality measures. The bottom threshold was based on the methods of Card and Lemieux (2001) and Green and Sand (2015) who drop individuals who have a weekly income of less than $75 in 2000 dollars. I limit this to a $50 a week minimum (in 2002 dollars) to maintain a slightly larger sample size. Minimum income thresholds are adjusted to inflation for each year in the sample size using the Consumer Price Index (Statistics Canada, 2023).

Many similar studies have also opted for a bottom age cut-off of the sample between 15 and 25 years of age (Bolton and Breau, 2012; Breau, 2015; Marchand et al., 2020). However, 25 risks excluding too many workers who enter the workforce after high school, CEGEP, 2-year degrees or other, while 15 includes a large number of students who do not have steady employment. Accordingly, I utilize a minimum cut-off of 20 years to capture individuals who enter the workforce after high-school, two-year degrees, and CEGEP. At the top end of the age distribution, 64 was selected in accordance with the average retirement age of 65. That said, it is important to note that average retirement age varies significantly by individual, industry, and gender and has been steadily increasing since the early 2000s (Lefebvre et al., 2011).

3.2.4. Inequality measures

There are several different methods of measuring income inequality that vary based on the type of income data used, the unit of analysis, and the inequality index utilized. The most commonly used measures are based on household and individual units of analysis. Given that households typically share income and expenditures, household income is a good functional measure of inequality. However, given the complexities in household size, structures (e.g., nuclear, single-parent, multi-generational, etc.), the likelihood of assortative mating (i.e. tendency for individuals to marry close to their income or education level) (e.g., see Lasse et al., 2019) and the gender dimensions of labour force participation, individual income inequality is a useful alternative (as argued above). Furthermore, given that the focus of this thesis in on the impact of technological change on wage structures, it is more useful to consider the individual scale, as opposed to a household one which is conflated by far more non-labour-market related variables. Therefore, for the purposes of this thesis, I opt to calculate inequality measures based on individual level income data.

Another key decision in putting together indicators of inequality is the concept of income used. Similar studies typically rely on pre-tax and pre-transfer income while others utilize post-tax and transfer income, also referred to as disposable income (Fortin et al., 2012). Inequality measures derived from pre-transfer income are highest, whilst inequality measures derived from post-tax and post-transfer income data are lower. Census data offer two main measures of income: wages, and total income which refers to all money received by an individual in a given year including wages, transfers such as child benefits, old age security pensions, employment insurance, and interest on savings and other bonds, before tax. For the purposes of this study, I opt to use pre-tax total income as the measure of income. The reasons for this are two-fold: First, using an income definition that includes transfers is a more accurate snapshot of perceived individual inequality, especially given the well-known difference government transfers make in reducing inequality. Second, since taxation varies significantly across provinces and territories, it is more intuitive to use a pre-tax income measure for cross-regional analysis.

Post-transfer, individual, total income was used to calculate two different measures of inequality: the Gini coefficient and the Theil index. Each of these indices has its strengths and drawbacks, and all three are utilized to ensure the robustness of the results to the use of different indices. The Gini coefficient, a widely used measure of inequality, is based on the Lorenz curve and presents a measure of inequality ranging from 0 (perfect equality) to 1 (perfect inequality). The Gini coefficient is more sensitive to changes in the middle of the distribution whilst the Theil index, an entropy-based inequality measure, is more sensitive to changes at the top (Jenkins, 2022). The Theil index is thus well suited to measuring the influence of the wealthiest 1%, a subset of the Canadian population that has seen a significant rise in their share of total national income (Breau, 2014). However, this feature of the Theil index can also be a drawback as it can be excessively influenced by high-income outlier values (Jenkins, 2022). Indeed, Jenkins (2022) has showed that the inequality index used made a significant difference in the conclusions drawn on the nature of change in inequality in the UK over the last 30 years. To ensure that results obtained from my model hold under the different distributional properties of measures of inequality, I build and use all both indicators for comparative purposes. Again, the Gini and Theil coefficients provide a middle-sensitive and a top-sensitive measure respectively (Trapeznikova, 2019).

3.3. Modeling the innovation-inequality nexus: A spatial panel model approach

Finally, to formally examine the relationship between income inequality, I develop and estimate a series of spatial panel models. In comparison to cross-sectional data, panel data makes it possible to account for unobservable heterogeneity reducing the possibility of omitted variables bias. For example, a recession, global health epidemic or other macro-level disruption may impact inequality across all Canadian census divisions but to varying extents. Similarly, a plant closure in southern Ontario or the resource boom in Alberta will have significant local effects and more marginal spillovers to other regions. Panel data can account for these unobserved heterogeneities.

Second, as previous studies have revealed, there is clear evidence of a geographic pattern to inequality levels across Canadian regions (Breau, 2015; Marchand et al., 2020). Therefore, typical OLS assumptions regarding the independence of errors are violated. To address this issue, I begin by testing for spatial autocorrelation and then employing different spatial models to account for the spillover effects between regions.

3.3.1. Panel dataset and model specification

As mentioned earlier, the final panel dataset consists of the 284 time-standardized census divisions over eight time periods, corresponding to every census held between 1981 to 2016, for a total of 2,272 regional observations. Using this panel dataset, I begin by estimating the following benchmark model (see Eq. 3.1)

$$INEQ_{it} = \alpha + \beta ln\ INNOV_{it} + lnCDSIZE_{it} + \delta\ ECON_{it} + \eta\ INST_{it} + gSOCDEM_{it} + \tau_t + \varepsilon_{it}, \quad \text{Eq. (3.1)}$$

where *i* represents the cross-sectional variable (or census division with *n* = 284) and *t* represents time (*n* = 8 corresponding to the five-year census cycles between 1981 and 2016). The dependent variable, $INEQ_{it}$, denotes the Gini coefficient (or the Theil or P90/P10 ratio) for each census division at each time period. $INNOV_{it}$ refers to the sum of patents per capita filed in a given census division in a given year based on inventor residence.

The model also includes a set of control variables derived from the previously discussed macro and micro forces related to income inequality (see section 2.4).

$CDSIZE_{it}$ refers to the size of the population in a given census division. As the work of Breau et al. (2014) demonstrates, the population size of a city is strongly linked to inequality therefore I include the population size of a region to account for the potential impact of agglomeration forces.

$ECON_{it}$ is a vector that reflects variables related to the strength and character of the local labour market in a given region and time. Here, I include the natural log of median income as a measure of local economic development related to the work of Kuznets (1955) who suggested a relationship between economic development and inequality. $ECON_{it}$ also includes the proportion of the working population that are unemployed and the proportion of the population that are self-employed, as these variables are also thought to have a large impact on local inequality. Finally, the industry composition of a region is included here as the proportion of working age individuals working in the secondary, tertiary or quaternary sectors. The primary sector is omitted to serve as the reference group. The manufacturing (secondary) sector has long been associated with the middle-class and is typically associated with lower levels of inequality (Bluestone & Harrison, 1988; Levernier et al., 1998). Meanwhile, the quaternary, or knowledge-based sector of the economy tends to be more associated with increased inequality (Breau et al., 2014).

$INST_{it}$ refers to local institutional factors related to inequality. Unionization rates and high minimum wages are both well-documented factors associated with lower inequality (Lemieux, 2008; Fortin & Lemieux, 2015; Card et al., 2020). Data for unionization rates and minimum wage were retrieved from Statistics Canada open data. Since minimum wages are provincially set, and data on unionization rates are also only available at the provincial level, these variables lack the same level of geographic precision as other variables and are included in the models only as contextual variables for the purposes of my analysis. Unionization data is not available for the Canadian Territories across the time period of interest therefore, unionization is not included in the main iteration of the model but is included in a truncated version that includes only the provinces.

Finally, $SOCDEM_{it}$ refers to the socio-demographics characteristics of the local labour force. These include the education levels of individuals in the workforce (measured here by a ratio of the fraction of the labour force with a high school degree or less, to the fraction of the labour force with a bachelor's degree or higher), the age structure of the population (i.e., proportion of individuals younger than 15 and the proportion of individuals older than 64) and finally the proportion of women in the active labour force, variables which have all been associated with an impact on inequality (Boudarbat et al., 2006; Pelletier et al., 2019; Card et al., 2020) . Whilst the proportion of visible minorities has also been linked to higher income inequality (Pendakur and Pendakur, 2007), due to the data security restrictions of the RDC, it was not possible to disclose data on visible minorities due to low counts in certain regions. Therefore, this variable is omitted from the analysis.

Time dummies for each census year are also included to capture broad variations in inequality with reference to the base year (1981). Finally, ε_{it} denotes the error term. As mentioned before, there is a high likelihood of a geographic pattern to the residuals, thus violating the OLS assumption of independent distribution. The next section delves into the methods used to explore and account for spatial autocorrelation.

3.3.2. Spatial autocorrelation and spatial modelling

As the research of Breau (2015), Breau and Saillant (2016) and Marchand et al. (2020) has demonstrated, there is considerable evidence of spatial autocorrelation in patterns of inequality across the country. In other words, regions with high inequality tend to be located near other regions of high inequality, whilst regions of low inequality are located near other regions of low inequality. This suggests the possibility of a spatial spillover effect between regions. To test for the presence of spatial autocorrelation in my dataset, I conduct a series of Moran's I tests. If significant, this violates the OLS assumption of independence in the residuals and requires the incorporation of spatial effects in the panel model.

3.3.3. Developing a spatial weights matrix

Testing for spatial autocorrelation (e.g., Moran's I) and running a model incorporating corrections for spatial dependence requires the development of a spatial weights matrix. A spatial weights matrix summarizes the relationship between regions, assigning a weight to indicate the strength of the spatial relationship between closely located regions. Commonly used spatial weights matrices include contiguity-based matrices (e.g., Rook's or Queen's matrices) based on the borders shared between regions, and distance-based matrices. Distance based matrices are calculated using the inverse distance between the centroids of two regions. For this study we utilize *k*-nearest neighbour distance weights where *k* (*k*=5) denotes the number of neighbours. Therefore, the applied contiguity matrix is as follows:

$$\text{Wij} = W\_ij = \begin{cases} 1 & if\ the\ centroid\ of\ j\ is\ one\ of\ the\ 5\ nearest\ centroids\ to\ i \\ 0 & otherwise \end{cases}$$

Eq. (3.2)

Since distance-based matrices are not impacted by regions that lack direct borders (e.g., islands) this makes it the simplest weights matrix to use for regional-scale work across Canada. The determination of the number of neighbours to use was made based on a connectivity histogram which showed that the median number of neighbours for each Census division in Canada is five.

3.3.4. Fitting a spatial model

To determine the spatial model of best fit, I follow the selection method proposed by Dubé and Legros (2014) which builds on earlier work developed by a number of other statisticians and social scientists. I begin by fitting a simple linear Ordinary Least Squares (OLS) regression model to serve as a benchmark. Second, a simple calculation of the Moran's I for the OLS residuals confirms (or not) the presence of some spatial autocorrelation in the data. Next, using the pooled OLS model residuals, I calculate the Lagrange Mutiplier (LM) tests, developed by Anselin et al. (1996) to distinguish whether the presence of spatial autocorrelation in the data is due to a spatial autocorrelation in the dependent variable (LM_{SAR} test) or due to a spatial autocorrelation in the error term (LM_{SEM} test) (see Figure 3.4).

Figure 3.4. Spatial model decision tree based on the Lagrange Multiplier tests developed by Anselin et al., 1996

Source. Dubé and Legros, 2014

Spatial autocorrelation is a substantive modelling issue if the dependent variable (in this case the inequality coefficient) is systematically related to inequality values in neighbouring regions, violating OLS assumptions of an unbiased estimate. Spatial autocorrelation can be accounted for by including a spatial lag on the dependent variable (see equation 3.3), based on a spatial weight matrix that accounts for the spillover effects of the dependent variable on neighbouring regions (Anselin, 2003)

$$Y = \rho WY + X\beta + u$$

Eq. (3.3)

where Y is the dependent variable, W is the spatial lag of the dependent variable, X is an explanatory variable, β the regression coefficient on X, and u is the error term. Here, ρ is the spatial autocorrelation coefficient.

In contrast, spatial error is another form of nuisance dependence, meaning the spatial dependence is related only to the model residuals, possibly due to an unobserved variable acting across regions. This is not as critical of an issue as a spatial lag since it only reduces the model efficiency as opposed to violating OLS assumptions; however, it is possible to account for spatial error by incorporating a spatial error term with a spatial lag on the errors (see equation 3.4) (Anselin et al., 1996; Anselin, 2003).

$$Y = X\beta + u$$
$$u = \lambda W u + \varepsilon$$

Eq. (3.4)

Here, a spatial lag (W) is applied instead to the error term with λ representing the spatial autocorrelation coefficient.

In cases where both standard and robust LM tests for spatial lag and spatial error are significant (P-Value > $Chi^2(1)$ = 0.0000), there is no clear way to distinguish between the appropriateness of a spatial lag model (SAR) or a spatial error model (SEM) (Anselin et al., 1996; Elhorst, 2010). For this reason, researchers can use a general spatial model (SAC) which accounts for both spatial lag and spatial error (Kelejian and Prucha, 1998; Elhorst, 2017).
The SAC model is a combination of the spatial lag and spatial error model defined as:

$$Y = \rho WY + X\beta + u$$
$$u = \lambda W u + \varepsilon,$$

Eq. (3.5)

where WY is a vector of spatial lags on the dependent variable Y and ρ is the spatial autoregressive coefficient. $X\beta$ is the matrix of observations on the exogenous explanatory variables and u is the error term. The error term is composed of Wu a spatial lag of the errors, λ the coefficient and ε the remaining error term (Elhorst, 2010; Baltagi et al., 2013).

In my case, all three spatial models (SAR, SEM and SAC) will be estimated to determine which is most appropriate based on the type of spatial dependence identified by the tests discussed above.

Chapter 4

RESULTS AND DISCUSSION

This chapter presents the results of the methods discussed in Chapter 3 and is organized into three sections. I begin by examining the broad changes in inequality across Canadian regions between 1981 and 2016, paying particular attention to diverging urban and rural trajectories. The second section discusses some of the main geographic and temporal trends in Canadian innovation including urban as well as some surprising non-urban elements to the Canadian innovation profile. Finally, the last section is dedicated to presenting the results of the spatial panel regression analysis.

4.1 Regional inequality trends

I begin by describing some of the key changes to Canadian income inequality between the 1981 to 2016 period, setting the stage for our subsequent analysis of the causes of regional inequality across the country. Table 4.1 presents a summary of regional Gini coefficients across provinces as well as the percentage change in levels of inequality over the 1981 to 2016 period. The highest levels of inequality and its greatest growth occurred in Ontario with a 17.3% relative change, closely followed by Alberta (17.1%), both growing well above the national average (12.5%). British Columbia came in at a not too distant third (14%). The provinces where inequality has grown more slowly are Saskatchewan (0.5%), Yukon (0.6%) and New Brunswick (0.6%). PEI was the only Province or Territory to experience a decline in inequality (-4.9%) over the period of study. Finally, there was moderately high inequality growth in Newfoundland and Labrador (11.8%), Nunavut (11.1%), and the Northwest Territories (9.8%), all just below the national average. These results are somewhat consistent with the work of Fortin and Lemieux (2015) who noted the wage inequality-reducing effects of the relative strength of minimum wages compared to median wages in Maritime provinces, which were much higher than Quebec, Ontario, BC and Alberta. Manitoba's wage profile appears similarly minimum wage linked (Fortin and Lemieux, 2015).

In contrast with the trends observed in Table 4.1, Fortin and Lemieux (2015) observe a small decrease in wage inequality in Alberta and Saskatchewan between 1997 and 2013 which they attribute to the boom in extractive resource sector employment "lifting all boats" and increasing wages across both ends of the distribution (Fortin and Lemieux, 2015). However, this can be attributed to the different definitions of income utilized (wages vs. total income), small differences in selected samples, and a shorter time-period of study. My results, consistent with the work of Marchand (2017), demonstrate that over the longer-term (1981-2016) there has been a net gain in inequality in the western provinces, specifically Alberta where the oil sands boom has been felt the strongest.

Table 4.1. Change in inequality in Canadian Provinces, Territories, and regions (1981-2016)

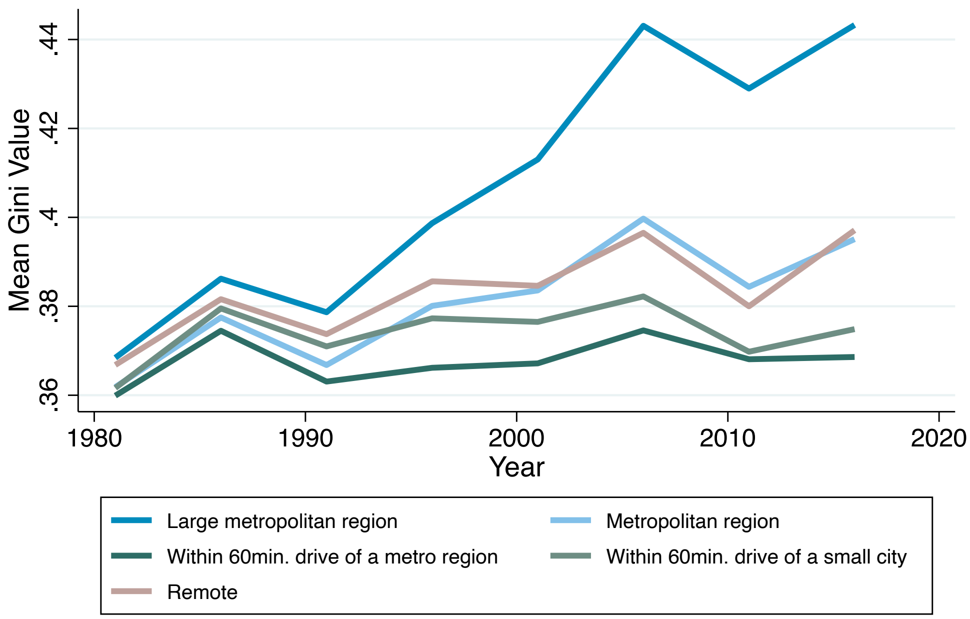
	Number of CDs	Gini Coefficient		
		1981	2016	%D
Canada	284	.364	0.410	12.5
Provinces				
Newfoundland and Labrador	10	.356	.398	11.8
Prince Edward Island	3	.369	.351	-4.9
Nova Scotia	18	.358	.381	6.4
New Brunswick	15	.355	.357	.6
Quebec	97	.358	.377	5.3
Ontario	49	.365	.428	17.3
Manitoba	23	.365	.381	4.4
Saskatchewan	18	.383	.385	.5
Alberta	18	.380	.445	17.1
British Columbia	27	.363	.414	14
Yukon	1	.347	.349	.6
Northwest Territories	2	.346	.380	9.8
Nunavut	3	.386	.429	11.1
Predominantly urban regions	30	.368	.435	18.2
Intermediate regions	35	.358	.384	7.3
Rural regions	219	.362	.374	3.3

Note: The reported Gini levels are population weighted averages of CDs within a given geographic entity.
Source: Author's calculations using data from Statistics Canada, Census of Population (1981, 2016)

When taking the mean inequality values of urban, rural, and intermediate (following the OECD's suggested classification system), it is quickly apparent that the bulk of inequality growth is being driven by urban areas (18.2%), a growth rate far higher than the rate of growth in any province or territory and significantly higher than the national average. In contrast, rural regions showed very moderate increases in inequality (3.3%). Given data dissemination restrictions, urban, rural, and intermediate inequality was calculated based on CD averages; however, it is possible these results may have differed slightly had inequality levels been calculated across all individuals in these pooled regions.

High urban inequality can help explain some provincial trends. Ontario is home to 16 (39%) of Canada's 41 Census Metropolitan Areas (CMA's) (Statistics Canada, 2022) which can explain in part its high provincial inequality growth. In contrast, some of the slowest growing provinces contain very few CMAs (Yukon and PEI contain none, Saskatchewan contains only one and New Brunswick, three).

Figure 4.1. Population-weighted growth in inequality across Canadian regions (1981-2016)



Source: Author's calculations, data from Statistics Canada, Census of Population (1981-2016)

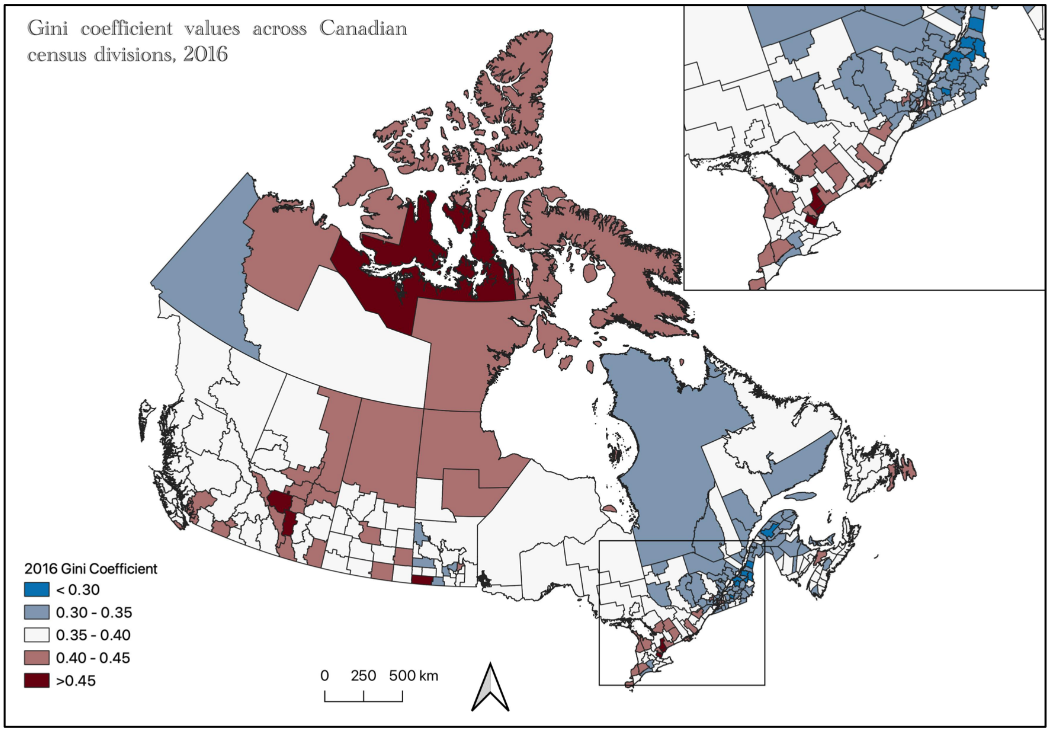
Figure 4.1 presents a more detailed temporal breakdown of diverging rural-urban inequality trajectories using the metropolitan/non-metropolitan classification developed by Fadic et al. (2019) (see section 3.1 for more details). Immediately evident is the vast majority of inequality growth in the 1990s and 2000s takes place in large metropolitan regions (>1.5 million individuals). This is in contrast with inequality trends before the 1990s where inequality was growing at an approximately equal pace across all regions, irrespective of their urban or rural nature. It should be noted however, that these results do not consider inter-regional inequalities. While it is clear that rural regions appear to have low within-region inequality, it is possible that there are high income disparities between many of these regions.

The rapid growth phase of the 1990s and 2000s is followed by a small but clear inequality decline in inequality across all regions between the 2006 and 2011 data points, corresponding to wage compressions after the 2008-2009 recession. Inequality growth resumes across all regions after 2011 but here too, the increase is more pronounced across metropolitan regions.

The relatively low rates of inequality in non-metropolitan regions compared to metropolitan regions observed in Figure 4.1 and Table 4.1 have interesting geo-political implications. The work of Rodríguez-Pose et al. (2021) suggests that geographic patterns in US populist support can be better explained by long-term declines in employment and population (so-called 'left behind places' see also Rodriguez-Pose (2018)), rather than discontent driven by interpersonal inequality. In Canada, geographic support for far-right parties in Provincial elections (see for example the 2022 election of the CAQ in Quebec, or the 2018 and 2022 elections of Doug Ford's conservatives in Ontario) has come primarily from rural and suburban regions, reflecting Canada's distinct rural-urban voter divide, a divide more prominent now compared to any other in the last century (Taylor et al., 2023). Significantly lower rates of inequality in rural and intermediate regions compared to urban ones provides some weak preliminary evidence that populist sentiment in non-urban regions may be driven more by interregional resentment (a sense of lagging regions vs prosperous cities) as opposed to local interpersonal inequality. However, more research is needed to draw any conclusions about the distribution and possible discontent of lagging regions in Canada.

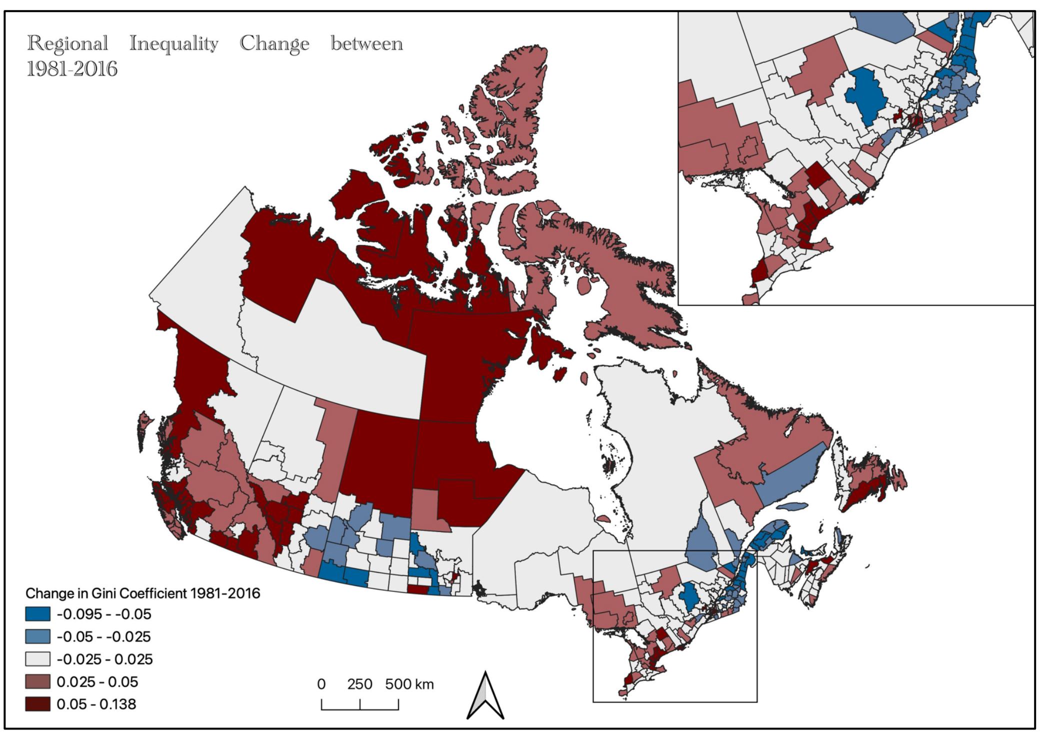
Figures 4.2 and 4.3 map out the distribution of inequality across the full set of 284 CDs across the country. Consistent with the observation of Breau (2015) and Marchand et al. (2020), Figure 4.2 shows clear evidence of spatial clustering of inequality. The most evident is the East-West divide, also observed by Breau (2015) and Marchand et al. (2020). Regions east of the Ottawa River exhibit considerably lower inequality level (Gini coefficient<0.35) compared to Western regions. The second trend is the rural-urban divide with major cities showing exceptionally high levels of inequality across the country. Toronto, Calgary and a few neighbouring regions show markedly high Gini scores (>0.45). Other major city-regions show moderately high inequality levels compared to their surroundings including the Vancouver, Ottawa-Gatineau and Saskatoon regions as well as multiple cities in the 'Golden Horseshoe' area of Southern Ontario. Even in the more relatively equal Eastern regions, the Montreal Island, surrounding census divisions, as well as Division 1 Newfoundland (encompassing St. Johns) stick out as areas of high inequality.

Figure 4.2. Income inequality across Canadian regions, measured by the Gini coefficient (2016)



Source: Author's calculations, data from Statistics Canada, Census of Population (1981-2016)

Figure 4.3. Growth in income inequality across Canadian regions (1981-2016)



Source: Author's calculations, data from Statistics Canada, Census of Population (1981-2016)

High inequality in the Southern Ontario regions, specifically Toronto, is not unexpected given both the significant population density of the region and its role as Canada's primary financial hub, major innovation cluster, and the main destination for recent immigrants.

Regions across Alberta, Saskatchewan, Newfoundland, the Northwest Territories and Nunavut, demonstrates both high inequality and high inequality growth (Figures 4.2, 4.3). Many of these regions are characterized by a strong extractive resource sector presence. Inequality remains persistently high in much of Alberta including very high inequality in the Calgary region, where the headquarters of a multitude of oil and gas conglomerates are located. Interestingly, while Figure 4.2 shows moderate to high inequality levels across most of Saskatchewan, Figure 4.3 reveals that apart from the northernmost edge of the province, inequality has been decreasing across most regions in the province. Fortin and Lemieux (2015) suggest spillovers from extractive resource sector growth may be responsible for some modest declines in inequality as extractive resource growth stimulates employment and wage growth for less-skilled workers. However, the same decline is not observed in Newfoundland, Alberta, and the Northwest Territories suggesting the likelihood of a provincial-level institutional factor (i.e., strength of minimum wage, government redistribution policies etc.) or other factors may play a more important role in Saskatchewan's declining inequality.

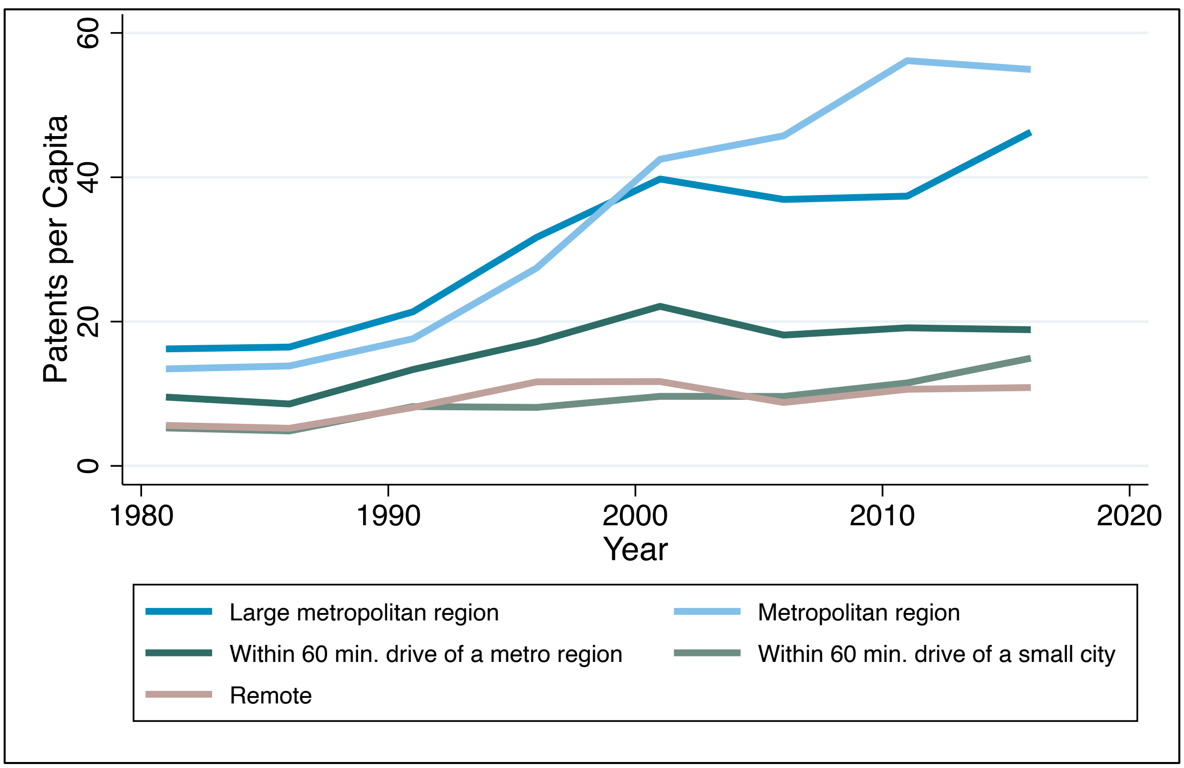
Similarly, Quebec's low inequality levels (Figure 4.2) are matched by inequality declines (4.3) across much of the province, ending abruptly at the New Brunswick border, implying a strong institutional effect on inequality. This is consistent with Quebec's reputation for a significantly stronger redistributive social model compared to the rest of the country (Dinan and Noël, 2020).

4.2. Regional innovation patterns

For this next section, we now turn our attention to the patent data with a series of descriptive analyses on the nature, frequency, and geography of innovation across Canada over the 1981-2016 period. While patenting has been steadily increasing Canada-wide (see Figure 3.3), this increase is not uniform across regions. Figure 4.4 breaks down the distribution of patents per capita according to the regional classification of Fadic et al. (2019). Interestingly, medium-sized metropolitan regions (where 50% or more of the inhabitants live in a metropolitan area with

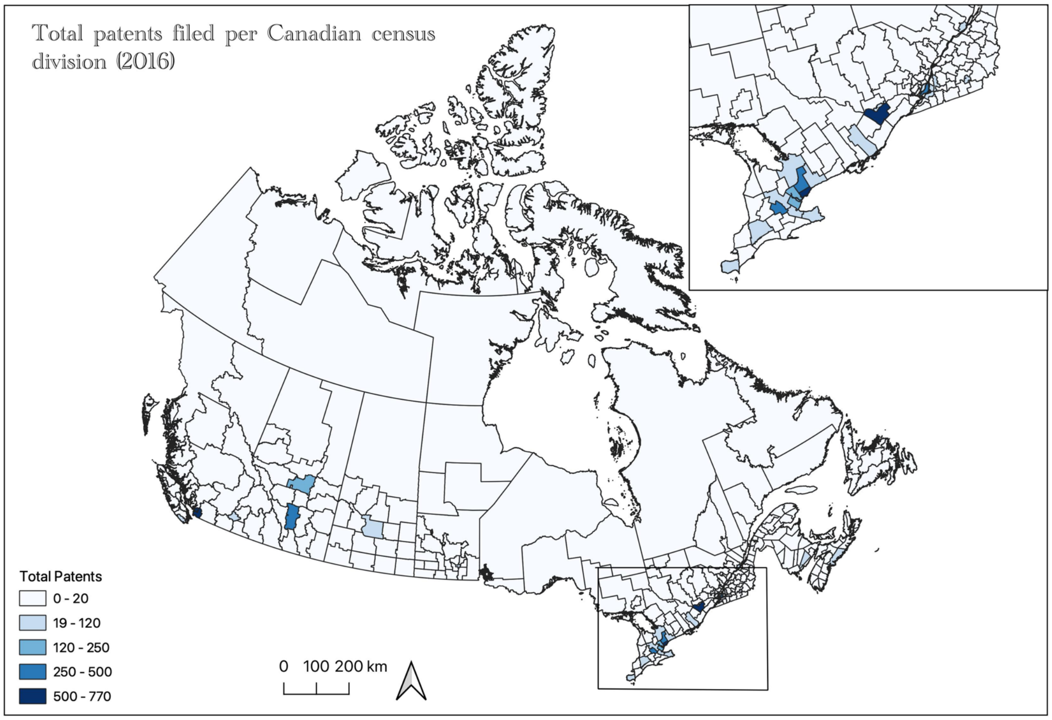
250k+ inhabitants) surpass large metropolitan areas in per capita patenting around 2000. However, this makes intuitive sense since both the Ottawa-Carleton and Waterloo regions, notorious for their large high-tech clusters, are classified as medium metropolitan areas. High patenting in large and medium metropolitan areas, compared to non-metropolitan and remote regions is consistent with the dominant literature on the geographies of innovation that suggest cities and their agglomerative forces are the essence of creativity and innovation (Florida, 2002; Glaeser, 2011; Wolfe, 2016). However, evidence that medium-metropolitan regions are out-patenting larger metropolitan areas on a per capita basis, suggests bigger is not necessarily better when it comes to productive output in a given region, though the gap between medium and large metropolitan regions appears to be shrinking, suggesting this pattern may not persist.

Figure 4.4. Patenting frequency across population-weighted Canadian regions (1981-2016) based on inventor geography



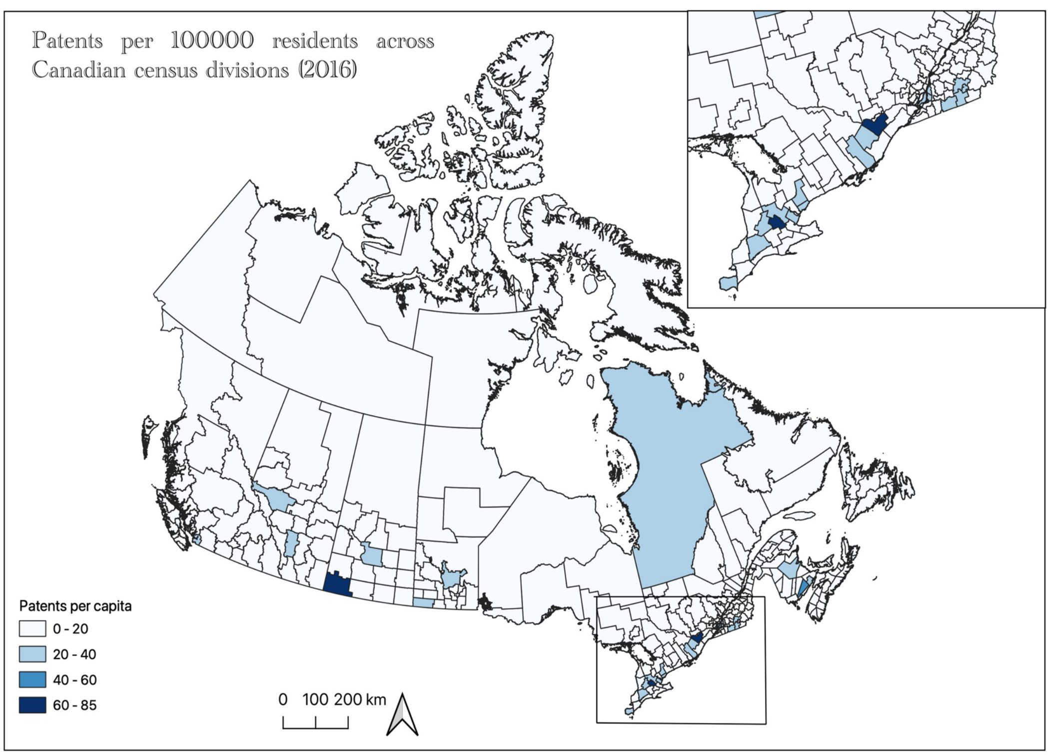
Source: Author's calculations, data from USPTO

Figure 4.5. Patenting frequency based on total patent counts (MA-3, 2016)



Source: Author's calculations, data from USPTO

Figure 4.6. Patenting frequency per capita across Canadian regions (MA-3, 2016)



Source: Author's calculations, data from USPTO

Figures 4.5 and 4.6 provide a visualization of the spatial distribution of total patents and patents per capita respectively. Patent counts are calculated based on the total inventor-weighted patents filed per census division based on a 3-year moving average (MA-3) for 2016. As expected, large metropolitan areas stand out as having the highest raw patenting activity (Figure 4.5), with Canada's largest metropolitan centers Toronto, Montreal and Vancouver all placing within the top 5 patenting regions (see also Table 4.2). This list is rounded out with the Ottawa-Carleton region and Division 6, Alberta (which encapsulates the Calgary metropolitan area). Other metropolitan regions with noticeable total patenting activity include Division 11 in both Alberta and Saskatchewan which encapsulate major cities (Edmonton and Saskatoon) in each respective province. Unsurprisingly, most of the census division in the greater Toronto area as well as a few of the census divisions surrounding the Montreal Island also demonstrate significant patenting activity. Total patenting is limited across the Atlantic provinces, despite Halifax's small but growing ICT sector.

While Figure 4.5 clearly demonstrates prolific levels of innovation in metropolitan areas and their surrounding regions, consistent with mainstream innovation literature, these results are subject to a bias by large population sizes of urban census divisions. Figure 4.6, which presents patenting intensity per capita, reveals a slightly different story. While some metropolitan areas remain highly significant (Ottawa-Carleton and Waterloo) other major metropolitan areas (Toronto, Montreal, Calgary and Vancouver) see their relative patent contributions greatly reduced. Interestingly, the patent per capita figure highlights a high degree of innovation in several unexpected non-metropolitan regions. The Nord-du-Quebec region stands out as a physically large and exceptionally remote region with high per-capita patenting. Similarly, Division 14 in Alberta, Divisions 5 and 18 in Manitoba and the Northumberland and Albert census divisions in New Brunswick stand out as regions with high per capita patenting not otherwise noticeable when looking at the gross patenting figures. These regions will be discussed in greater detail later.

Considering the temporal volatility of patents, results should be interpreted with some caution and again as Hall and Vodden (2019) remind us, patents alone cannot capture the full story of rural innovation. Therefore, it is important to recognize that the results shown here are subject to some level of urban bias based on the use of a patent-proxy measure of innovation.

Table 4.2. Top patenting regions by total patents and per capita patents, including top industry in which patents were filed

Rank	Census code	Census name	Total patents	Patents per capita	Top industry
1	3506	Ottawa-Carleton, ON	769	84	Communications Equipment Manufacturing
2	5915	Greater Vancouver, BC	757	31	Computer and Peripheral Equipment Manufacturing
3	3520	Toronto, ON	637	24	Computer and Peripheral Equipment Manufacturing
4	2466	Montréal, QC	464	25	Computer and Peripheral Equipment Manufacturing
5	4806	Division 6, AB (Calgary)	393	27	Metalworking Machinery Manufacturing
Rank Per Capita					
1	3506	Ottawa-Carleton, ON	769	84	Communications Equipment Manufacturing
2	3530	Waterloo, ON	367	70	Computer and Peripheral Equipment Manufacturing
3	4704	Division 4, SK	6	67	Support Activities for Crop Production
4	1305	Kings, NB	38	56	Other Miscellaneous Manufactured Commodities
5	4618	Division 18, MB	9	37	Computer and Peripheral Equipment Manufacturing

Source: Calculations by author, data from USPTO

Table 4.2 contrasts the top five patenting regions by total and per capita patent count respectively. The Ottawa-Carleton region had both the highest total *and* per capita patenting activity 2014-2016 with 769 total patents and 84 patents per capita. This is unsurprising given Ottawa's well-established ICT and software sector, an industry well-known for its intensive propensity to patent. Similarly, Waterloo, a region with another notable high-tech sector, has the second highest patents-per-capita count at 70. The top five per capita patenting regions include a surprising mix of metropolitan (Ottawa-Carleton and Waterloo, ON), suburban (Kings, NB) and two highly rural census division (Division 4, SK and Division 18, MB).

What is interesting to note here is that the Ottawa-Carleton and Waterloo regions demonstrate higher per capita innovation than major cities like Toronto, Montreal, and Vancouver. This makes intuitive sense as Ottawa-Carleton and Waterloo are well-known for their high-tech clusters.[2] However, that major cities like Toronto and Montreal, with much larger and diversified economies (Wolfe, 2009) are not innovating as much on a per capita basis as smaller cities with more specialized economies like Ottawa and Waterloo may suggest that the cross-fertilization of ideas between different industries (Jacobs, 1969; Feldman and Audretsch, 1999) may be less significant of a factor in determining innovative output compared to labour specialization and spillovers that occur when an industry clusters in space (Griliches, 1992; Jaffe et al., 1993).

However, it should be noted that the measure of innovation used does not take into account the complexity or novelty of innovations. It is possible that the innovations taking place outside of the largest, most diversified city-regions are smaller, incremental, or more R&D intensive product innovations that benefit from cheaper land costs (Gordon and McCann 2005; McCann, 2007; Shearmur, 2011). Future research should examine whether more complex innovations are occurring more frequently in major metropolitan centres or if smaller, more specialized cities are producing more ground-breaking innovations (see, for instance, Pinheiro et al. 2022).

Tables 4.2 also includes the top industry in which patents were filed. These results are based on the NAICS 2007 industrial classification system using the crosswalk developed by Lybbert and Zolas (2014). In four of the five top gross patenting regions, the top patented industry was some form of information communications technology (ICT) manufacturing, indicating a clear prevalence of ICT industries in major cities. The exception was Division 6, AB (Calgary) where the top industry was metalworking machinery manufacturing, reflecting the province's oil and gas-based economy. In contrast, the three non-metropolitan regions in the top five per-capita patenting regions showed slightly more variability with 'support activities for crop production' as the top industry in Division 4 of Saskatchewan, and 'miscellaneous manufacturing' in Kings County, New Brunswick.

While a quick glance at Figure 4.6 and Table 4.2 cause some the general urban-biased, agglomeration theories of innovation (Gertler, 2003; Glaeser, 2011), there is need for caution when interpreting high patenting numbers in regions with very low population counts as these

[2] Often referred to colloquially as the 'Silicon Valley of the North' the Ottawa-Carleton was well known as the headquarter of the former telecommunications giant Nortel and more recently as home to emerging e-commerce giant Shopify. Similarly, Waterloo was long synonymous with tech giant Blackberry and continues to host a large number of tech startups.

may inflate very low levels of patenting. For example, Kings County presents an interesting case as a primarily suburban census division with an uncharacteristically high level of patenting. However, upon further investigation, it appears that the vast majority of patenting activity region is attributable to a single, highly prolific inventor. Furthermore, upon cross-reference with media references[3], it appears patent geography may have been mistakenly filed to Hampton, NB as opposed to Hampton, ON (a small village east of Oshawa). More research is required on this front to confirm the geographical origins of the patent filer in this case, but it does show how sensitive some of the smaller and more rural regions maybe to measurement errors in the patent data itself.

Another interesting case is Division 4 in Saskatchewan which is ranked third in per capita patenting in MA-3 2016, with most patents filed in the field of 'support activities for crop production' (Table 4.3). Upon further investigation, the majority of these patents were filed by one specific family-run farming business (Honey Bee Manufacturing) specializing in farming equipment innovation and manufacturing[4]. The case of Honey Bee Manufacturing is an interesting study on the isolated nature of rural innovation. Despite the absence of a cluster, an enormous amount of per-capita innovation is taking place, driven largely by one organization. While easy to dismiss these cases as a fluke, it is important to first acknowledge the impressive creative power of individuals, and second to recognize the vitality of rural innovation. This case study also highlights the different creative needs of different types of innovation. For example, in the case of the Honey Bee Manufacturing, innovation appears driven by *in-situ* R&D and manufacturing designs to meet local farming needs, as opposed to knowledge-spillovers more likely to occur in a city.

In the same vein, the Nord-du-Québec region, a highly rural and sparsely populated census division, shows a small but persistent level of patenting from 2006 onward. Gross patents in Nord-du-Québec in 2016 were about 10, comparable to the far less remote region of Memphrémagog (QC). The most-patented industry in Nord-du-Québec was in 'metalworking and machinery manufacturing' (Table 4.3) suggesting the high innovation rates are possibly

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[3] See article in The Financial Post: https://financialpost.com/technology/chasing-edison-meet-canadas-most-prolific-arguably-inventor-who-sees-ideas-everywhere

[4] See the Business in Focus magazine article on Honey Bee Manufacturing, based in Bracken Saskatchewan: https://businessinfocusmagazine.com/2019/03/a-commitment-to-faith-family-community-and-innovation/

related to the region's significant mining[5] or hydroelectricity stations[6]. While it is difficult to draw conclusions based simply on an industry class, the numbers shown here do provide some preliminary evidence that different types of innovation derive different levels of benefit from the agglomeration forces of cities as described by Asheim and Hansen (2009). Persistent patenting in remote Quebec and rural Saskatchewan indicates innovation can and does occur without the cluster-effects of cities. Innovation in these remote regions appears to be place and industry specific, based on local industry needs. Further research is needed however to determine the specific creative process of these innovations, the specific nature of the innovations (what needs are they meeting) and the local consequences - do small-scale innovation clusters influence local inequality?

Table 4.3. Table 4.3. Regional innovation profiles for non-urban regions with high per-capita patenting activity based on MA-3, 2016 patent data.

CD	Region	Patents per capita	Total patents	Top industry (based on patents filed)
	New Brunswick			
1309	Northumberland	24.7	10.9	Engine, turbine and power transmission equipment manufacturing
1306	Albert	25.5	7.4	Gambling industries
	Quebec			
2499	Nord-du-Quebec	23.3	10.2	Metalworking machinery manufacturing
	Manitoba			
4605	Division 5	21.6	2.3	Grain and oilseed milling
4618	Division 18	37.1	8.7	Computer and peripheral equipment manufacturing
	Saskatchewan			
4704	Division 4	67.4	6.3	Support activities for crop production
	Alberta			
4814	Division 14	28.2	8.2	Metalworking Machinery Manufacturing

Source: Calculations by author, data from USPTO

[5] 90% of Quebec's mining investment are made in Nord-du-Québec, Abitibi-Témiscamingue and Côte-Nord regions, with most new mining projects requiring significant investments in automation and AI. (Service Canada, 2022)

[6] Nord-du-Quebec encapsulates the Robert-Bourassa facility, Canada's largest hydro plant. (Canada Energy Regulator, n.d.)

Figure 4.6 also reveals a small cluster of relatively high-patenting census divisions in southeastern Quebec near the city of Sherbrooke. These census divisions include Sherbrooke, Le-Val-Saint-François, Memphrémagog, and Brome-Missisquoi (see Figure 4.7) which are home to dynamic manufacturing firms as part of what has been referred to Québec's new manufacturing crescent (Proulx, 2006) or industrial arc (Polese, 2009). The eastern townships have a long link with aerospace and other transport-related manufacturing (e.g., Joseph-Armand Bombardier was born in Valcourt, in the Le-Val-Saint-François census division). While the bulk of aerospace R&D is concentrated in the Greater Montreal region[7] including the head offices of Bombardier and Rolls-Royce, these conglomerates operate some manufacturing operations outside the Greater Montreal area such as the Bombardier plant in Valcourt, QC or GE Aerospace in Bromont (one of the most modern manufacturing plants in the world producing aircraft engine parts). Aerospace's influence is evident in the eastern townships, where 'transportation equipment manufacturing' was the most common industry in which patents were filed in Sherbrooke, Memphrémgog and Val-Saint-François (Table 4.4). The importance of aerospace innovation in Quebec is well-recognized. In July 2023, the federal government announced over $32 million in funding to select aerospace firms and organizations in Quebec. However, the bulk of this funding is dedicated to firms located in the urban core with just over $4 million (12.9%) planned for firms based outside of the Greater Montreal area.[8]

Table 4.4. Patent summary for regions in Quebec's 'arc industriel' (MA-3 2016)

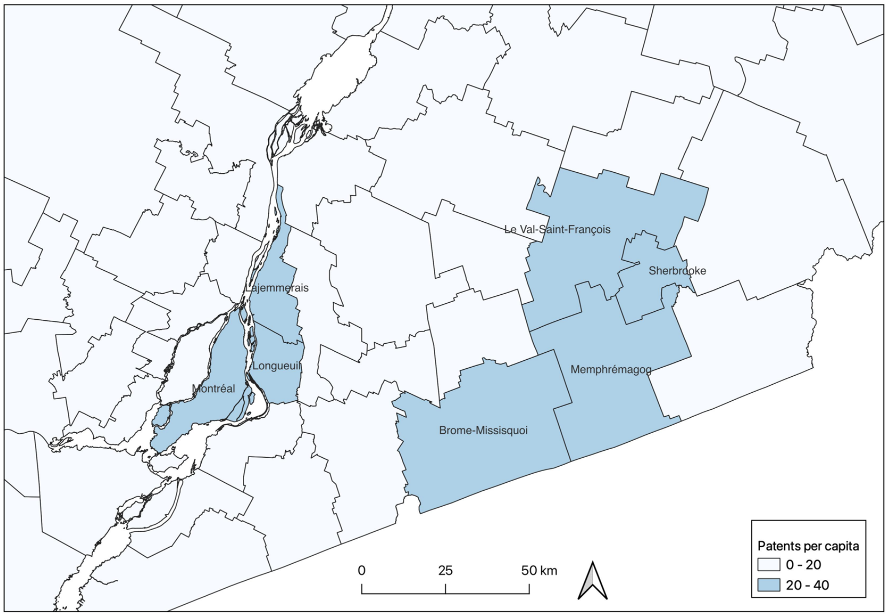
CD	Region	Patents per capita	Total patents	Top industry
2442	Le Val-Saint-François	22.9	6.9	Transportation equipment manufacturing
2443	Sherbrooke	23.3	36.4	Transportation equipment manufacturing
2445	Memphrémagog	28.1	13.8	Transportation equipment manufacturing
2446	Brome-Missisquoi	21.1	12.0	Fish & other marine products

Source: Calculations by author, data from USPTO.

[7] 75% of Quebec aerospace R&D is concentrated in the Greater Montreal area according to the Quebec ministry of Economy, innovation and energy (n.d.) https://www.economie.gouv.qc.ca/en/outside-quebec/home/translate-to-english-secteurs-dexcellence/aerospace

[8] Government of Canada (2023) https://www.canada.ca/en/economic-development-quebec-regions/news/2023/07/backgrounder-ced-support-for-the-recovery-of-quebecs-aerospace-sector.html

Figure 4.7. A closer look at regional innovation in the Greater Montreal area and Quebec's Industrial Arc regions.



Source: Calculations by author, data from USPTO.

The eastern townships also benefit from the presence of local research institutions such as l'Université de Sherbrooke, which has been collaborating since 2011 with IBM on their MiQro Innovation Centre focused primarily on microelectronics innovation, located in Bromont (a part of the Brome-Missiquoi CD). While evidence of this is not yet registered in the top patenting class (fish & other marine products, Table 4.4) it is likely that this region will see a larger amount of patenting in ICT and tech industries in the coming years as the MiQro Innovation Centre becomes more established.

Finally, Table 4.5 provides a look at cumulative patent trends in the entire time-period of study. The results show Vancouver, BC to be the cumulatively top patenting region over the 1979-2016 time period with 15, 272 patents. The top patenting regions in the 1979-1981 period were Montreal, Toronto and Vancouver however, these regions showed relatively weak patent growth between 1981 and 2016. In contrast, medium-sized cities: Waterloo (ON), Division 6 (AB)-(Calgary), Durham (ON), and York (ON) experienced the fastest patent growth, far outstripping Toronto, Montreal, and Vancouver.

Table 4.5. Growth in innovation across Canadian regions classified by cumulative total patenting intensity between 1981 and 2016

Census division in rank order	Patents				National Share		Cumulative Share		Patents per 100000 residents	
	Total (1979-2016)	1979-1981	2014-2016	Growth (%)	1979-1981	2014-2016	1979-81	2014-16	Patents per Capita (2016)	Ranking
Greater Vancouver, BC	15272	121	757	524	10.1	12.0	10.1	12.0	31	7
Ottawa-Carleton, ON	14834	90	769	759	7.4	12.2	17.5	24.3	84	1
Toronto, ON	13256	142	637	349	11.8	10.1	29.3	34.4	24	19
Montréal, QC	9937	144	463	222	12.0	7.4	41.3	41.8	25	17
Waterloo, ON	8288	27	367	1280	2.2	5.8	43.5	47.7	70	2
York, ON	6391	35	324	834	2.9	5.2	46.4	52.8	29	8
Division 6, AB	6074	35	393	1011	2.9	6.3	49.3	59.1	27	12
Peel, ON	6028	51	205	306	4.2	3.3	53.5	62.3	15	41
Halton, ON	4332	39	175	346	3.3	2.8	56.8	65.1	32	6
Division 11, AB	4234	45	196	334	3.8	3.1	60.5	68.2	15	46
Durham, ON	2244	9	111	1096	0.8	1.8	61.3	70.0	17	35
Division 11, MB	2001	25	68	178	2.0	1.1	63.4	71.1	10	70
Québec, QC	1982	17	98	466	1.4	1.6	64.8	72.6	18	32
Middlesex, ON	1929	23	99	339	1.9	1.6	66.7	74.2	22	24
Essex, ON	1824	23	86	279	1.9	1.4	68.5	75.6	22	25

Source: Calculations by author

Based on their long economic, historical, and geographical importance (both located along key waterways and with excellent proximity to the US border), Toronto and Montreal boast the most diversified industrial profiles across Canadian cities, serving as hubs of both manufacturing, financial services, and creative and media industries (Wolfe, 2009). In contrast, Vancouver was established primarily as a command and control hub for the Western staples economies and its local economy did not diversify until the mid-1970s when it developed a knowledge-based economy similar to US west-coast cities (Wolfe, 2009). Given their large population size, diversified economies, large immigrant populations, and important role as financial and creative hubs, it's no surprise that Vancouver, Toronto, and Montreal are some of the top innovating regions over the 35-year period of study.

However, consistent with Figure 4.4 innovation *growth* in these major cities is outstripped by growth in medium-sized cities. The Waterloo, York, Peel, Halton, Wellington and Middlesex regions of Ontario all have high levels of gross patenting with Waterloo, York and Halton also placing within the top 10 per-capita patenting regions in Canada (see Table 4.5). High per-capita patenting in less diversified, smaller cities, all within close geographic proximity to Toronto, may be interpreted as evidence of the nursery city hypothesis (Duranton and Puga, 2001). Firms, once they have established their niche product or process, no longer benefit from the diversity and knowledge spillovers of the city and tend to move outwards where real estate and production costs are lower (Duranton and Puga, 2001). Further research into firm relocation behaviour is needed to confirm whether this is the case in the Southern Ontario context.

Taken together, the descriptive results drawn from the patent data demonstrate cities make up the bulk of gross patenting activity in Canada with 47.7% of patents over the 2014-2016 average being filed by inventors in the top five metropolitan regions (see Table 4.5). However, the large per-capita contributions of more specialized medium-sized cities, as well as a small but not-insignificant amount of patenting in many rural regions suggests the need for more research and emphasis on non-urban innovation in Canada.

4.3 Modeling Results

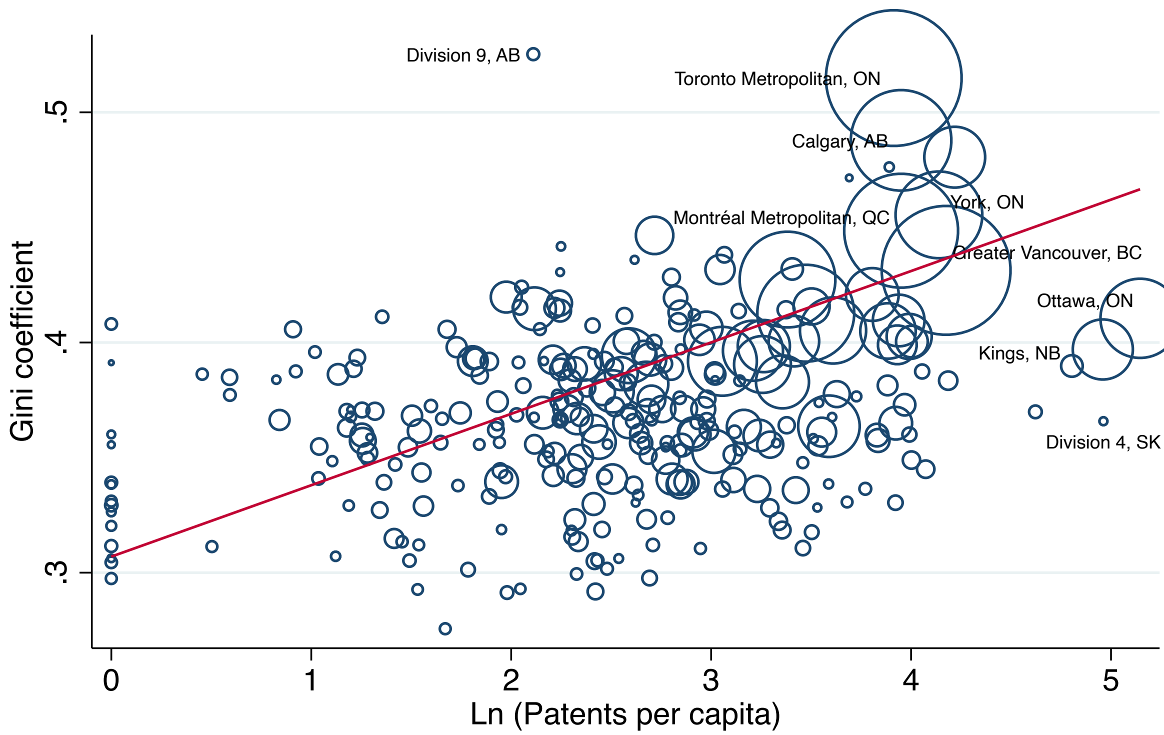
This final section brings together the patent and inequality datasets to econometrically model the relationship between innovation and inequality across Canadian regions.

Figure 4.8 provides a visual overview of the relationship between innovation and inequality across census divisions in 2016. The x-axis plots the natural log of the MA-3 patents per capita in 2016, while the y-axis plots the Gini coefficients for regions according to the 2016 census. Each point is population-weighted by the total population in each region.

The results of the graph demonstrate a clear positive correlation, with higher rates of innovation generally corresponding to higher levels of inequality. Regions with higher innovation (on the right side of the graph) tend to display higher levels of inequality, evident with metropolitan areas like Toronto, Montreal, Vancouver, Calgary (Division 6, AB), Halton and York. Some notable exceptions are the Ottawa-Carleton and Waterloo regions which have the highest levels of innovation but only slightly above average levels of inequality. These results are consistent with those reported by Breau et al. (2014) who show a similar pattern of innovation and inequality across Canadian cities.

Another trend worth noting is that regions with larger population sizes - typically metropolitan regions - appear significantly and positively correlated with both inequality and innovation, even when using a per capita measure of innovation. Higher rates of innovation in larger cities are consistent with mainstream geographies of innovation literature (Gertler, 2001; Florida, 2002; Wolfe, 2016). A correlation between the population size of a region and local inequality levels was also observed by Breau et al. (2014) at the city-scale. This makes intuitive sense, as more people in a given region means more potential for a broader range of incomes. It also suggests that density and agglomeration forces themselves may somehow be linked to inequality, perhaps through the co-existence of distinct service and creative classes in cities as per Florida's (2002) work.

Figure 4.8. Income inequality (Gini coefficient) and innovation (patents per capita) by population-weighted census divisions (2016)



Source: Calculations by author

Table 4.6 presents the results of the spatial panel models estimated as per the discussion in section 3.3 of the thesis. Columns (1) and (2) show the results for the primary model estimated using the Gini coefficient as the dependent variable and using the SAC spatial autocorrelation model with maximum-likelihood estimators (MLE). Details on the selection process of the model are included in Appendix A. Column (1) presents the results for the parsimonious model-estimated using only the natural logs of per-capita innovation, working population, and median total income (as a proxy for economic development). Column (2) presents the results of the full model including all predictors described in the previous chapters (economic, institutional, and sociodemographic).

Columns (3) and (4) present parsimonious and full results for the SAC spatial panel model run on only the ten provinces (thus reducing the cross-sectional sample size from 284 regions to 278). Since unionization rates were unavailable for Canadian territories across the time period of interest, this version of the model was run excluding territories but including the unionization variable. This model serves as a robustness check and to estimate the potential influence of unionization rates on inequality (measured here using the Gini coefficient) in parallel with the original model.

Table 4.6. Spatial panel model results

	Gini (SAC)		Gini (SAC) excluding Territories		Theil (GS2SLS)	
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.002***	0.002**	0.002**	0.001**	0.001	0.002*
Working population	0.004***	0.005***	0.004***	0.005***	0.009***	0.013***
W1y					0.618***	0.568***
Economic						
Median total income (economic development)	-0.030***	0.022***	-0.027***	0.027***	0.002	0.011
Unemployment rate		0.076***		0.109***		0.088**
Part time (%)		0.238***		0.212***		0.186**
Self-employed (%)		0.071***		0.096***		0.089**
Secondary industries (%)		-0.096***		-0.086***		-0.077**
Tertiary industries (%)		0.030**		0.040**		-0.029
Quaternary industries (%)		0.020*		0.022**		0.034
Institutional						
Minimum Wage		-0.016		-0.014		-0.005
Unionization				-0.051***		
Sociodemographic						
Female participation (%)		-0.015		-0.031		-0.177**
Education ratio		0.118***		0.120***		0.162***
Young (%)		0.085***		0.004		-0.050
Senior (%)		0.115***		0.052**		0.008
Time-effects						
1986		0.003		0.002		0.001
1991		0.004		0.006		0.015
1996		0.004		-0.001		0.012
2001		0.006		-0.001		0.021
2006		0.016		0.007		0.036**
2011		0.003		-0.006		0.028
2016		0.003		-0.006		0.034
Constant	0.862***	0.051	0.822***	0.197**	-0.012	-0.158
Rho	-0.600***	-0.130	-0.600***	-0.091	0.675	0.568
Lambda	0.861***	0.646***	0.856***	0.554***		
R^2	0.002	0.425	0.010	0.500	0.316	0.397
Log likelihood function	5502.4	5837.8	5420.1	5794.0	3704.3	3846.8
# of observations (n)	2272	2272	2224	2224	2272	2272
# of regions (groups)	284	284	278	278	284	284

Note. *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.001 level respectively
Source: Calculations by author.

Finally, Columns (5) and (6) present results of the spatial panel model estimated using the Theil index as an alternative measure of income inequality. Use of a secondary inequality measure is to provide robustness for the results as well as examine how innovation may affect a top-heavy inequality coefficient differently. Due to the computational complexity of such large spatial panel models, issues were encountered when running the SAC model with the Theil index. To get around these issues, this model is estimated using the generalized spatial two-stage least squares (GS2SLS) model as proposed by Kapoor et al. (2007). Like the SAC model, the GS2SLS model accounts for both a spatial lag on the dependent variable and a spatially autoregressive error term but using GS2SLS estimators as opposed to MLE, making the model more computationally feasible for large sample sizes (Kapoor et al., 2007).

The model results indicate a positive and significant relationship between innovation and income inequality across all model variations using the Gini coefficient as the dependent variable. It therefore appears that more innovative Canadian regions are also more unequal ones, even when controlling for other variables driving innovation. This positive relationship persists when using Theil as a measure of inequality though the significance is much weaker (this latter finding may indicate that a higher parameter adjustment for the entropy measure, such as using half the squared coefficient of variation – or GE(2) – may be better suited than the Theil – GE(1) in capturing top end movements in the distribution).

Almost all other model variables were significant, with the exception of minimum wage, which is somewhat unsurprising given that it is a provincial level variable included primarily for context.

Population size was positively and significantly correlated with inequality across all model variables. This is expected given that regions with larger population sizes are metropolitan regions and as Bolton and Breau (2012) and Baum-Snow and Pavan (2013) have demonstrated, city size tends to exacerbate inequality. This is also consistent with the results of Florida et al. (2012) who show that larger cities tend to reward certain skills (associated with creative industries) more than physical skills, exacerbating wage inequalities.

Of the economic variables, the unemployment rate, the percentage of self-employed workers and part-time workers were all significantly and positively correlated with inequality across models. This is expected given the precarity of these labour conditions (Norcliffe, 1994).

Median total income is interestingly negatively and significantly correlated with income inequality, but only so for the parsimonious models (1) and (3). The direction of this relationship changes when adding to full set of controls to the model suggesting higher levels of economic development are correlated with higher inequality, a result that is consistent with those of Marchand et al. (2020).

Secondary industry employment is negatively and significantly correlated with inequality across all models. In contrast, tertiary and quaternary sector employment are positively correlated with inequality, albeit less significantly so. These results are consistent with literature on the decline of stable, manufacturing jobs that have traditionally formed the basis of the middle-class (Bluestone & Harrison, 1988).

In terms of sociodemographic factors, the education ratio remains strongly positively correlated and significant across all model iterations, consistent with the results of Marchand et al. (2020). The proportion of seniors in the population is strongly positively and significantly correlated with inequality. This is in contradiction to Milanovic (2016) who suggests that population aging acts as a benign force reducing inequality by increasing the demand for social protection. A potential link between population aging and inequality is worrisome as Canada's population aged 65 and above saw its two largest periods of increase between 2011 and 2016 and 2016 and 2021, a trend that is expected to continue (Statistics Canada, 2022). However, further research would be required to determine a causal link between population aging and regional inequality and the mechanisms through which population aging may worsen inequality.

The female participation rate in the labour force appears insignificant in models using the Gini coefficient as a measure of inequality; however, it is significantly negatively correlated with the Theil index. This is in contrast to Marchand et al. (2020) who find a positive and significant correlation between female participation in the workplace and inequality (measured using the Gini coefficient). A negative relationship with the Theil index, a more top-heavy measure of inequality, but not the Gini coefficient, may suggest women's participation in the workplace has a greater impact on reducing inequality between the top-most incomes and the rest.

4.4. Robustness checks: Isolating the effect of 'high tech' innovation

As discussed earlier, one issue with using aggregate patent counts as a proxy for innovation is that it does not discriminate for the impact (incremental, market, technological, radical) or type (product, process, process, market, organisation) of innovation (Edison et al., 2013). While it is difficult to assess every patent on each of these axes, it is possible to separate out patents based on the category in which they were filed. Using the Lybbert and Zolas (2014) concordance with NAICS classes and the high-tech classification system developed by Hecker (2005), I run a series of models using only patents filed in industries deemed 'high-tech'. High-technology is identified and used as a separate category because of its associations with innovation at the 'cutting edge' or 'frontier' of technological change. While this by no means guarantees patents filed in these fields yield or lead to high-impact technological innovations, it nevertheless helps narrow the pool towards the innovations with the most high-impact potential.

Hecker (2005) classifies high-tech industries into three tiers based on the degree to which occupations in each industry are high-technology occupations. High technology occupations include computer and math scientists, engineers and engineering technicians, physical and life scientists and technicians and life science, computer science and engineering managers. High tech industries are then classified based on the proportion of jobs within each industry that are high-tech, relative to the US average of 4.9% across all industries (Hecker, 2005) (Table 4.7). A detailed breakdown of high technology occupations by tier is provided in Table 4.8.

Table 4.7. High-Tech industry classification tiers metrics

	Proportion of high-tech occupations relative to national average	% of total employment
Tier I	≥5.0x	≥24.7
Tier II	3.0-4.9x	14.8-24.7
Tier III	2.0-2.9x	9.8-14.7

Source. Adapted from Hecker, 2005

Table 4.9 presents results for a series of spatial panel models measuring the strength of the relationship between innovation and inequality using only innovation in high-technology industries. Since the cut-off for 'high-tech' industries (2x the national average) is quite low, the lower tiers tend to incorporate a large number of industries not necessarily at the cutting edge of technological change and innovation. Therefore, two series of models are presented here, the first (columns (1) and (3)) use the full definition of high-tech industries according to Hecker (2005), amalgamating Tier I, II and III. The second uses only the Tier I high-tech industries, which are limited to industry classes most associated with digital and computer technologies including computer and peripheral equipment manufacturing, communications equipment manufacturing, semiconductor manufacturing and computer systems design (see Figure 4.9).[9] This class also includes pharmaceutical manufacturing and aerospace manufacturing. The results of the spatial panel model presented in Table 4.9, while similar to those of Table 4.6, actually show a stronger and more robust relationship between high-tech innovation and inequality, compared to innovation defined more broadly across all fields. This relationship was robust across all models tested (panel with fixed-effects, spatial panel corrected for spatial autocorrelation and spatial panel corrected for spatial error). However, this positive and significant relationship between high-tech innovation and inequality is weaker when Theil is used as the measure of inequality instead. What this result suggests is that while high-tech innovation may play a part in general income inequality, it is not as powerful of an influence on growing inequality at the very top of the distribution. The growth and income dynamics in the 1% or even the 0.1% may thus be somewhat detached from any skill-biased renumeration and are perhaps more reflective of the kinds of unfair rewards suggested by Lazonick and Mazzucato (2013).

A significant relationship between high-tech innovation and income inequality is also consistent with the work of Echeverri-Caroll and Ayala (2009) who reveal the presence of a 'tech-city' wage premium where workers in high-tech cities earn higher wages than workers in other cities. The possibility of tech-city wage premium in a Canadian context as well suggests that high-tech innovation may be associated not just with within-region inequality but inter-regional inequality as well, with a few innovative 'superstar' city-regions pulling ahead, similar to what has been observed in the US (Kemeny et al., 2022).

[9] For model results using all three high-tech classification tiers see Figure A4 in the appendix.

Table 4.8. High-tech NAICS sectors

High-Tech Industries by NAICS		
Level	**NAICS**	**Industry Title**
I	3254	Pharmaceutical and medicine manufacturing
I	3341	Computer and peripheral equipment manufacturing
I	3342	Communications equipment manufacturing
I	3344	Semiconductor and other electronic component manufacturing
I	3345	Navigational, measuring, electromedical, control instrument mfg
I	3364	Aerospace product and parts manufacturing
I	5112	Software publishers
I	5179	Other telecommunications
I	5182	Data processing, hosting, and related services
I	5191	Other information services
I	5413	Architectural, engineering, and related services
I	5415	Computer systems design and related services
I	5417	Scientific research and development services
II	1131	Timber tract operations
II	1132	Forest nurseries and gathering of forest products
II	2111	Oil and gas extraction
II	2211	Electric power generation, transmission, and distribution
II	3251	Basic chemical manufacturing
II	3252	Resin, synthetic fiber, artificial synthetic fiber/filament mfg
II	3332	Industrial machinery manufacturing
II	3333	Commerical and service industry machinery manufacturing
II	3343	Audio and video equipment manufacturing
II	3346	Manufacturing and reproducing magnetic and optical media
II	4234	Professional/commercial equipment/supplies, merchant wholesalers
II	5416	Management, scientific, and technical consulting services
III	3241	Petroleum and coal products manufacturing
III	3253	Pesticide, fertilizer, other agricultural chemical manufacturing
III	3255	Paint, coating, and adhesive manufacturing
III	3259	Other chemical product and preparation manufacturing
III	3336	Engine, turbine, and power transmission equipment manufacturing
III	3339	Other general purpose machinery manufacturing
III	3353	Electrical equipment manufacturing
III	3369	Other transportation equipment manufacturing
III	4861	Pipeline transportation of crude oil
III	4862	Pipeline transportation of natural gas
III	4869	Other pipeline transportation
III	5173	Wired and wireless telecommunications carriers
III	5174	Satellite telecommunications
III	5211	Monetary authorities, central bank
III	5232	Securities and commodity exchanges
III	5511	Management of companies and enterprises
III	5612	Facilities support services
III	8112	Electronic and precision equipment repair and maintenance

Source. Hecker, 2005

Table 4.9. Spatial panel model results using only patents in high-tech industries

	Gini (SAC)		Theil (GS2SLS)	
	Total high tech	T1 high tech	Total high tech	T1high tech
Independent variables	(1)	(2)	(3)	(4)
Innovation	0.002***	0.003***	0.003**	0.002
Working population	0.005***	0.005***	0.012***	0.013***
W1y			0.565***	0.563***
Economic				
Median total income (economic development)	0.021***	0.022***	0.009	0.011
Unemployment rate	0.074***	0.073***	0.089**	0.084**
Part time (%)	0.237***	0.235***	0.185**	0.186**
Self-employed (%)	0.071***	0.070***	0.091**	0.090**
Secondary industries (%)	-0.097***	-0.097***	-0.081**	-0.079**
Tertiary industries (%)	0.030**	0.028*	-0.029	-0.033
Quaternary industries (%)	0.018*	0.015	0.030	0.028
Institutional				
Minimum Wage	-0.015	-0.015	-0.004	-0.004
Unionization				
Sociodemographic				
Female participation (%)	-0.014	-0.011	-0.177**	-0.169**
Education ratio	0.116***	0.113***	0.157***	0.158***
Young (%)	0.085***	0.085***	-0.049	-0.052
Senior (%)	0.115***	0.119***	0.005	0.007
Time-effects				
1986	0.003	0.003	0.001	0.000
1991	0.004	0.004	0.015	0.014
1996	0.004	0.003	0.012	0.011
2001	0.006	0.005	0.021	0.019
2006	0.016	0.014	0.036**	0.034**
2011	0.003	0.001	0.028	0.026
2016	0.003	0.001	0.034	0.032
Constant	0.061	0.061	-0.137	-0.158
Rho	-0.132	-0.138	0.565	0.563
Lambda	0.647***	0.653***		
R^2	0.425	0.424	0.398	0.396
Log likelihood function	5839.9	5839.9	3849.2	3845.2
# of observations	2272	2272	2272	2272
# of regions (groups)	284	284	284	284

Note. *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.001 level respectively
Source: Calculations by author

Chapter 5

CONCLUSION

The last 40 years have seen drastic changes in the economic fortunes of Canadians. A shrinking middle-class, a rapidly aging population and multiple housing and cost-of-living crises have increasingly rendered many Canadian's dreams of financial stability, home ownership and comfortable retirement a pipe dream. While many Canadians have been struggling with unprecedently high housing costs, runaway inflation, and a general sense of unattainability of the middle-class dream, a minority is experiencing unprecedented prosperity, the resulting inequality boom culminating in deep disaffection and resentment, increasingly making itself felt in the voting polls and in the streets (Breau 2014, Erl, 2021).

Income inequality growth in Canada has not been even across space. Generally, western provinces and regions are growing more unequal than their eastern counterparts and cities (across all regions) are experiencing the fastest rates of inequality growth.

Research on the causes of this concerning trend in increasing inequality has revealed a wide variety of related causes from declining union membership rates, political-economic restructurings to globalization. One important angle has been the influence of innovation and technological change on labour demand and wages. The results of this investigation find a significant and positive regional correlation between local innovation and income inequality, suggesting technological change has been playing an important role in exacerbating regional income inequalities over a 36-year period in Canada. Most interestingly, when patents are limited only to those filed in the most disruptive 'high-tech' industries, this relationship is stronger, suggesting innovations pushing at the current frontier (software, pharmaceuticals, aerospace etc.) are more strongly linked to local inequality. However, more research is needed to parse the effects of innovation by industry, and by degree of impact. In this context, patent data was limited in its ability to distinguish between high and low impact innovations. However, future innovation-inequality research should engage concepts of knowledge complexity to understand innovation quality affects inequality (Balland and Rigby, 2017; Pinheiro et al. 2022).

The results, specifically those pertaining to the rural dimension of innovation, were also limited by the patent proxy employed. While the primary aim of this research was to capture a pan-Canadian perspective, it became increasingly clear throughout this process that the non-urban dimension requires further investigation. Moving forward, research specifically interested in the innovation-inequality dynamic in rural regions would do well to employ a more inclusive definition and measure of inequality (such as surveys or qualitative methods) to capture the unique forms of innovation taking place in rural regions, and their local impacts.

A second, and critical issue with macro-level, quantitative research on innovation and inequality emphasized by Fragkandreas (2022) is the inability for such methods to distinguish the specific mechanism through which innovation and inequality interact. While popular labour economic theories emphasize the impact of technological change on skills premiums and skill-demand, there are compelling arguments put forth by sociologists who argue that within-firm dynamics of profit-capture may be more complicated than a simple skilled vs. less-skilled labour dichotomy.

Furthermore, the work carried out in this thesis hinges on the assumption that the location in which the innovative process is occurring is also the location where the consequences are felt, an assumption that is not necessarily true (Lee, 2016). While some innovation may be developed and applied in the same location, other types of innovation, especially for innovations within multi-national firms, may have labour-market consequences geographically distant from their source of origin. For example, consider a process innovation developed at a petroleum company headquarters in Calgary, which alters the extraction process in the oil sands, causing job losses in the northeast of Alberta.

As the work of Fragkandreas (2022) demonstrates, the bulk of innovation-inequality research has so far been mostly macro and quantitative in its methods and scale. Smaller-scale, qualitative research is required to parse the specific mechanism through which innovation may influence inequality, and how this differs based on the type of innovation and the geographic context in which it takes place. Qualitative methods can also help parse the consequences of innovation that are not felt locally.

While my research has focused on the so-called 'dark side' of inequality, the suggested intention is not to disparage innovation in its entirety. A lack of innovation (and assumedly the resulting economic growth it brings) may leave some regions behind, worsening inter-regional inequalities. Much like the paper mills replaced by innovation in recycling technology (Polese and Shearmur, 2006), if regions do not adapt, they may find themselves victims of innovation, and trapped in decline. However, as Shearmur (2016) argues, the evidence that innovation improves local economic development is itself severely lacking. Successfully innovative local firms (unless directly tied to the locality) do not necessarily translate to increased local prosperity. In fact, once they achieve success, firms may choose to move to denser regions to access larger and more diversified pools of labour (Shearmur, 2016).

Despite a lack of robust place-based evidence for the local benefits of innovation, innovation-based growth policies- like the federal-level Global Innovation Clusters program- continue to be popular policy frameworks. The Global Innovation Cluster program is intended to build innovation superclusters centered on distinct regions and existing regional industries with the goal of growth and job creation (Doloreux and Frigon, 2022). Despite making broad claims about regional innovation, the superclusters initiative is fuzzy on the specific geographies it seeks to target, making it likely the benefits will skew towards large urban centres, who have the agglomeration economies and infrastructure in place to support it (Doloreux and Frigon, 2022). Without a clear geographic angle, or a mitigation plan for the inequalities associated with innovation-based growth, large-scale projects like these may inadvertently contribute to both inter- and intra-regional inequalities.

If the aim of policymaking is to achieve inclusive growth through innovation, there are two axes through which policy intervention may mitigate the innovation-inequality dilemma. The first is the need to address the local cost consequences of innovation-driven growth that directly impact the quality of life of local inhabitants. Successfully innovative firms tend to attract highly educated and highly-paid workers driving up rental prices and displacing original inhabitants (Peck, 2005; Markusen, 2006). Therefore, any policy framework that seeks to build inclusive growth needs to prevent rising local costs (Lee, 2016).

The second axis involves empowering the rights of labour in relation to automation. As Acemolgu and Johnson (2023) argue, technology needs to be conceptualized as a tool to work in conjunction with labour, contributing to worker efficiency and productivity as opposed to a cost-cutting and automation-based approach. In a joint policy-memo Acemoglu, Autor and Johnson (2023) propose a series of specific federal policies broadly aimed at creating pro-worker AI. One such policy involves equalizing tax rates between labour and machines to encourage retention of human workers (Acemoglu et al., 2023). This axis is less place-specific and focused on the broader labour consequences of technological change. However, the local is still an important frontier for cultivating a pro-union political environment, the benefit of which will be some reclamation of labour rights for workers faced with replacement by automation[10].

Ultimately, as mentioned earlier, the aim of this thesis is not to oppose innovation but merely to encourage critical reflection of the mainstream 'positive normative associations' (Shearmur, 2012 p. 9) that have been unquestionably assigned to innovation and technological change, specifically as when used as tools to stimulate economic growth. If the aim is a more equitable, just, and fair society, one must be careful with the priorities that we consider. Innovation, more broadly conceptualized here as the invention and proliferation of new ideas, has the potential for more radical forms of socio-structural reconfiguration. The goal should not be technological progress for the sake of economic growth, but rather a more inclusive approach to innovation for the betterment of our communities.

[10] See for example Calacci (2023) on the WGA labour strike and worker autonomy in the face of generative AI.

Bibliography

Acemoglu, D., Autor, D., & Johnson, S. (2023). *Can we Have Pro-Worker AI?* (Shaping the Future of Work). MIT.

Acemoglu, D., & Johnson, S. (2023). Choosing AI's Impact on the Future of Work (SSIR). *Stanford Social Innovation Review*. Retrieved February 12, 2024.

Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., & Hemous, D. (2019). Innovation and Top Income Inequality. *The Review of Economic Studies*, *86*(1), 1–45.

Anselin, L. (2003). Spatial Econometrics. In B. H. Baltagi (Ed.), *A Companion to Theoretical Econometrics* (1st ed., pp. 310–330). Wiley.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104.

Asheim, B., & Hansen, H. K. (2009). Knowledge Bases, Talents, and Contexts: On the Usefulness of the Creative Class Approach in Sweden. *Economic Geography*, *85*(4), 425–442.

Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature*, *49*(1), 3–71.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, *29*(3), 3–30.

Autor, D. H., & Dorn, D. (2009). Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States. *NBER Working Paper Series, 15150*.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Avent-Holt, D., & Tomaskovic-Devey, D. (2014). A Relational Theory of Earnings Inequality. *American Behavioral Scientist*, *58*(3), 379–399.

Bain, A. (2013). *Creative Margins: Cultural Production in Canadian Suburbs*. University of Toronto Press.

Balland, P.-A., & Rigby, D. (2017). The Geography of Complex Knowledge. *Economic Geography*, *93*(1), 1–23.

Baltagi, B. H., Egger, P., & Pfaffermayr, M. (2013). A Generalized Spatial Panel Data Model with Random Effects. *Econometric Reviews*, *32*(5–6), 650–685.

Banting, K., & Myles, J. (2013). *Inequality and the Fading of Redistributive Politics*. UBC Press.

Banting, K., & Myles, J. (2016). Framing the New Inequality: The Politics of Income Redistribution in Canada. *Framing the New Inequality: The Politics of Income Redistribution in Canada*, 509–536.

Bathelt, B., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56.

Baum-Snow, N., & Pavan, R. (2012). Understanding the City Size Wage Gap. *The Review of Economic Studies*, *79*(1), 88–127.

Béland, D., & Prince, M. J. (2019). Social Policies for a Stronger Middle Class: Toward Policy Transformation. In L. Birch & F. Pétry (Eds.), *Assessing Justin Trudeau's Liberal Government: 353 promises and a mandate for change*. Presses de l'Université Laval.

Bluestone, B., & Harrison, B. (1982). *The Deindustrialization of America*. Basic Books.

Bluestone, B., & Harrison B. (1988). *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. Cambridge University Press.

Bolton, K., & Breau, S. (2012). Growing Unequal? Changes in the Distribution of Earnings across Canadian Cities. *Urban Studies*, *49*(6), 1377–1396.

Boschma, R. (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies*, *39*(1), 61–74.

Boudarbat, B., Lemieux, T., & Riddell, W. C. (2006). Recent Trends in Wage Inequality and the Wage Structure in Canada. *Dimensions of Inequality in Canada*, 273–306.

Bourdin, S., & Torre, A. (2023). Geography of contestation: A study on the Yellow Vest movement and the rise of populism in France. *Journal of Regional Science*, *63*(1), 214–235.

Boyce, J. K. (2018). The environmental cost of inequality. *Scientific American*, *319*(5), 72–79.

Breau, S. (2007). Income inequality across Canadian provinces in an era of globalization: Explaining recent trends. *Canadian Geographies / Géographies Canadiennes*, *51*(1), 72–90.

Breau, S. (2014). The Occupy Movement and the Top 1% in Canada. *Antipode*, *46*(1), 13–33.

Breau, S. (2015). Rising inequality in Canada: A regional perspective. *Applied Geography*, *61*, 58–69.

Breau, S., Kogler, D. F., & Bolton, K. C. (2014). On the Relationship between Innovation and Wage Inequality: New Evidence from Canadian Cities: Innovation and Wage Inequality. *Economic Geography*, *90*(4), 351–373.

Breau, S., & Lee, A. (2023). The evolution of the Kuznets curve in Canada. *Papers in Regional Science*, *102*(4), 709–735.

Breau, S., & Saillant, R. (2016). Regional income disparities in Canada: Exploring the geographical dimensions of an old debate. *Regional Studies, Regional Science*, *3*(1), 463–481.

Breau, S., Shin, M., & Burkhart, N. (2018). Pulling apart: New perspectives on the spatial dimensions of neighbourhood income disparities in Canadian cities. *Journal of Geographical Systems*, *20*(1), 1–25.

Bye, L. M. (2009). 'How to be a rural man': young men's performances and negotiations of rural masculinities. *Journal of rural studies*, *25*(3), 278-288.

Cairncross, F. (2001). *The Death of Distance: How the Communications Revolution Will Change Our Lives*. Harvard Business School Press.

Calacci, D. (2023). Building Dreams Beyond Labor: Worker Autonomy in the Age of AI. *Interactions*, *30*(6), 48–51.

Canada Energy Regulator. (2024). *CER – Provincial and Territorial Energy Profiles – Quebec*. Government of Canada. https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/provincial-territorial-energy-profiles/provincial-territorial-energy-profiles-quebec.html

Canada Revenue Agency. (2022). *Canada Emergency Response Benefit (CERB)*. Government of Canada. https://www.canada.ca/en/revenue-agency/services/benefits/apply-for-cerb-with-cra.html

Card, D., & DiNardo, J. E. (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics*, *20*(4), 733–783.

Card, D., & Lemieux, T. (2001). Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis. *The Quarterly Journal of Economics*, *116*(2), 705–746.

Card, D., Lemieux, T., & Riddell, W. C. (2020). Unions and wage inequality: The roles of gender, skill and public sector employment. *Canadian Journal of Economics/Revue Canadienne d'économique*, *53*(1), 140–173.

Castells, M. (1996). *The rise of the network society*. Blackwell Publishers.

Chancel, L., Piketty, T., Saez, E., & Zucman, G. (2022). *World Inequality Report 2022*. World Inequality Lab.

Christopherson, S., Kitson, M., & Michie, J. (2008). Innovation, networks and knowledge exchange. *Cambridge Journal of Regions, Economy and Society*, *1*(2), 165–173.

Churchill, S. A., Peng, B., Smyth, R., & Quanda Zhang. (2021). R&D Intensity and Income Inequality in the G7: 1870-2016. *Scottish Journal of Political Economy*, *69*(3), 263–282.

Cohen, G., & Ladaique, M. (2018). Drivers of Growing Income Inequalities in OECD and European Countries. In R. M. Carmo, C. Rio, & M. Medgyesi (Eds.), *Reducing Inequalities: A Challenge for the European Union?* (pp. 31–43). Palgrave Macmillan Cham.

Connor, D. S., Kemeny, T., & Storper, M. (2023). Frontier workers and the seedbeds of inequality and prosperity. *Journal of Economic Geography*. https://doi-org.proxy3.library.mcgill.ca/10.1093/jeg/lbad018

Consoli, D., Castellacci, F., & Santoalha, A. (2023). E-skills and income inequality within European regions. *Industry and Innovation*, *30*(7), 919–946.

Crosby, M. (2000). Patents, Innovation and Growth. *Economic Record*, *76*(234), 255–262.

Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). Causes and Consequences of Income Inequality: A Global Perspective. IMF *Staff Discussion Notes*, 15(3) *2015*(013).

Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). *Causes and Consequences of Income Inequality: A Global Perspective* [IMF Staff Discussion Note]. International Monetary Fund. https://www.elibrary.imf.org/view/journals/006/2015/013/article-A001-en.xml

Davies, J. B., & Di Matteo, L. (2021). Long Run Canadian Wealth Inequality in International Context. *Review of Income and Wealth*, *67*(1), 134–164.

Di Matteo, D., & Mariotti, I. (2020). Italian discontent and right-wing populism: Determinants, geographies, patterns. *Regional Science Policy & Practice*, *13*(2), 371–396.

Dicken, P. (2011). Technological Change: ‘Gales of Creative Destruction.’ In *Global Shift: Mapping the Changing Contours of the World Economy* (Sixth Edition). Guilford Press.

Dinan, S., & Noël, A. (2020). Quebec’s resilient redistribution model: Activation policies in the 2010s. *Canadian Public Administration*, *63*(3), 473–497.

Doloreux, D., & Frigon, A. (2022). The Innovation Superclusters Initiative in Canada: A new policy strategy? *Science and Public Policy*, *49*(1), 148–158.

Donegan, M., & Lowe, N. (2008). Inequality in the creative City: Is there still a place for “Old-fashioned” institutions? *Economic Development Quarterly*, *22*(1), 46–62. Scopus.

Drache, D., & Gertler, M. S. (1991). *The New Era of Global Competition: State Policy and Market Power* (1st edition). McGill-Queen's University Press.

Dubé, J., & Legros, D. (2014). *Spatial Econometrics using Microdata*. John Wiley & Sons.

Dubé, J., & Polèse, M. (2014). Resource Curse and Regional Development: Does Dutch Disease Apply to Local Economies? Evidence from Canada. *Growth and Change*, *46*(1), 38–57.

Duranton, G., & Puga, D. (2001). Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products. *American Economic Review*, *91*(5), 1454–1477.

Echeverri-Carroll, E., & Ayala, S. G. (2009). Wage differentials and the spatial concentration of high-technology industries. *Papers in Regional Science*, *88*(3), 623–641.

Economic Council of Canada. (1990). *Good Jobs, Bad Jobs: Employment in the Service Economy*. Supply and Services Canada.

Edison, H., Bin Ali, N., & Torkar, R. (2013). Towards innovation measurement in the software industry. *Journal of Systems and Software*, *86*(5), 1390–1407.

Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*, *5*(1), 9–28.

Elhorst, J. P. (2017). Spatial Panel Data Analysis. In S. Shekhar, H. Xiong, & X. Zhou (Eds.), *Encyclopedia of GIS* (2nd edition, pp. 2050–2058). Springer International Publishing.

Entezarkheir, M. (2017). Patent thickets, defensive patenting, and induced R&D: An empirical analysis of the costs and potential benefits of fragmentation in patent ownership. *Empirical Economics*, *52*(2), 599–634.

Erl, C. (2021). The People and The Nation: The "Thick" and the "Thin" of Right-Wing Populism in Canada. *Social Science Quarterly*, *102*(1), 107–124.

Fadic, M., Garcilazo, J. E., Monroy, A. M., & Veneri, P. (2019). *Classifying small (TL3) regions based on metropolitan population, low density and remoteness* (OECD Regional Development Working Papers). OECD.

Falkinger, J., & Zweimüller, J. (1997). The Impact of Income Inequality on Product Diversity and Economic Growth. *Metroeconomica*, *48*(3), 211–237.

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409–429.

Ferguson, S. J. (2016). *Women and Education: Qualification, Skills and Technology* (89-503–X). Statistics Canada.

Florida, R. (2002). *The Rise of the Creative Class*. Basic Books.

Florida, R. L. (2005). *The flight of the creative class: The new global competition for talent* (1st ed). Harper Business.

Florida, R. L. (2012). *The rise of the creative class, revisited*. Basic Books.

Florida, R., & Mellander, C. (2016). The Geography of Inequality: Difference and Determinants of Wage and Income Inequality across US Metros. *Regional Studies*, *50*(1), 79–92.

Fortin, N., Green, D. A., Lemieux, T., Milligan, K., & Riddell, W. C. (2012). Canadian Inequality: Recent Developments and Policy Options. *Canadian Public Policy*, *38*(2), 121–145.

Fortin, N. M., & Lemieux, T. (2015). Changes in wage inequality in Canada: An interprovincial perspective. *Canadian Journal of Economics/Revue Canadienne d'économique*, *48*(2), 682–713.

Fragkandreas, T. (2022). Three decades of research on innovation and inequality: Causal scenarios, explanatory factors and suggestions. *Prometheus*, *38*(2), 147–193.

Frenette, M., Green, D. A., & Milligan, K. (2009). Taxes, Transfers, and Canadian Income Inequality. *Canadian Public Policy*, *35*(4), 389–411.

Gertler, M. S. (1988). The Limits of Flexibility: Comments on the Post-Fordist Vision of Production and Its Geography. *Transactions of the Institute of British Geographers*, *13*(4), 419–432.

Gertler, M. S. (1995). "Being There": Proximity, Organization, and Culture in the Development and Adoption of Advanced Manufacturing Technologies. *Economic Geography*, *71*(1), 1–26.

Gertler, M. S. (2001). *Urban economy and society in Canada: Flows of people, capital and ideas*. *2*(3), 119–130.

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). *Journal of Economic Geography*, *3*(1), 75–99.

Gibson-Graham, J. K., & Roelvink, G. (2009). Social Innovation for Community Economies. In D. MacCallum, F. Moulaert, J. Hillier, & S. Vicari Haddock (Eds.), *Social Innovation and Territorial Development* (pp. 25–38). Routledge.

Gillies, J., Raynauld, V., & Wisniewski, A. (2023). Canada is No Exception: The 2022 Freedom Convoy, Political Entanglement, and Identity-Driven Protest. *American Behavioral Scientist*. 1-15. DOI: 10.1177/00027642231166885

Glaeser, E. (2011). *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier*. Penguin.

Glaeser, E. L., & Gottlieb, J. D. (2006). Urban Resurgence and the Consumer City. *Urban Studies*, *43*(8), 1275–1299.

Goldin, C., & Katz, L. F. (2010). *The Race between Education and Technology*. Harvard University Press

Goldin, C., & Margo, R. A. (1992). The Great Compression: The Wage Structure in the United States at Mid- Century. *The Quarterly Journal of Economics*, *107*(1), 1–34.

Goos, M., & Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *The Review of Economics and Statistics*, *89*(1), 118–133.

Gordon, I. R., & McCann, P. (2005). *Clusters, Innovation and Regional Development*. *5*(5), 523–543.

Government of Canada. (n.d.). *Quebec Sectoral Profile: Mining, Quarrying, and Oil and Gas Extraction*. Retrieved March 15, 2024, from http://www.jobbank.gc.ca/contentjmr.xhtml

Government of Canada, C. E. R. (n.d.). *Provincial and Territorial Energy Profiles – Quebec*. Retrieved February 12, 2024 from https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/provincial-territorial-energy-profiles/provincial-territorial-energy-profiles-quebec.html

Green, D. A., & Sand, B. M. (2015). Has the Canadian labour market polarized? *Canadian Journal of Economics/Revue Canadienne d'économique*, *48*(2), 612–646.

Griliches, Z. (1987). R&D and Productivity: Measurement Issues and Econometric Results. *Science*, *237*(4810), 31–35.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 1661–1707.

Griliches, Z. (1992). The Search for R&D Spillovers. *The Scandinavian Journal of Economics*, *94*, S29–S47.

Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review*, *35*(2–3), 517–526.

Guo, Q. (2019). Analysis on the Relationship between Regional Innovation and Income Inequality in Chinese City Regions. *The Professional Geographer*, *71*(3), 472–490.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools* (Working Paper 8498). National Bureau of Economic Research.

Hall, H. M., & Donald, B. (2009). Innovation and Creativity on the Periphery: Challenges and Opportunities in Northern Ontario. *Working Paper Series: Ontario in the Creative Age*.

Hall, H. M., & Vodden, K. (2019). Learning, knowledge flows, and innovation in Canadian regions. In K. Vodden, D. J. A. Douglas, S. Markey, S. Minnes, & B. Reimer (Eds.), *The Theory, Practice and Potential of Regional Development: The Case of Canada* (pp. 183–211).

Hanley, C. (2014). Putting the Bias in Skill-Biased Technological Change? A Relational Perspective on White-Collar Automation at General Electric. *American Behavioral Scientist*, *58*(3), 400–415.

Harrison, B., & Bluestone, B. (1988). *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. Cambridge University Press.

Harvey, D. (1989). From Managerialism to Entrepreneurialism: The Transformation in Urban Governance in Late Capitalism. *Geografiska Annaler: Series B, Human Geography*, *71*(1), 3–17.

Harvey, D. (2005). *A Brief History of Neoliberalism*. Oxford University Press.

Harvey, D. (2007). Neoliberalism as Creative Destruction. *Annals of the American Academy of Political and Social Science*, *610*, 22–44.

Heckler, D. E. (2005). High-Technology Employment: A NAICS-Based Update High-Tech Employment. *Monthly Labor Review*, *128*(7), 57–72.

Held, D., McGrew, A., Goldblatt, D., & Perraton, J. (1999). Global Transformations: Politics, Economics and Culture. In C. Pierson & S. Tormey (Eds.), *Politics at the Edge: The PSA Yearbook 1999* (pp. 14–28). Palgrave Macmillan UK.

Hinze, S., & Schmoch, U. (2004). Opening the Black Box. In H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems* (pp. 215–235). Springer Netherlands.

Holland, T. G., Peterson, G. D., & Gonzalez, A. (2009). A Cross-National Analysis of How Economic Inequality Predicts Biodiversity Loss. *Conservation Biology*, *23*(5), 1304–1313.

Hope, D., & Martelli, A. (2019). The Transition to the Knowledge Economy, Labor Market Institutions, and Income Inequality in Advanced Democracies. *World Politics*, *71*(2), 236–288.

Isaksen, A., & Karlsen, J. (2010). Different Modes of Innovation and the Challenge of Connecting Universities and Industry: Case Studies of Two Regional Industries in Norway. *European Planning Studies*, *18*(12), 1993–2008.

Islam, S. N., & Winkel, J. (2017). *Climate Change and Social Inequality* (UN/DESA Working Papers 152). United Nations Department of Economic and Social Affairs.

Jacobs, J. (1969). *The Economy of Cities*. Random House.

Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, Citations, and Innovations: A Window on the Knowledge Economy*. MIT Press.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics*, *108*(3), 577–598.

Jenkins, S. P. (2022). Getting the Measure of Inequality. *IZA Discussion Papers*, 32.

Jessop, B. (1994). The transition to post-Fordism and the Schumpeterian workfare state. In R. Burrows & B. Loader (Eds.), *Towards a Post-Fordist Welfare State?* (pp. 13–37). Routledge.

Kapoor, M., Kelejian, H. H., & Prucha, I. R. (2007). Panel data models with spatially correlated error components. *Journal of Econometrics*, *140*(1), 97–130.

Katz, L. F. (1999). Technological Change, Computerization, and the Wage Structure. In E. Brynjolfsson & B. Kahin (Eds.), *Understanding the Digital Economy* (pp. 217–244). The MIT Press.

Kelejian, H. H., & Prucha, I. R. (1998). *A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances*. *17*(1), 99–121.

Kemeny, T., Petralia, S., & Storper, M. (2022). Disruptive innovation and spatial inequality. *Regional Studies*, *0*(0), 1–18.

Kogler, D. F. (2010). *The Geography of Knowledge Formation—Spatial and Sectoral Aspects of Technological Change in the Canadian Economy as indicated by Patent Citation Analysis, 1983-2007*.

Kristal, T. (2013). The Capitalist Machine: Computerization, Workers' Power, and the Decline in Labor's Share within U.S. Industries. *American Sociological Review*, *78*(3), 361–389.

Kristal, T., & Cohen, Y. (2017). The causes of rising wage inequality: The race between institutions and technology. *Socio-Economic Review*, *15*(1), 187–212.

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, *45*(1), 1–28.

Eika, L., Mogstad, M., & Zafar, B. (2019). Educational Assortative Mating and Household Income Inequality. *Journal of Political Economy*, *127*(6), 2795–2835.

Lazonick, W., & Mazzucato, M. (2013). The risk-reward nexus in the innovation-inequality relationship: Who takes the risks? Who gets the rewards? *Industrial and Corporate Change*, *22*(4), 1093–1128.

Leamer, E. E., & Storper, M. (2001). The Economic Geography of the Internet Age. *Journal of International Business Studies*, *32*(4), 641–665.

Lee, N. (2011). Are innovative regions more unequal? Evidence from Europe. *Environment and Planning C: Government and Policy*, *29*(1), 2–23. Scopus.

Lee, N. (2016). Growth with inequality? The local consequences of innovation and creativity. In R. Shearmu, C. Carrincazeaux, & D. Doloreux (Eds.), *Handbook on the Geographies of Innovation*. Edward Elgar Publishing.

Lee, N., & Rodríguez-pose, A. (2013). Innovation and spatial inequality in europe and USA. *Journal of Economic Geography*, *13*(1), 1–22. Scopus.

Lefebvre, P., Merrigan, P., & Michaud, P.-C. (2011). *The Recent Evolution of Retirement Patterns in Canada* (SSRN Scholarly Paper 2423356).

Lemieux, T. (2008). The changing nature of wage inequality. *Journal of Population Economics*, *21*(1), 21–48.

Levernier, W., Partridge, M., & Rickman, D. (1998). Differences in Metropolitan and Nonmetropolitan U.S. Family Income Inequality: A Cross-Country Comparison. *Journal of Urban Economics*, *44*, 272–290.

Levy, F., & Murnane, R. J. (2004). *The New Division of Labor: How Computers Are Creating the Next Job Market*. Princeton University Press.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42.

Lybbert, T. J., & Zolas, N. J. (2014). Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, *43*(3), 530–542.

Marchand, J. (2015). The distributional impacts of an energy boom in Western Canada. *Canadian Journal of Economics/Revue Canadienne d'économique*, *48*(2), 714–735.

Marchand, Y. (2017). *A study of the causes and consequneces of regional income inequality in Canada: A spatial panel data approach* [Master of Arts]. McGill University.

Marchand, Y., Dubé, J., & Breau, S. (2020). Exploring the Causes and Consequences of Regional Income Inequality in Canada. *Economic Geography*, *96*(2), 83–107.

Markusen, A. (2006). Urban Development and the Politics of a Creative Class: Evidence from a Study of Artists. *Environment and Planning A: Economy and Space*, *38*(10), 1921–1940.

Massey, D. (1995). *Spatial Divisions of Labour: Social Structures and the Geography of Production* (2nd Edition). Bloomsbury Publishing.

McCann, P. (2007). Sketching Out a Model of Innovation, Face-to-face Interaction and Economic Geography. *Spatial Economic Analysis*, *2*(2), 117–134.

Mikkelson, G. M., Gonzalez, A., & Peterson, G. D. (2007). Economic Inequality Predicts Biodiversity Loss. *PLoS ONE*, *2*(5), e444.

Milanovic, B. (2016). *Global Inequality: A New Approach for the Age of Globalization*. Harvard University Press.

Moreno, R., Paci, R., & Usai, S. (2005). Spatial Spillovers and Innovation Activity in European Regions. *Environment and Planning A: Economy and Space*, *37*(10), 1793–1812.

Morgan, K. (2004). The exaggerated death of geography: Learning, proximity and territorial innovation systems. *Journal of Economic Geography*, *4*(1), 3–21.

Norcliffe, G. (1994). Regional Labour Market Adjustments in a Period of Structural Transformation: An Assessment of the Canadian Case. *Canadian Geographies / Géographies Canadiennes*, *38*(1), 2–17.

OECD. (2018). Executive summary. In *Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innnovation* (4th Edition). OECD Publishing.

OECD. (2023). *Income Inequality*.

Orloff, A. S. (2002). *Women's Employment and Welfare Regimes: Globalization, Export Orientation and Social Policy* (12; Social Policy and Development Program). United Nations Institute for Social Development.

Osberg, L. (2018). *The Age of Increasing Inequality: The Astonishing Rise of Canada's 1%*. James Lorimer & Company.

Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics Letters*, *5*(4), 377–381.

Papson, S. (1990). The IBM tramp. *Jump Cut: A Review of Contemporary Media*, *35*, 66–72.

Pastor, M., Sadd, J., & Hipp, J. (2001). Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice. *Journal of Urban Affairs*, *23*(1), 1–21.

Paul Krugman. (1991). *Geography and Trade*. MIT Press.

Peck, J. (2001). Neoliberalizing states: Thin policies/hard outcomes. *Progress in Human Geography*, *25*(3), 445–455.

Peck, J. (2005). Struggling with the Creative Class. *International Journal of Urban and Regional Research*, *29*(4), 740–770.

Pelletier, R., Patterson, M., & Moyser, M. (2019). *The gender wage gap in Canada: 1998 to 2018* (Labour Statistics: Research Papers). Statistics Canada.

Pendakur, K., & Pendakur, R. (2007). Minority Earnings Disparity Across the Distribution. *Canadian Public Policy*, *33*(1), 41–61.

Pickett, K. E., & Wilkinson, R. G. (2015). Income inequality and health: A causal review. *Social Science & Medicine*, *128*, 316–326.

Piketty, T. (2014). *Capital in the Twenty-First Century* (A. Goldhammer, Trans.). Harvard University Press.

Pinheiro, F. L., Balland, P.-A., Boschma, R., & Hartmann, D. (2022). The dark side of the geography of innovation: Relatedness, complexity and regional inequality in Europe. *Regional Studies*, 1–16.

Polanyi, M. (1962). Tacit Knowing: Its Bearing on Some Problems of Philosophy. *Reviews of Modern Physics*, *34*(4), 601–616.

Polèse, M. (2009). Les nouvelles dynamiques régionales de l'économie québécoise: Cinq tendances. *Recherches sociographiques*, *50*(1), 11–40.

Polèse, M., & Shearmur, R. (2006). Why some regions will decline: A Canadian case study with thoughts on local development strategies. *Regional Science*, *85*(1), 23–46.

Proulx, M.-U. (2006). La mouvance contemporaine des territoires: La logique spatiale de l'économie au Québec. *Recherches sociographiques*, *47*(3), 475–502.

Puli, C. (2023). The world through the comedian's lens: The political and social commentary of Charles Chaplin. In M. T. Vassallo & A. P. Debattista (Eds.), *The Different Faces of Politics in the Visual and Performative Arts* (1st Edition, pp. 149–162). Routledge India.

Rodríguez-Pose, A. (2018). The revenge of the places that don't matter (and what to do about it). *Cambridge Journal of Regions, Economy and Society*, *11*(1), 189–209.

Rodríguez-Pose, A., & Bartalucci, F. (2023). The green transition and its potential territorial discontents. *Cambridge Journal of Regions, Economy and Society*. https://doi.org/10.1093/cjres/rsad039

Rodríguez-Pose, A., Lee, N., & Lipp, C. (2021). Golfing with Trump. Social capital, decline, inequality, and the rise of populism in the US. *Cambridge Journal of Regions, Economy and Society*, *14*(3), 457–481.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, *98*(5).

Rosenberg, N. (1983). *Inside the Black Box: Technology and Economics*. Cambridge University Press.

Saez, E. (2017). Income and Wealth Inequality: Evidence and Policy Implications. *Contemporary Economic Policy*, *35*(1), 7–25.

Saez, E., & Zucman, G. (2016). Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data. *The Quarterly Journal of Economics*, *131*(2), 519–578.

Sassen, S. (2001). *The Global City: New York, London, Tokyo*. Princeton University Press.

Schmookler, J. (1966). *Invention and Economic Growth*. Harvard University Press.

Schumpeter, J. A. The theory of economic development. An inquiry into profits, capital, credit, interest, and the business cycle. Cambridge: Harvard University Press; 1934. (first published in 1911 in German)).

Schumpeter, J. A. (1942). Capitalism, Socialism, and Democracy. Harper & Brothers.

Scott, A. J. (2006). Creative Cities: Conceptual Issues and Policy Questions. *Journal of Urban Affairs*, *28*(1), 1–17.

Service Canada. (2022). *Mining, Quarrying and Oil and Gas Extraction-Quebec- Horizon 2022-2024* (Sectorial Profile: NAICS 21).

Shearmur, R. (2011). Innovation, Regions and Proximity: From Neo-Regionalism to Spatial Analysis. *Regional Studies*, *45*(9), 1225–1243.

Shearmur, R. (2012). Are cities the font of innovation? A critical review of the literature on cities and innovation. *Cities*, *29*, S9–S18.

Shearmur, R., Carrincazeaux, C., & Doloreux, D. (2016). Cities, innovation and creativity: Introduction. In *Handbook on the Geographies of Innovation* (Vol. 2016). Edward Elgar Publishing.

Simmie, J. (2002). Knowledge Spillovers and Reasons for the Concentration of Innovative SMEs. *Urban Studies*, *39*(5–6), 885–902.

Simmie, J. (2003). Innovation and Urban Regions as National and International Nodes for the Transfer and Sharing of Knowledge. *Regional Studies*, *37*(6–7), 607–620.

Simmonds, C. (2017, December 12). The Silicon Valley paradox: One in four people are at risk of hunger. *The Guardian*. https://www.theguardian.com/us-news/2017/dec/12/the-silicon-valley-paradox-one-in-four-people-are-at-risk-of-hunger

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economic Statistics*, *39*(3), 312–320.

Sonn, J. W., & Storper, M. (2008). The Increasing Importance of Geographical Proximity in Knowledge Production: An Analysis of US Patent Citations, 1975–1997. *Environment and Planning A: Economy and Space*, *40*(5), 1020–1039.

Statistics Canada. (2018). *The fall and rise of Canada's top income earners*. https://www150.statcan.gc.ca/n1/pub/11-630-x/11-630-x2016009-eng.htm

Statistics Canada. (2020, May 12). *Census of Population*.

Statistics Canada. (2022). *Illustrated Glossary—Census division (CD)*. https://www150.statcan.gc.ca/n1/pub/92-195-x/2021001/geo/cd-dr/cd-dr-eng.htm

Statistics Canada. (2022b, February 9). *Population counts, for census metropolitan areas, census agglomerations, population centres and rural areas*.

Statistics Canada. (2023a). *Consumer Price Index, annual average, not seasonally adjusted: Table 18-10-0005-01*.

Statistics Canada. (2023b). *High-income Canadians and capital gains, 2021*. https://www150.statcan.gc.ca/n1/daily-quotidien/231110/dq231110a-eng.htm

Stiglitz, J. E. (2012). *The price of inequality: How today's divided society endangers our future*. W.W. Norton & Company.

Storper, M., & Manville, M. (2006). Behaviour, Preferences and Cities: Urban Theory and Urban Resurgence. *Urban Studies*, *43*(8), 1247–1274.

Taylor, Z., Lucas, J., Armstrong, D. A., & Bakker, R. (2023). The Development of the Urban-Rural Cleavage in Anglo-American Democracies. *Comparative Political Studies*, 1–36.

Torre, A. (2008). On the Role Played by Temporary Geographical Proximity in Knowledge Transmission. *Regional Studies*, *42*(6), 869–889.

Trajtenberg, M. (1999). *Is Canada Missing the "Technology Boat"? Evidence from Patent Data*.

Trapeznikova, I. (2019). Measuring income inequality. *IZA World of Labor*, *462*.

Veall, M. R. (2012). Top income shares in Canada: Recent trends and policy implications. *Canadian Journal of Economics/Revue Canadienne d'économique*, *45*(4), 1247–1272.

Vodden, K., Carter, K., & White, K. (2013). A primer on innovation, learning, and knowledge flows. *Canadian Regional Development Report*, *6*, 373–393.

Watkins, M. (1963). A Staple Theory of Economic Growth. *Canadian Journal of Economics and Political Science*, *29*(2), 141–158.

Wellstead, A. (2007). The (Post) Staples Economy and the (Post) Staples State in Historical Perspective. *Canadian Political Science Review*, *1*(1), 8–25.

Wilkinson, R. G. (2006). The Impact of Inequality. *Social Research: An International Quarterly*, *73*(2), 711–732.

Winters, J. V. (2014). STEM graduates, human capital externalities, and wages in the U.S. *Regional Science and Urban Economics*, *48*, 190–198.

Wolfe, D. A. (2009). *21st Century Cities in Canada: The Geography of Innovation*. Conference Board of Canada.

Wolfe, D. A. (2014). *The staple theory and Canada's innovation challenge* (50; The Staple Theory, pp. 118–125). Canadian Centre for Policy Alternatives.

Wolfe, D. A. (2016). Innovation and creativity in city-regions. In R. Shearmur, C. Carrincazeaux, & D. Doloreux (Eds.), *Handbook on the Geographies of Innovation* (pp. 174–186). Edward Elgar Publishing.

Appendix A

A1. Non-Spatial Model (Gini)

This table presents the results from the first step of the spatial panel model decision making process (Dubé and Legros, 2014). The first step is to estimate a non-spatial (Pooled OLS) model. Table A1 presents the results of the Pooled OLS model using the Gini coefficient as the measure of income inequality. The table also includes results of the Fixed-Effect Panel model. Fixed-Effects were selected based on the result of the Hausman tests as well as deduction based on the unique properties of each census division. The residuals from these a-spatial models were preserved and used to run a Moran's I test for spatial autocorrelation.

	OLS	Panel-FE
Independent variables	(1)	(2)
Innovation	0.003***	0.004
Working population	0.007***	0.014**
Economic		
Median total income (economic development)	0.032***	0.050***
Unemployment rate	0.117***	0.189***
Part time (%)	0.316***	0.161***
Self-employed (%)	0.083***	0.011
Secondary industries (%)	-0.099***	-0.075**
Tertiary industries (%)	0.015	-0.033
Quaternary industries (%)	0.004	0.004
Institutional		
Minimum Wage	-0.015**	-0.011**
Unionization		
Sociodemographic		
Female participation (%)	-0.010	-0.232***
Education ratio	0.104***	0.094***
Young (%)	0.142***	-0.159***
Senior (%)	0.078***	-0.111**
Time-effects		
1986	-0.005**	0.022***
1991	-0.005	0.038***
1996	-0.010**	0.046***
2001	-0.006	0.058***
2006	0.004	0.075***
2011	-0.007	0.072***
2016	-0.009	0.084***
Constant	-0.132**	0.752***
Rho		
Lambda		
R^2	0.458	0.011
Log likelihood function	5614.7	6622.8
# of observations	2272	2272
# of regions (groups)	284	284

Note: *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.001 level respectively

A.2. Results of Moran's I and Lagrange Multiplier Tests (Gini).

The results of the Global Moran's I indicate the presence of spatial autocorrelation in the data. Subsequently, the Lagrange Multiplier Tests (LM) were run to distinguish between spatial autocorrelation in the dependent variable or spatial autocorrelation in the residuals. The results of the tests, indicate both are strongly significant. This effect persists with the robust LM tests as well. Therefore, given that the strength of significance between the tests is indecipherable, the outcome concluded is the need for a general spatial model (SAC) which accounts for both spatial autocorrelation in the dependent variable and spatial autocorrelation in the error term.
As a note, this decision tree was repeated for the Theil index as well and the same conclusion was reached, thus a generalized spatial model was used for models calculated using the Theil index as well.

Test	Coefficient	Test-Statistic	Outcome	Conclusion
Global Moran's I	0.2969	P-Value > Z(22.928)	0.0000	Reject the null hypothesis. Indicates the need to account for spatial autocorrelation
LM_{SEM}	512.0990	P-Value > Chi2(1)	0.0000	Reject the null hypothesis. Indicates the need to account for spatial error in residuals.
LM_{SEM} (Robust)	1.32e+06	P-Value > Chi2(1)	0.0000	Reject the null hypothesis. Indicates the need to account for spatial error in residuals.
LM_{SAR}	772.1070	P-Value > Chi2(1)	0.0000	Reject the null hypothesis. Indicates the dependent variable has spatial autocorrelation.
LM_{SAR} (Robust)	1.32e+06	P-Value > Chi2(1)	0.0000	Reject the null hypothesis. Indicates the dependent variable has spatial autocorrelation.
LM_{SAC}	1.32e+06	P-Value > Chi2(2)	0.0000	Reject the null hypothesis. Indicates the model has general spatial autocorrelation (SAR+SEM)
LM_{SAC} (Robust)	1.32e+06	P-Value > Chi2(2)	0.0000	Reject the null hypothesis. Indicates the model has general spatial autocorrelation (SAR+SEM)

A.3. Results across all three spatial models (Gini).

To ensure model robustness all three major spatial models were run and compared. The comparison indicates variable direction and significance remains nearly identical across models suggesting the results are highly robust.

	SAR	SEM	SAC
Independent variables	(3)	(4)	(5)
Innovation	0.003***	0.002***	0.002**
Working population	0.005***	0.005***	0.005***
W1y			
Economic			
Median total income (economic development)	0.012**	0.023***	0.022***
Unemployment rate	0.078***	0.080***	0.076***
Part time (%)	0.218***	0.247***	0.238***
Self-employed (%)	0.053***	0.074***	0.071***
Secondary industries (%)	-0.071***	-0.094***	-0.096***
Tertiary industries (%)	0.016	0.029*	0.030**
Quaternary industries (%)	0.014	0.018	0.020*
Institutional			
Minimum Wage	-0.006	-0.014	-0.016
Unionization			
Sociodemographic			
Female participation (%)	-0.031	-0.160	-0.015
Education ratio	0.093***	0.118***	0.118***
Young (%)	0.053**	0.085**	0.085***
Senior (%)	0.043*	0.109***	0.115***
Time-effects			
1986	-0.003	0.000	0.003
1991	0.001	0.002	0.004
1996	-0.002	0.000	0.004
2001	0.002	0.002	0.006
2006	0.009	0.012	0.016
2011	0.003	0.000	0.003
2016	0.003	-0.000	0.003
Constant	-0.041	-0.008	0.051
Rho	0.440***		-0.130
Lambda		0.559***	0.646***
R^2	0.442	0.431	0.425
Log likelihood function	5817.1	5837.0	5837.8
# of observations	2272	2272	2272
# of regions (groups)	284	284	284

Note: *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.001 level respectively

A4. Model results for the impact of high-tech innovations on inequality.

This table contains the spatial panel model results for models run using only patents filed in high-tech industries. This panel includes the results across all three high-tech tiers developed by Hecker (2005). The correlation between high-tech innovation and inequality remains positive and significant across all tiers when using the Gini coefficient as the measure of inequality. Interestingly, high-tech innovation is not correlation with inequality measured by the Theil index *except* for Tier 3 high-tech industries which are strongly significantly positively correlated with inequality. Tier 3 industries notably include petroleum and coal product manufacturing and crude and natural gas pipeline transportations industries suggesting the model may be picking up on a relationship between the extractive resource sector innovation and top 1% inequality.

	Gini			Theil		
	T1	T2	T3	T1	T2	T3
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.003***	0.003**	0.002***	0.002	0.000	0.005***
Working population	0.005***	0.005***	0.005***	0.013***	0.014***	0.013***
W1y				0.563***	0.535***	0.552***
Economic						
Median total income (economic development)	0.022***	0.022***	0.022***	0.011	0.014	0.009
Unemployment rate	0.073***	0.073***	0.072***	0.084**	0.086**	0.090**
Part time (%)	0.235***	0.236***	0.239***	0.186**	0.196**	0.190**
Self-employed (%)	0.070***	0.073***	0.073***	0.090**	0.096**	0.094**
Secondary industries (%)	-0.097***	-0.095***	-0.096***	-0.079**	-0.078**	-0.081**
Tertiary industries (%)	0.028*	0.029**	0.030**	-0.033	-0.036	-0.029
Quaternary industries (%)	0.015	0.017*	0.020**	0.028	0.032	0.035
Institutional						
Minimum Wage	-0.015	-0.015	-0.016	-0.004	-0.004	-0.004
Unionization						
Sociodemographic						
Female participation (%)	-0.011	-0.013	-0.016	-0.169**	-0.172**	-0.181**
Education ratio	0.113***	0.115***	0.118***	0.158***	0.163***	0.159**
Young (%)	0.085***	0.084***	0.083***	-0.052	-0.046	-0.052
Senior (%)	0.119***	0.116***	0.111***	0.007	0.005	-0.002
Time-effects						
1986	0.003	0.004	0.003	0.000	-0.000	0.001
1991	0.004	0.005	0.005	0.014	0.013	0.015
1996	0.003	0.004	0.004	0.011	0.010	0.012
2001	0.005	0.006	0.006	0.019	0.019	0.029
2006	0.014	0.016	0.016*	0.034**	0.035**	0.038**
2011	0.001	0.003	0.004	0.026	0.026	0.029
2016	0.001	0.003	0.004	0.032	0.032	0.036*
Constant	0.061	0.062	0.055	-0.158	-0.188	-0.138
Rho	-0.138	-0.155	-0.121	0.563	0.536	0.552
Lambda	0.653***	0.663***	0.640***			
R^2	0.424	0.419	0.426	0.396	0.394	0.400

Log likelihood function	5839.9	5835.6	5839.0	3845.2	3841.3	3852.5
# of observations	2272	2272	2272	2272	2272	2272
# of regions (groups)	284	284	284	284	284	284