Three Essays on CDS and Market Integration

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To my wife, my daughter, and my parents

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Abstract

Literature proposes various ways to understand the corporate credit risk using different financial assets. This thesis empirically verifies these practices, by studying the relations between the credit and equity (derivatives) markets, as well as addressing the methodological issue in investigating such relations. The first essay studies methodologies in computing CDS returns. While existing CDS return metrics in the literature are poor proxies for the real CDS return, our novel metric has no less than 99% of the correlation with the real CDS return. Our empirical evidence demonstrates the importance of this metric in various empirical settings, such as evaluating a CDS investment strategy.

In the second essay, we examine the predictability between the CDS term structure and equity returns. We find that the information set for the predictability can be significantly improved by incorporating the term structure of CDS spreads. The sign of the predictability is dependent on the shape of the term structure. A structural credit risk framework shows that the term structure contains information on the endogenous default boundary and the asset volatility. This information is tightly related to the equity risk premium. Our work highlights the importance of incorporating the credit spread term structure information in examining the relation between the equity and credit markets.

The third essay studies the integration between the option and CDS markets. By comparing the credit spreads implied from the option (IS) and the credit spreads observed in the CDS market, we find significant short-lived price discrepancies between the IS and CDS spreads. These price discrepancies are related to frictions associated with limits to arbitrage, such as asset illiquidity, idiosyncratic risk, information uncertainty, as well as the intermediary funding constraint. We develop a stylized intermediary based asset pricing framework, which can rationalize the empirical findings.

Résumé

La littérature propose différentes manières de comprendre le risque de crédit des entreprises en utilisant différents actifs financiers. Cette thèse vérifie empiriquement ces pratiques, en étudiant les relations entre les marchés du crédit et des actions (produits dérivés), ainsi qu'en abordant la question méthodologique dans l'étude de ces relations. Le premier essai étudie les méthodologies de calcul des rendements CDS. Alors que les mesures de rendement CDS existantes dans la littérature sont de mauvais indicateurs du rendement réel des CDS, notre nouvelle mesure n'a pas moins de 99% de la corrélation avec le rendement réel des CDS. Nos données empiriques démontrent l'importance de cette mesure dans divers contextes empiriques, comme l'évaluation d'une stratégie d'investissement CDS.

Dans le deuxième essai, nous examinons la prévisibilité entre la structure à terme du CDS et les rendements des actions. Nous constatons que l'ensemble d'informations pour la prévisibilité peut être considérablement amélioré en incorporant la structure à terme des spreads de CDS. Le signe de la prévisibilité dépend de la forme de la structure à terme. Un cadre de risque de crédit structurel montre que la structure à terme contient des informations sur la limite de défaut endogène et la volatilité des actifs. Ces informations sont étroitement liées à la prime du risque des actions. Nos travaux soulignent l'importance d'incorporer les informations sur la structure à terme de écart de crédit dans l'examen de la relation entre les marchés des actions et du crédit.

Le troisième essai étudie l'intégration entre les marchés de l'option et des CDS. En comparant les spreads de crédit implicites de l'option (IS) et les spreads de crédit observés sur le marché des CDS, nous constatons des écarts de prix de courte durée significatifs entre les spreads IS et CDS. Ces écarts de prix sont liés aux frictions liées aux limites

de l’arbitrage, telles que l’illiquidité des actifs, le risque idiosyncratique, l’incertitude de l’information, ainsi que la contrainte de financement intermédiaire. Nous développons un cadre stylisé de valuation des actifs basé sur des intermédiaires, qui peut rationaliser les résultats empiriques.

Contribution of Authors

The first two essays are collaborative works. The first essay entitled “CDS Returns” is in collaboration with Professor Patrick Augustin, from McGill University and Professor Fahad Saleh, from Wake Forest University. I was responsible for programming, designing and conducting empirical tests. The second essay entitled “Why does the CDS Term Structure Predict Equity returns?” is joint work with Professor Patrick Augustin and Professor Jan Ericsson, from the finance department at McGill University. I was responsible for designing and conducting empirical analysis, developing economic intuition, as well as devising a theoretical framework. The third essay entitled “Are Option and CDS Markets Integrated?” is single authored work.

My main contributions go beyond doing empirical work. The first essay involves implementing the novel CDS return metric in a variety of empirical settings to answer a fundamental methodology question: what is the right CDS return metric to use under different economic contexts. This provides further guidance on the return comparison between the CDS and other asset markets. In the second essay, my empirical work contributes to a recent debate in the literature on the predictability between the equity and credit markets. Furthermore, I revisit the classic structural credit risk framework and provide novel implications on the relation between the credit spread term structure and equity returns. My third essay empirically verifies a fundamental assumption, on whether option and credit markets are integrated, in a recent growing literature on using options to implement credit risk models. My work provides important guidance on when we might have bias inference using the option implied credit spreads.

Overall, all three essays of this thesis shed new light on the relation between CDS and equity (derivatives) markets. This yields important implications on understanding the corporate credit risk based on various financial assets. This thesis thus constitutes original work.

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Chapter 1

Introduction

Corporate credit risk is one of the main topics in financial markets, as the US corporate debt outstanding increases tremendously over the past decade. It is important to understand the credit risk at the individual firm level for credit risk management, which has been more and more emphasized after the 2008 financial crisis.

To understand the credit risk, many studies use different corporate contingent claims to extract credit spreads. Among credit claims, credit default swaps (henceforth CDS) are documented to be more efficient in reflecting the firm's credit risk compared to corporate bonds (e.g. Blanco, Brennan, and Marsh, 2005; Norden and Weber, 2009). Despite its efficiency over the corporate debt market, to enrich the credit risk information set, many studies start to use other corporate contingent claims to understand the credit risk of the firms, based on the structural models of credit risk (e.g. Merton, 1974; Vassalou and Xing, 2004; Hull, Nelken, and White, 2005; Carr and Wu, 2011; Culp, Nozawa, and Veronesi, 2018).

Given all these instruments in understanding the credit risk, to see which claim is more effective in reflecting the credit risk, on the one hand, it is important to investigate the lead-lag relation between the credit and equity markets. On the other hand, It is important to understand whether the credit risk is priced consistently among these markets, empirically.

In the first chapter, to facilitate the investigation on cross-market relations, we start by developing a novel cash flow based CDS return metric, since it is a fundamental economic quantity, which can be directly compared across different markets. Despite the existence of various CDS return metrics in the literature, the 2009 CDS reform significantly changes the cash flow structure of the CDS contract. This might jeopardize the accuracy of the traditional metrics. Furthermore, the real CDS return metric proposed by ISDA is difficult to implement. To solve these problems, we construct a CDS return metric that is easy to implement and has a correlation of no less than 99% with the real CDS return.

In the second chapter, we study the predictability between the CDS term structure and equity returns. There has been a debate in the literature about whether the credit market predicts the equity market or vice versa. However, most of these papers focus exclusively on the credit spread level in examining the predictive relation. This inference might omit a significant amount of information embedded in the term structure of the credit spread. Therefore, we revisit the predictive evidence by focusing on the term structure of the credit spread. First, we find that the information set for the predictability can be significantly improved by relying on the term structure. Second, we find that the sign of the predictability is dependent on the shape of the term structure. A stylized structural credit risk framework shows that the shape of the term structure contains important information on the asset volatility and endogenous default boundary of the firm, which are crucial in understanding the equity risk premium.

In the third chapter, we explore the integration between the option and CDS markets. Since an increasing number of studies extract the credit spread using the option data based on the market integration assumption implied by the structural models of credit risk, it is important to empirically verify whether the credit risk is priced consistently between the option and CDS markets in practice. By comparing the credit spreads implied from the options (henceforth IS) and the credit spreads observed in the CDS market, we find an existence of short lived price discrepancies between IS and CDS spreads. These price discrepancies are closely associated with variables related to limits to arbitrage, such as illiquidity, idiosyncratic risk, institutional ownership, and analyst coverage, as well as the health of financial intermediaries. We provide a stylized intermediary asset pricing framework which can rationalize the salient features of the empirical evidence and show that the intermediary funding constraint is the main drivers of the time series dynamic of the price discrepancy, compared to other frictions.

This thesis contributes to our understanding on the integration between the CDS and other asset classes. First, we provide an innovative CDS return metric and highlight its importance in evaluating an investment strategy involving buying or selling a CDS contract. This facilitates the research on cross-market relation, such as constructing a cross-asset arbitrage strategy. Second, we show that it's important to incorporate the CDS term structure in order to better understand the relation between the CDS and equity markets. This could potentially resolve the conflicting evidence on the predictability between the credit and equity markets in the literature. Third, our findings sheds light on the conditions under which it is appropriate to extract and use credit spreads implied from option prices under the structural framework. By understanding the patterns between CDS and other financial markets, this thesis provides important guidance on the structural credit risk model development, as well as the empirical implementation to extract credit spreads using other corporate contingent claims, based on the joint market dynamics implied by the theory.

This thesis is organized as follows. Chapter 2 provides a literature review. Chapter 3 constructs a novel CDS return metric for understanding the relation between CDS and equity (derivatives) markets. Chapter 4 examines the predictive relation between the CDS term structure and equity returns. In Chapter 5, I study the integration between the option and CDS markets. Chapter 6 concludes.

Chapter 2

Literature Review

This thesis builds on the literature on structural models of credit risks. Dating back to the seminal work of Merton (1974), a number of papers develop structure frameworks in jointly pricing the equity and credit claims, as well as corporate decision making (e.g. Black and Cox, 1976; Leland, 1994; Leland, 1998; Goldstein, Nengjiu, and Leland, 2001; Du, Elkamhi, and Ericsson, 2019). Given the market integration implication from the literature, this thesis examines the relations between credit and equity markets both empirically and theoretically, as well as addressing a methodological issue in comparing these markets.

The first essay studies the methodologies in computing the CDS returns. It is related to the literature on the usage of CDS returns. There are various CDS return metric in the literature, such as simple spread changes (e.g. Ericsson, Jacobs, and Oviedo, 2009; Augustin and Izhakian, 2020), percentage or log spread changes (e.g. Acharya and Johnson, 2007; Hilscher, Pollet, and Wilson, 2015), or duration based measure (e.g. Duarte, Longstaff, and Yu, 2007; Berndt and Obreja, 2010; Bongaerts, De Jong, and Driessen, 2011; Palhares, 2014; He, Kelly, and Manela, 2017; Kelly, Manzo, and Palhares, 2019). However, these metrics do not take into account the new cash flow structure of the CDS contract after the 2009 CDS Big Bang. This thesis provides a simple novel cash flow based CDS return metric which takes into account such changes.

In the second essay, we study the predictive relation between the CDS term structure and equity returns. It is related to the literature on the debate on the lead lag relation between the equity and credit market. Acharya and Johnson (2007) and Han, Subrahmanyam, and Zhou (2017) find that the CDS market leads the equity market due to informed trading in the CDS market. Ni and Pan (2020) also find that the credit market predicts the equity market because of equity short selling constraints. On the contrary, Hilscher, Pollet, and Wilson (2015) show that the equity market predicts the CDS market and the informed trader prefers the equity market because of lower transaction cost. Similarly, Norden and Weber (2009) provide statistical evidence that the equity market leads the credit market. More recently, Lee, Naranjo, and Velioglu (2018) finds that the equity market leads the CDS market unconditionally. However, the CDS market predicts the equity market when the credit event takes place.

Most of these studies focus exclusively on the credit spread level. This is likely to omit significant information embedded in the credit spread term structure, which might be helpful in predicting the equity returns. This essay presents both theoretical and empirical evidence to show that the credit spread term structure can reflect different combinations of asset volatility and default boundary, even though these combinations might produce the same credit spread level. Table A.1 summarizes the main differences between our and the existing contributions.

Furthermore, this essay also relates to the cross-sectional stock return predictability. On the one hand, some papers argue that the predictive power of firm characteristics, such as size, book-to-market ratio, and momentum, results from rational expected returns across firms (e.g. Fama and French, 1992; Fama and French, 1996; Jagannathan and Wang, 1996; Zhang, 2005). On the other hand, many studies explain the stock predictability based on investor irrationality or market imperfection (e.g. Shleifer and Vishny, 1997; Jegadeesh and Titman, 1993; Lakonishok, Shleifer, and Vishny, 1994; Nagel, 2005). This essay contributes to the former stream of literature in understanding the equity risk premium through the credit spread term structure.

In addition, many studies have shown that the term structure of different asset classes, such as currencies, equity and dividend derivatives, inflation, U.S. government bonds, and volatility, contains valuable information on the pricing of risk (e.g. Cochrane and Piazzesi, 2005; Binsbergen, Brandt, and Koijen, 2012; Zviadadze, 2017; Fleckenstein, Longstaff, and Lustig, 2017; Augustin, 2018; Gruber, Tebaldi, and Trojani, 2020). This essay contributes to this literature by showing that the term structure of credit spreads contains important information on the equity risk premium.

The third essay studies the integration between the option and CDS markets. It is related to the literature on the integration among different corporate contingent claims. There are a number of papers studying the integration between equity and credit markets such as equity and bonds (Choi and Kim, 2018; Lewis, 2019; Sandulescu, 2020; among others), equity and CDS (Acharya and Johnson, 2007; Das and Sundaram 2007; Kapadia and Pu, 2012; Ni and Pan, 2020; Friewald, Wagner, and Zechner, 2014; Hilscher, Pollet, and Wilson, 2015; Forte and Lovreta, 2015; Han, Subrahmanyam, and Zhou, 2017; Lee, Naranjo, and Velioglu, 2018; Augustin, Jiao, Sarkissian, and Schill, 2019; among others).

In terms of the literature on the integration between option and CDS markets, a few papers document the integration by showing the unconditional moments of the option implied credit spreads and CDS spreads, such as unconditional averages or correlations (Hull, Nelken, and White, 2005; Carr and Wu, 2011). Furthermore, recent studies focus on the aggregate dynamics of the option and CDS. For example, Cremers, Driessen, and Maenhout (2008) show that the option implied jump risk premium can explain the observed level of credit spreads by ratings. Culp, Nozawa, and Veronesi (2018) show that the pseudo credit spread constructed from the options closely matches the CDS spread dynamic at the aggregate level. Forte and Lovreta (2019) examine the price discovery between the CDS implied equity volatility index and the option implied volatility index. Collin-Dufresne, Junge, and Trolle (2020) build a structural model to price the CDX and SPX options and find that the credit and equity market are not fully integrated.

The SPX option and CDX do not have the same underlying basket. On the contrary, the single name equity options and corporate credit claims share the exact same underlying firm value. Complementing these studies, this paper provides firm level evidence not only on the unconditional relation but also the conditional short-run relation between the IS and CDS spreads.

In addition, this essay relates to the large body of literature on the deviation of law of one price. Most studies attribute the price discrepancy to asset spercific frictions and the frictions associated with the market participants. On the asset-specific friction side, a number of studies show that limits to arbitrage impact the law of one price (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010; among others). Empirically, Kapadia and Pu (2012) document that arbitrage costs contribute to the price discrepancy between the equity and CDS markets. Cao and Han (2013) find that the premiums of options increase with the arbitrage cost. Complementing these empirical studies, we provide evidence on the relation between the arbitrage costs and the price discrepancy between the option and CDS.

On the market participant side, financial intermediaries are documented to be important market players in various asset classes. For example, a growing literature shows both theoretically and empirically that the intermediary funding constraint is priced in various asset classes (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Haddad and Muir, 2018; Hitzemann, Hofmann, Uhrig-Homburg, and Wagner, 2018; Andersen, Duffie, and Song, 2019; among others), and the dealer's risk bearing capacity is a priced factor (Kyle and Xiong, 2001; Gârleanu, Pedersen, and Poteshman, 2009; Cao and Han, 2013; Barras and Malkhozov, 2016; Kondor and Vayanos, 2019; among others). Several papers document that the intermediary funding constraint is responsible for the deviation of law of one price (Gromb and Vayanos, 2002; Duffie, 2010; Gârleanu and Pedersen, 2011; Mitchell and Pulvino, 2012; Du, Tepper, and Verdelhan, 2018; Fleckenstein and Longstaff, 2020; Du, Hebert, and Wang, 2020; among others).

In addition, the wealth of the intermediary is shown to impact the premium of trading costs. For example, Bongaerts, De Jong, and Driessen (2011) show that the zero net supply assets can have either positive or negative liquidity premium depending on the buyer's and seller's relative wealth and risk aversion.

Building on this literature, this essay provides significant evidence that the financial intermediary health impacts the price discrepancy between the IS and CDS spreads, contributing to the growing literature on whether the intermediary constraint is priced. This essay also provides new insight on the relative impacts of financial intermediary health on the dynamics of both the liquidity premium and the premium associated with the intermediary margin type constraint, both shown to affect the price discrepancy in the literature.

Furthermore, the essay contributes to the growing literature in using options to implement credit risk models. Hull, Nelken, and White (2005) extend the Merton (1974) model to price the equity option as a compound option of the firm value to extract the default intensity from the options. In a similar fashion, Kuehn, Schreindorfer, and Schulz (2017) estimate a structural model of credit risk with a representative agent with recursive preferences and Markov-switching states using both the options and CDSs information. Instead of building on the structural model, Carr and Wu (2009) extend the Merton (1976) model to incorporate stochastic volatility and use options and CDSs to jointly extract the parameters governing the firm underlying dynamic. Culp, Nozawa, and Veronesi (2018) develop an empirical methodology to construct pseudo credit spreads from option prices based on the Merton model. Carr and Wu (2011) establish a robust link between deep out of the money (DOTM) put options and CDSs. This essay adopts the methodologies from Culp, Nozawa, and Veronesi (2018) and Carr and Wu (2011) to study the integration between option and CDS markets at the firm level. The evidence of options having superior information over the CDSs for firms that are less transparent provides additional incentives to use options in implementing credit risk models.

Chapter 3

CDS Returns

3.1 Introduction

What defines a financial return? At first reflection, this question seems trivial, especially in the context of financial securities, such as stocks or bonds. But a more sincere assessment evokes the sensation that the answer to this question is not as straightforward as it may appear. The ambiguity surrounding the definition of a financial return is especially pronounced in the context of credit default swaps (CDS), for which there exists significant divergence in empirical applications. Surveying the literature, we find at least four different methodologies to compute the return from buying or selling a CDS. Against the backdrop of this disagreement, we show that results from academic research, both qualitative and quantitative in nature, largely depend on the type of definition used for the computation of CDS returns. We find this important to highlight, especially given the growing use of CDS time series in empirical research.

Our first objective is to clarify the concept of CDS returns, and to parallel the different computations applied in the literature. In that context, we provide a simple approximation to the true CDS return, using as inputs CDS prices, rather than the conventionally quoted break-even credit swap spreads. This has become especially important since the regulatory overhaul instigated by the 2009 Big and Small Bang Protocols, which prescribes standardized insurance premium payments together with up-front cash flows settled between protection buyers and protection sellers. The main concern is that the change in regulation has altered the cash flow structure of CDS transactions, which increases the need for a cash flow-based return measure.

Our second objective is to illustrate that commonly used approximations of CDS returns, such as simple changes in CDS spreads, or their log differences, poorly approximate true CDS returns. In fact, we show that the time series correlation between simulated time series of approximated CDS returns and true CDS returns based on prices, are often below 20%. The simple approximation of CDS returns we propose, on the other hand, has a time series correlation of at least 99% with the true return series. Such stark differences become of paramount importance in the examination of the relation between returns on stocks and securities subject to credit risk (such as bonds, for example), for which CDS are often used as a first best approximation. Thus, we illustrate that the relation between stocks and CDS returns varies substantially across different CDS return definitions, and such differences vary as a function of firm leverage and asset volatility.

Taken at face value, our comments indicate a criticism of prior empirical work. Does this mean that earlier findings in the literature based on approximations of CDS returns should be dismissed? Certainly not! However, our examination emphasizes an important distinction that needs to be made among notions of CDS returns. The natural question that is implied is about the appropriateness of various CDS return approximations in different contexts. In a third instance, we thus provide some guidance for when researchers can rely on simple or percentage changes of CDS spreads, and when it is necessary to compute true CDS returns. We argue that the computation of true CDS returns is particularly relevant for studies that examine investment strategies and return performance, which critically depend on the cash flows attached to the underlying securities.

This paper is organized as follows. Section 3.2 describes the structure of a plain vanilla CDS contract and parallels different methods for computing CDS returns. Section 3.3 introduces a practically useful metric that approximates true CDS returns. Section 3.4 examines the relation among simulated CDS return approximations, and their relation with equity returns. In Section 3.5, we revisit the evidence from existing papers that use CDS returns. Section 3.6 concludes.

3.2 Existing Definitions of CDS Returns

We first describe the CDS contract and its payment structure before the 2009 Big Bang Protocol. We then discuss existing metrics of CDS returns commonly used in the literature. We end with a discussion of how the standardization of contracts through the Big Bang Protocol changed the cash flow structure of CDS contracts.

3.2.1 The CDS Contract before the Big Bang

A CDS contract represents a bilateral credit default insurance between a protection buyer and a protection seller. The contract specifies a reference entity that may default on a basket of eligible reference obligations, which are usually standard corporate bonds for conventional plain-vanilla single-name contracts. In return for protection on a face value N until a terminal date T, the insurance buyer compensates the insurance seller by paying an insurance price. Historically, that price was quoted in terms of the "running" or "break-even" spread (henceforth the break-even CDS spread), which would reflect the annualized quarterly payment that the insurance buyer would make per unit of insurance protection. This spread payment would be determined such that the present value of the contract would be zero at initiation of the trade, hence the spread being referred to as a break-even CDS spread.

Formally, we denote the break-even CDS spread at time t by s_t. The insurance premium is paid in regular intervals, typically quarterly, until the earlier of a credit event trigger or the terminal date T of the contract, such that there are n payments at times $\{t_i\}_{i=1}^{n}$. Prior to the Big Bang, each payment was proportional to the break-even CDS spread and determined by the time interval (day count) $\Delta_i \equiv t_i - t_{i-1}$ between two payment periods, with the requirement that $\forall i, j \in \{1, ..., n\} : i > j$, we have that $t_i > t_j$. Further, the final payment occurs at maturity (i.e., $t_n = T$), and we define $t_0 \equiv t$, with t being taken to be the current date hereafter. Upon a default contingency, the protection seller commits to compensate the protection buyer for any losses incurred in excess of the recovery value R, which is also defined as a percentage of the contract's face value. The constant recovery rate is determined in a two-stage auction process through a dealer poll

(Chernov, Gorbenko, and Makarov, 2013; Gupta and Sundaram, 2015; Du and Zhu, 2017). Even though the ex-post recovery rate may vary across defaulted reference entities, it is the convention to fix a constant recovery rate for pricing purposes. For additional regulatory details and explanations on the market structure, we refer to Chapter 2 in Augustin, Subrahmanyam, Tang, and Wang (2014).

Prior to the Big Bang, a CDS contract had zero value at initiation. Thus, the break-even CDS spread s_t was chosen such that the present value of the expected payments made by the protection seller equals the present value of the expected payments made by the protection buyer:[1]

$$s_t = \frac{\mathbf{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{\tau-t} r_t(u)du}(1-R)\,\mathcal{I}\,(\tau \leq T)\right]}{\mathbf{E}^{\mathbb{Q}}\left[\sum\limits_{i=1}^{n} e^{-\int\limits_0^{t_i-t} r_t(u)du}\Delta_i\,\mathcal{I}\,(\tau > t_i)\right]}, \tag{3.1}$$

where $r_t(u)$ denotes the risk-free funding rate that applies between times t and $t+u$, $\mathcal{I}$ is an indicator function that takes the value one if the condition inside the brackets is met, and 0 otherwise, and τ defines the random default time. If default occurs in between two payment dates, the insurance buyer is also liable for the fraction of the quarterly insurance premium that has accrued since the last installment. While we take such accrual payments explicitly into account in our empirical implementation, we omit them in Equation (3.1) to simplify the exposition.

Assuming that interest rates and default are independent of each other, the CDS break-even spread can be expressed as:

$$s_t = \frac{(1-R)\sum\limits_{i=1}^{n} DF_t\,(t_i-t)\left[Q_t\,(t_{i-1}-t) - Q_t\,(t_i-t)\right]}{\sum\limits_{i=1}^{n} DF_t\,(t_i-t)\,Q_t\,(t_i-t)\,\Delta_i}, \tag{3.2}$$

[1] All expectations are taken with respect to the time-t information set and the risk-neutral $\mathbb{Q}$-measure, unless otherwise stated.

where $DF_t(s)$ defines the value at time t of a contract paying \$1 at time $t+s$, and $Q_t(s)$ defines the risk-neutral probability of survival at time $t+s$ conditional on the information available at time t.

3.2.2 Existing CDS Return Definitions

The academic literature has used different metrics of CDS returns. Ericsson, Jacobs, and Oviedo (2009), for example, use break-even CDS spread changes to test the explanatory power of variables suggested by structural credit risk models. We refer to $R_{t,t+1}^{CDS,1}$ as:

$$R_{t,t+1}^{CDS,1} \equiv \Delta s_{t+1} \equiv s_{t+1} - s_t. \tag{3.3}$$

Another metric, used by Hilscher, Pollet, and Wilson (2015), is based on percentage changes of CDS spreads.[2] We refer to $R_{t,t+1}^{CDS,2}$ as:

$$R_{t,t+1}^{CDS,2} \equiv \frac{\Delta s_{t+1}}{s_t}, \tag{3.4}$$

which can also be approximated using the differences of the natural logarithms of CDS spreads, $R_{t,t+1}^{CDS,3}$, which is defined by the following expression:

$$R_{t,t+1}^{CDS,3} \equiv \Delta \log s_{t+1} \equiv \log \frac{s_{t+1}}{s_t}. \tag{3.5}$$

One other commonly used solution is to approximate returns using simple changes in CDS spreads multiplied by the value of a defaultable annuity of appropriate maturity (Duarte, Longstaff, and Yu, 2007; Berndt and Obreja, 2010; Bongaerts, De Jong, and Driessen, 2011; Hilscher, Pollet, and Wilson, 2015). Palhares (2014), He, Kelly, and Manela (2017), and Kelly, Manzo, and Palhares (2019) add the carry component of the return from the CDS insurance payments. We adopt the implementation of He, Kelly, and Manela (2017) and define a fourth metric, $R_{t,t+1}^{CDS,4}$, which approximates the gain or loss from buy-

[2] In their appendix, Hilscher, Pollet, and Wilson (2015) also compute returns using the change in CDS spreads multiplied by an annuity factor, similar to Bongaerts, De Jong, and Driessen (2011), and Berndt and Obreja (2010).

ing a CDS contract if the break-even CDS spread is paid continuously over 250 trading days:

$$R_{t,t+1}^{CDS,4} \equiv -\frac{s_t}{250} + \Delta s_{t+1} RD_t. \tag{3.6}$$

RD_t is called the risky duration and approximates the sensitivity of the CDS contract value to changes in the break-even CDS spread. Following He, Kelly, and Manela (2017), we let $RD_t \equiv \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-j(r_t^{j/4})/4}$, where $r_t^{j/4}$ is the risk-free rate for quarter $j/4$, $e^{-j\gamma/4}$ is the corresponding survival probability extracted using the approximation $\gamma \equiv 4\log(1 + s_t/4(1-R))$.

3.2.3 The CDS Contract after the Big Bang

Due to the involvement of over-the-counter (OTC) derivatives in the 2008/2009 global financial crisis, regulators around the world encouraged the standardization of OTC products to facilitate central clearing. The regulatory push for standardization resulted in a regulatory overhaul of the CDS market, referred to as the North America CDS Big Bang Protocol, which started in April 2009. A similar standardization was instigated for European markets by the CDS Small Bang Protocol in June 2009. One major change brought about by these new industry conventions is a standardization of the payment structure of CDS contracts, whereby counterparties no longer pay the break-even CDS spread. Instead, investors pay a fixed annual coupon c. Specifically, North American single name CDS contracts trade with a fixed coupon of 100 or 500 basis points (bps). Standard European corporates may trade with additional fixed coupons of 25bps and 1,000bps.

Because the coupon usually differs from the break-even CDS spread, the CDS contract has non-zero value at initiation. We refer to that value as the upfront payment or price, P_t, of the CDS contract because it reflects the cash flow paid at initiation for the protection buyer to acquire the CDS contract. In practice, many CDS contracts are quoted in terms of the break-even CDS spread, and CDS prices are then inferred from those quotes using a standardized model provided by the International Swaps and Derivatives Association (ISDA). That standardized model (henceforth ISDA model) maps break-even CDS spreads to CDS prices and vice versa. As such, while the CDS contract structure no longer involves payments proportional to the break-even CDS spread, this spread nonetheless maintains relevance as a quoting convention. We provide further detail regarding CDS pricing following the Big Bang within Section 3.3.

Ignoring the price paid for a CDS contract may have a significant impact on the computation of returns of any financial security, which in the most generic case is given by

$$R_{t,t+1} \equiv \frac{CF_{t+1} - CF_t}{CF_t}, \tag{3.7}$$

where CF_t defines the cash flow payed at time t (Cochrane, 2009).

3.3 CDS Prices and Cash Flow-Based CDS Returns

Computing a cash flow-based CDS return metric requires the computation of the CDS price P_t. The price P_t is determined by the difference between the present value of all expected future payments to be made by the protection seller, i.e., the contingent leg, π_t^s, and the present value of all expected future payments made by the protection buyer, i.e., the fee leg, π_t^b. We define the contingent leg, the fee leg, and the CDS price in sequence.

The value of the contingent leg is given by:

$$\pi_t^s = (1-R) \sum_{i=1}^{n} DF_t\left(t_i - t\right)\left[Q_t\left(t_{i-1} - t\right) - Q_t\left(t_i - t\right)\right], \tag{3.8}$$

and the value of the fee leg is given by:

$$\pi_t^b = c \sum_{i=1}^{n} DF_t\left(t_i - t\right) Q_t\left(t_i - t\right) \Delta_i, \tag{3.9}$$

such that the price of the CDS contract is determined by their difference:

$$P_t = \pi_t^s - \pi_t^b. \tag{3.10}$$

The computation of the CDS price is facilitated by the ISDA model, which allows for the mapping between the break-even CDS spread s_t, and the cash price P_t.[3] Obtaining a closed-form price for the CDS contract requires an assumption for the random default time τ, which ISDA assumes to follow an exponential distribution with mean $1/\lambda_t$, where λ_t represents a strictly positive default intensity $\lambda_t \equiv \lim_{\Delta t \to 0^+} Prob(t < \tau \leq t + \Delta t \mid \tau > t)/\Delta t$ (e.g., Lando, 2004). Assuming in addition that the timing of default is independent of the interest rate environment, that the default intensity is constant, and that payments are made periodically, then Equations (3.2), (3.8), (3.9) and (3.10) imply that the price of the CDS contract is given by:

$$P_t = (s_t - c) \sum_{i=1}^{n} DF_t\,(t_i - t)\,\Delta_i e^{-\lambda_t (t_i - t)}. \tag{3.11}$$

Using this price, we can define a true cash flow-based measure of CDS returns, as suggested by Equation (3.7). The return from buying a CDS contract on date t, and entering into an offsetting trade at $t+1$ is thus given by:

$$R^{CDS,5}_{t,t+1} = \frac{P_{t+1} - P_t}{P_t}, \tag{3.12}$$

where, for expositional simplicity, we have again omitted the accrual payments that arise in the case of default in between two payment dates. While the computation of the CDS price is straightforward, it is inconvenient to implement. The computation of the CDS return requires first a bootstrap of the hazard rate from the term structure of CDS spreads, followed by a sizable summation that is expanding with the contract horizon, as indicated by Equation (3.11). In addition, it requires the need to keep track of day-count conventions, the timing of coupon payments, as well as the entire term structure of interest rates. This can become computationally involved in the context of empirical analysis that involves a long time-series and a large cross-section of assets.[4] A simplification of such tedious computations could be particularly advantageous for Monte Carlo simulations

[3]The ISDA model and the corresponding documentation is available at http://www.cdsmodel.com/cdsmodel/.

[4]Computation of CDS prices via our approximate metric, introduced in Equation (3.13), is approximately one thousand times faster than direct computation of CDS prices in MATLAB.

and other risk management applications. We, therefore, provide a simple approximation to the true cash flow-based CDS return that is easy to implement and has a correlation of no less than 99% with actual CDS returns. This approximation invokes a single interest rate, r_t, which we take to be the $(T-t)$-year risk-free rate at time t. Our approximation of the CDS upfront price, $\widetilde{P}_t$, is given by:

$$\widetilde{P}_t \equiv \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-\left(r_t + \frac{s_t}{1-R}\right)(T-t)}\right), \tag{3.13}$$

which relies on directly available quantities.[5] Our approximation, therefore, is simpler and significantly faster to implement in empirical applications.

With the simple approximation of the CDS price $\widetilde{P}_t$ provided in Equation (3.13), we define the approximated cash flow-based CDS return as:

$$R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1} - \widetilde{P}_t}{\widetilde{P}_t}. \tag{3.14}$$

Proposition 3.3.1 highlights in which sense $\widetilde{P}_t$ approximates P_t. $\widetilde{P}_t$ equals P_t exactly if the CDS buyer makes payments continuously (i.e., $\Delta \to 0^+$) and if there exists a flat term-structure of interest rates. We show below that, even in the absence of a flat term structure of interest rates, our approximation captures true CDS returns with a correlation of no less than 99%. We provide a formal proof of Proposition 3.3.1 in Appendix A.

Proposition 3.3.1.

If there exists a flat term-structure of interest rates characterized by a non-negative interest rate level r_t, then $\lim_{\Delta \to 0^+} P_t = \widetilde{P}_t$ with $\Delta \equiv \max_i \Delta_i$.

3.4 CDS Return Correlations and CDS-Equity Relation

In Section 3.4.1, we parallel the different CDS return metrics and evaluate their suitability in approximating the cash flow-based measures of CDS returns, including our simple

[5] Both the break-even CDS spread, s_t, and the interest rate, r_t, are available from market data. The coupon, c, and contract terminal date, T, are parameters of a CDS contract. The recovery rate R is set by convention for pricing purposes, typically at 0.4 for U.S. corporate CDS contracts.

approximation. We elaborate on the underlying reason for the observed differences between existing metrics and cash flow-based measures of CDS returns in Section 3.4.2, and extend all computations to take into account collateralization. In Section 3.4.3, we also evaluate the impact of cash flow-based returns on the relation between credit and equity markets.

3.4.1 CDS Return Correlations

We compare time-series correlations between the true CDS return series and each of the CDS return approximations. We show that the time series correlations between existing approximations of CDS returns and cash flow-based CDS returns imputed from CDS prices are often below 20%. The simple approximation of CDS returns we propose, on the other hand, has a time series correlation of no less than 99% with the true return series. We conduct this empirical exercise both for a sample of investment grade (IG) and high yield (HY) firms.

Investment Grade Credit Analysis

We use 5-year USD denominated break-even CDS spreads from Markit for a sample of 25 U.S. IG firms. We use data from May 2009 until September 2016, given that the Big Bang Protocol changed the payment structure of standard North-American single-name CDS contracts in April 2009.

Table 3.1 provides basic summary statistics for our IG sample, which spans firms with long-term Standard & Poor's issuer credit ratings varying from AAA to BBB+. The average 5-year break-even CDS spread ranges from 24bps for Exxon Mobil to 145bps for Goldman Sachs. There is also significant degree of heterogeneity in the volatility of break-even CDS spreads, with sample standard deviations ranging from 5bps for Microsoft to 66bps for Goldman Sachs. To provide some additional information on the characteristics of these firms, we report balance sheet information from the Chicago Center for Research in Security Prices and Compustat. While annualized equity volatility, measured as the annualized sample standard deviation of quarterly cum-dividend equity returns, ranges from 12% to 34% in the sample, quarterly leverage ratios can be as high as 93%, and as low as 33%.

Table 3.2 reports time-series correlations between the various proxies for CDS returns and the cash flow-based returns series based on Equation (3.12). Computing the cash flow-based CDS return metric requires the choice of a fixed coupon that will be exchanged as compensation for default insurance. Coupons are generally 100bps for single-name IG North-American contracts, while European names may trade with an additional coupon of 25bps. We illustrate our analysis for coupons of both 25bps and 100bps.

Focusing first on Panel A, the time series correlation between cash flow-based CDS returns and the commonly used approximations can work reasonably well in some instances, as is demonstrated by the results for American Express (ticker AXP). The correlation is 81% based on simple changes, while it is as high as 96% based on log changes. Nonetheless, all measures perform significantly worse in approximating the true CDS return, compared with the simple approximation that we propose for the cash flow-based return measure. In some instances, the differences are striking. For example, for Microsoft (ticker MSFT), the correlation between true CDS returns and simple break-even CDS spread changes equals 2%, whereas the correlation between cash flow-based CDS returns and our approximate CDS returns metric is at least 99% (and mostly close to 100%) for all CDS reference entities.

Overall, the patterns across firms suggest that, among those metrics used in the literature, simple changes, log percentage changes and the metric used by Palhares (2014) and He, Kelly, and Manela (2017) exhibit similar correlation patterns with the benchmark return measure, while correlations for simple break-even CDS spread changes are comparatively weaker. Importantly, they all are consistently lower, in a significant way, than the correlations between the cash flow-based CDS returns and our suggested approximation of them.

One perhaps surprising fact among the results in Panel A is that correlations may even be negative (see ticker PFE, for instance). This arises because the cash flow structure of CDS transactions since the CDS Big Bang depends on the magnitude of the difference between the break-even spread and the fixed coupon. Thus, the up-front payment may have to be settled by either the protection seller or the protection buyer, depending on whether the break-even spread is above or below the fixed coupon. The fact that the direction of payments may change does, however, not undo the finding that existing metrics of CDS returns poorly approximate cash flow-based measures of CDS returns. This is further underscored in Panel B of Table 3.2, which illustrates the same results based on absolute correlations. In Section 3.4.2, we generalize our results to collateralized CDS trades.

Panels C and D repeat the exercise reported in Panels A and B, assuming a fixed coupon of 100bps. While the magnitudes of the correlations change, the finding that existing metrics of CDS returns poorly approximate the cash flow-based measure of CDS returns remains intact. In all cases, the simple approximation of CDS returns metric bears a correlation with the true return series of no less than 99%.

High Yield Credit Analysis

To study high yield firms, we choose among the Markit universe of firms with a credit rating BB+ or lower the 25 CDS reference entities with the largest market capitalization. As for the investment grade analysis, we use 5-year USD denominated break-even CDS spreads between May 2009 and September 2016. We report the credit ratings as of September 30, 2016.

Table 3.3 provides basic summary statistics for our HY sample, which spans firms with long-term Standard & Poor's issuer credit ratings varying from BB+ to D. The lowest credit rating of D (i.e., default) is recorded for Peabody Energy, which filed for Chapter 11 bankruptcy protection in April 2016, with a subsequent credit event auction on May 4, 2016. The average 5-year break-even CDS spreads are substantially higher than in our IG sample, ranging from 88bps for Yum Brands to 1371bps for Peabody Energy. The break-even CDS spread volatility is also substantially higher, with sample standard deviations ranging from 32bps for Ball Corporation to 3509bps for Peabody Energy. Annualized equity volatility, measured as the annualized sample standard deviation of quarterly cum-dividend equity returns, ranges from 18% to 76% in the sample, and quarterly leverage ratios range between 42% and 175%.

Table 3.4 reports time-series correlations between the various proxies for CDS returns and the cash flow-based returns series based on Equation (3.12) for the HY sample. While the fixed coupons are generally 500bps for single-name HY North-American contracts, counterparties may adopt a coupon of 100bps instead. We, therefore, illustrate our analysis for both coupons of 100bps and 500bps.

As for the IG analysis, we find that our approximate CDS returns metric consistently outperforms other metrics. Our approximate return metric always produces at least a 99% correlation with the true return series. In contrast, each of the other metrics produces widely varying correlations with cash flow-based returns, even generating near zero correlations in some cases.

3.4.2 What Explains the Differences?

Our approximated CDS return metric matches the properties of the true cash flow-based CDS returns series because our approximate CDS price, $\widetilde{P}_t$, closely matches the true CDS price, P_t. Proposition 3.3.1 formalizes that assertion, even providing conditions under which our approximation is exact. Other measures fail to adequately capture the cash flow-based return because they fail to capture the CDS price, P_t.

Our analysis within Section 3.4.1 implicitly assumes no initial margin, but our reasoning holds regardless of that assumption. Section 3.4.2 elaborates on the case of no initial margin, whereas Section 3.4.2 repeats our analysis with collateralization, corroborating that our results hold even in that case.

The Case of No Initial Margin

Our analysis within Section 3.4.1 implicitly assumes that counterparties do not post initial margins to collateralize CDS trades. This assumption was widely followed prior to 2016 for interdealer trades (Du, Gordy, Gadgil, and Vega, 2016). However, even today, initial margins tend to be small. For contracts with maturities of five years or less, and with differences of break-even CDS spreads over LIBOR of 300bps or less, the initial margin does not exceed 7% of face value, according to FINRA rule 4240. The initial margins imposed for CDS buyers are even lower and set to 50% of the requirements imposed for CDS sellers.

For centrally cleared contracts, margin rules tend to be more standardized and are typically calculated at the portfolio level. Using a proprietary data set for contracts cleared on one of the major CDS clearinghouses ICE Clear Credit, Capponi, Cheng, Giglio, and Haynes (2019) report that 92.3% of their observations cluster around a mean ratio of initial margin to net notional CDS exposure of 2.4%.

In the absence of margins, the leverage of the trade depends exclusively on the initial price of the CDS contract, P_t. As illustrated by Equation (3.11), this price approaches zero as the break-even CDS spread, s_t, approaches the fixed coupon, c. In turn, that leads to a high volatility in the true cash flow-based CDS returns.[6] Since $\widetilde{P}_t$ approximates P_t effectively, $\widetilde{P}_t$ also approaches 0 as the break-even CDS spread approaches the fixed coupon, so that our metric captures the high volatility well and generates high correlations with the true return. Other metrics do not capture the high volatility and correlate poorly with true CDS returns.

Existing metrics perform poorly in approximating cash flow-based CDS returns in particular when the break-even CDS spread, s_t, approaches the fixed coupon c. This insight is demonstrated in Figures 3.1 and 3.2, which graphically illustrate, using scatterplots, the relation between simulated time-series of cash flow-based (x-axis) and approximated (y-axis) CDS return series, for five different return approximations. Figure 3.1 presents the simulation of an IG CDS contract, whereas Figure 3.2 presents the simulation of a HY CDS contract. Both figures are based on a simulation of a time series of CDS spreads that is equivalent to 50 years of daily data, and it is assumed that the break-even CDS spread s_t at time t follows the process $\Delta s_t = \theta(\mu - s_t) + \sigma\sqrt{s_t}\varepsilon_t$, where ε_t follows an i.i.d. standard normal random variable, i.e., $\varepsilon_t \sim \mathcal{N}(0, 1)$. For Figure 3.1, we use the parameter values $\theta = .005$, $\mu = .0125$, and $\sigma = .002$, and we set the fixed coupon c equal to 100bps. In the rare occasion that a realization of the break-even CDS spread s_t is negative, we replace

[6] In Appendix Tables C.1 and C.2, we provide descriptive statistics for each return metric. These computations highlight that both the true cash flow-based returns, $R^{CDS,4}_{t,t+1}$, and our approximation, $R^{CDS,5}_{t,t+1}$, exhibit higher return volatility than the other metrics.

it with a value of 1 basis point. For Figure 3.2, we use the parameter values $\theta = .013$, $\mu = .06$, and $\sigma = .004$, and we set the fixed coupon c equal to 500bps.

Figures 3.1 and 3.2 show that there is an important non-linearity between the standard approximations of CDS returns and their cash flow-based counterparts, which have become particularly relevant since the CDS Big Bang regulatory overhaul. As the break-even spread s_t moves closer to the fixed coupon c, the commonly used approximations of the CDS return become less sensitive to the cash flow-based CDS returns, i.e., the fitted line of the scatter plot flattens. Our proposed approximation does not exhibit the same behavior, as the two return series are perfectly aligned, independently of the level of spreads and the contract's coupon. The approximation error ultimately depends on the leverage implied by the CDS trade. As the break-even spread varies in response to firm-specific and macroeconomic shocks, while the coupon remains fixed, the leverage varies, so that the relation between true CDS return and standard CDS return approximations varies. In contrast, our metric maintains an approximately one-to-one relation with true CDS returns irrespective of the level of s_t.

For robustness, we also simulate the CDS spread using the strictly positive ARG(1) process of Gourieroux and Jasiak (2006). Hence, we assume that the break-even CDS spread follows the autoregressive process $s_{t+1} = \nu \cdot c + \phi s_t + \eta_{t+1}$, where η_{t+1} represents a martingale difference sequence. We use $\phi = 0.9998$, $c = 5e-8$, and $\nu = 50$. Results, which are similar, are provided in Figure 3.3.

The Case of Collateralization

As described above, our previous results implicitly assume absence of collateralization through the posting of initial margins. We next extend our analysis to account for collateralization and show that our results hold nonetheless. In our extended set-up, we closely follow the notation in Loon and Zhong (2014).

Specifically, we adjust our metrics of true and approximate cash flow-based CDS returns, $R_{t,t+1}^{CDS,4}$ and $R_{t,t+1}^{CDS,5}$, respectively, to account for collateral and then repeat the previous analysis. We define true and approximate collateralized CDS returns (CCDS) by

$$R^{CCDS,4}_{t,t+1} = \frac{P_{t+1} - P_t}{\phi}, \quad R^{CCDS,5}_{t,t+1} = \frac{\widetilde{P}_{t+1} - \widetilde{P}_t}{\phi}, \tag{3.15}$$

where $\phi \in (0, 1]$ represents the extent of collateralization, as in Loon and Zhong (2014). We do not define new expressions for the other three return metrics (i.e., we let $R^{CCDS,i}_{t,t+1} = R^{CDS,i}_{t,t+1}$ for $i = 1, 2, 3$) because those metrics do not explicitly incorporate the initial cash flow and, therefore, they do not vary as a function of collateral.

Tables 3.5 and 3.6 report time-series correlations between the various proxies for CDS returns and the true returns series when the CDS position is collateralized as in Equation (3.15). Table 3.5 provides results for each IG reference entity, whereas Table 3.6 provides results for each HY reference name. In both cases, we fix $\phi = 1$, but this restriction is without loss of generality, because correlations are invariant to scaling. As in the case without collateralization, correlations between our approximate return metric and the true CDS return are usually 100%, and hardly ever below 99%. Moreover, our metric always produces greater correlations with true CDS returns than those obtained from other metrics.

The ability of our approximate CDS return metric to capture the true cash flow-based return depends on its ability to capture the non-linear behavior between CDS prices, P_t, and break-even CDS spreads, s_t. That non-linearity can be seen from Equation (3.11) because P_t depends non-linearly upon λ_t, which, in turn, is implied from s_t as part of the ISDA Model's pricing. Proposition 3.3.1 also alludes to that non-linearity by establishing the true CDS price as non-linear in s_t under certain conditions.[7]

To underscore the aforementioned point, we provide in Figure 3.4 additional illustrations, similar to those in Figures 3.1 to 3.3. We report, using scatterplots, the relation between simulated time series of fully collateralized true CDS returns (i.e., $R^{CCDS,4}_{t,t+1}$ with $\phi = 1$) and all other return metrics for two different levels of volatility, keeping all other parameters constant. In Panel A, the simulated break-even CDS spread series have a low

[7]More precisely, Proposition 3.3.1 demonstrates that the CDS price equals $\widetilde{P}_t$ under certain conditions, and Equation (3.13) gives $\widetilde{P}_t$ as a non-linear function of s_t.

degree of volatility ($\sigma = 0.004$), while those in Panel B have a high degree of volatility ($\sigma = 0.04$). Panel A of Figure 3.4 shows that when break-even CDS spread volatilities are low, our metric performs best, but the other return proxies nonetheless perform modestly well. This latter finding arises because movements in the break-even CDS spread are sufficiently small that the non-linear relation between CDS prices and break-even CDS spreads are not pronounced. On the other hand, when the volatility of break-even CDS spreads is high, then that non-linear relation becomes more relevant, and standard CDS return proxies deteriorate in their performance. Panel B demonstrates this point, showing the poor correlation of standard CDS return proxies to true CDS returns for a high break-even CDS spread volatility. In contrast, our approximate return metric closely tracks the non-linear relation between CDS prices and break-even CDS spreads, resulting in an almost perfectly linear relation with the true CDS return irrespective of the level of break-even CDS spread volatility.

We validate this result empirically using our samples of 25 U.S. investment grade and 25 U.S. high yield reference entities. For each series $i \in \{1, 2, 3, 4, 6\}$, we compute the correlation with the collateralized CDS return metric $R_{t,t+1}^{CCDS,4}$. We then regress $Corr(R_{t,t+1}^{CDS,i}, R_{t,t+1}^{CCDS,4})$ against the sample volatility of CDS spreads. We report the results in Table 3.7. We find a negative and statistically significant relation in columns (1) to (3), corroborating our theory that correlations for standard return metrics decrease in break-even CDS spread volatility. On the other hand, there is a statistically insignificant relation in column (4), where we use the correlation between the collateralized true and approximated CDS return series. That lack of statistical significance arises because our approximate CDS return produces near perfect correlation with true CDS returns irrespective of any other factor.

Taken at face value, the large differences in correlations across firms and across metrics suggest that existing research results may depend on the specific method applied to compute CDS returns. We therefore examine another aspect of CDS returns that is of common interest in the literature, i.e., the relation between CDS and equity returns.

3.4.3 CDS-Equity Correlations

In light of the predictions of structural credit risk models going back to the Merton model (Merton, 1974), a large literature is interested in understanding the relation between equity and credit markets (Collin-Dufresne, Goldstein, and Martin, 2001; Schaefer and Strebulaev, 2008). The return on the corporate bond is often approximated using break-even CDS spreads, as they allow for a more homogenous comparison across companies, given the nature of constant maturity spreads with identical contract definitions for all reference entities (Acharya and Johnson, 2007; Hilscher, Pollet, and Wilson, 2015). As we have shown that different CDS return metrics lead to different time series of CDS returns, we examine potential differences in CDS-equity return correlations, perhaps to provide some guidance on the interpretation of results in the literature. We do this by simulating equity and CDS returns for different assumptions of leverage and asset volatility, using the Merton (1974) model.[8] We report the hedge ratios between equity returns and different metrics of CDS returns, given by the sensitivity of CDS returns to changes in the value of equity. This delivers tables similar to Table 5 in Schaefer and Strebulaev (2008).

More specifically, we simulate 1,000 time-series of 25-months of CDS and equity returns, similar to Schaefer and Strebulaev (2008), and run time-series regressions for each reference entity, which is defined in terms of initial leverage and asset volatility. We vary initial leverage (quasi-market debt-to-asset ratios) from 50% to 90%, and asset volatility ratios from 20% to 50%. The quasi-market value of debt is defined as the face value of debt, which we discount at the constant riskless interest rate of 5%. The time to maturity of the debt contract is assumed to be 10 years. Details of the simulation steps are provided in Appendix B. Table 3.8 reports the mean hedge ratios with their corresponding t-statistics (in parentheses), obtained from simple OLS regressions of CDS returns on equity returns, where the equity return is defined as $R^E_{t,t+1} = \frac{P^E_{t+1} - P^E_t}{P^E_t}$, and CDS returns are defined as before. We examine four different CDS return metrics, namely break-even CDS spread changes (Equation (3.3)), break-even CDS spread percentage returns (Equa-

[8]We use the zero-coupon bond spread under Merton's model as the CDS spread, which we use to compute the different CDS return metrics.

tion (3.4)), cash flow-based CDS returns (Equation (3.12)), and the simple approximation suggested in Equation (3.14). All simulations assume coupons of 25bps.

To highlight the validity of the simulations, we first report the results on hedge ratios for bond returns in Panel A of Table 3.8, similar to the results in Table 5 of Schaefer and Strebulaev (2008). We note that while the regression coefficients between equity and CDS returns are *negative*, the sign for the regression coefficient with bond returns should be *positive*. The top left panel of Figure 3.8 shows that the values are very close to those reported in the aforementioned reference.[9] All other panels report the average regression coefficients for estimations that use different metrics of CDS returns.[10] The differences across the panels in Table 3.8 are quite striking. Taking for example the case of 50% asset volatility and 90% leverage, the average simulated regression coefficient is about -0.11 for the true CDS-equity relationship (Panel E), while the suggested approximation yields a coefficient that is very close, i.e, -0.13 (Panel F). Panels B, C, and D, however, highlight that the sensitivities based on other metrics can significantly deviate from these values. In particular, for break-even CDS spread changes in Panel B, the average regression coefficient is -0.04, while it is -0.43 for the CDS return approximation based on break-even CDS spread percentage changes (Panel C). Such differences are visible across all simulations. Overall, our findings strengthen the conclusion that empirical regression results significantly depend on the type of CDS return metric.

3.5 Guidance for Future Research

To provide guidance for future research, we revisit several papers from the CDS literature and highlight the implications of our analysis for their work. We distinguish between the usage of CDS return metrics as a proxy for credit risk and the usage of CDS returns for the purpose of examining risk-and-return trade-offs. In the former case, standard metrics such as changes in break-even CDS spreads are appropriate precisely because

[9]Note that we report the results in percent instead of basis points. Thus, the coefficients in Table A need to be multiplied by a factor of 100 to make them directly comparable to the results in Schaefer and Strebulaev (2008).

[10]We omit $R^{CDS,4}_{t,t+1}$ from Table 3.8 because of space constraints. In unreported computations, we find that $R^{CDS,4}_{t,t+1}$ produces results similar to $R^{CDS,1}_{t,t+1}$.

such analysis seeks a proxy for credit risk rather than CDS returns per se. In the latter case, standard return metrics are not appropriate when actual CDS trades are not collateralized because such metrics overlook the trade leverage and, therefore, understate the volatility associated with the trade. Section 3.5.1 examines CDS returns used as a proxy for credit risk, whereas Section 3.5.2 examines risk-and-return profiles for CDS trading strategies.

3.5.1 CDS Returns and Credit Risk

We revisit the main findings of Ericsson, Jacobs, and Oviedo (2009), Acharya and Johnson (2007), and Hilscher, Pollet, and Wilson (2015). Following Collin-Dufresne, Goldstein, and Martin (2001), Ericsson, Jacobs, and Oviedo (2009) (henceforth EJO) examine the relation between changes in CDS spreads and variables suggested by structural models of credit risk. The key drivers of credit risk in these models is a firm's leverage, equity volatility, and the level of interest rates. In column (1) of Table 3.9, we report the main result from their Table 2. The reported estimates represent cross-sectional mean coefficient estimates from firm-by-firm regressions. Consistent with economic theory, leverage and equity volatility increase credit risk, while interest rates bear a negative relation to credit risk.

We do not have access to the same data as EJO, who use prices from CreditTrade between 1999 and 2002. We use the universe of Markit firms between January 2002 and September 2016 and drop financial and utility firms, following EJO. After matching with leverage data from Compustat and stock price information from CRSP, we are left with a sample of 499 firms. In columns (2) to (4) of Table 3.9, we revisit the evidence using the different return metrics. When we use break-even CDS spread changes, as in EJO, we recover similar regression coefficients and statistical significance. The precise values are slightly different due to a different sample composition and time period.

In column (3), we run the same regressions, but replace the dependent variable with our approximation of the cash flow-based CDS return metric that takes into account upfront payments. Strikingly, none of the regression coefficients bears statistical significance. The reason is that the size of the upfront payment, which drives the leverage of the return position, is unrelated to fundamentals. The cash flow-based metric depends on the upfront payment, which in turn depends on the magnitude of the distance between the break-even CDS spread and the fixed coupon.

In column (4), we report results using the approximated CDS return metric when it is fully collateralized ($\phi = 1$). Our results reveal that the fully collateralized returns behave qualitatively similar to break-even CDS spread changes. This result arises because fully collateralized CDS returns always correlate postively with break-even CDS spread changes. To see this, note that collateralized CDS returns are increasing in changes in break-even spreads, so that collateralized CDS returns relate to firm fundamentals in a qualitatively similar manner as break-even CDS spread changes. More formally, $R_{t,t+1}^{CCDS,5} \geq 0$ if and only if $\Delta s_{t+1} \geq 0$, because $R_{t,t+1}^{CCDS,5} = \frac{1}{\phi}\int_{s_t}^{s_{t+1}} \frac{\partial \widetilde{P_t}}{\partial s} ds$. Then, Equation (3.13) implies that $\frac{\partial \widetilde{P_t}}{\partial s} > 0$, and it follows immediately that $R_{t,t+1}^{CCDS,5} \geq 0$ if and only if $\Delta s_{t+1} \geq 0$.

The findings in Table 3.9 further support our previous conclusion that it is important to account for the upfront payments in computing cash flow-based returns. This is necessary when the objective is to examine the performance of investment strategies. However, because the sign of the upfront payment is unrelated to firm fundamentals, it is not useful to use the approximated CDS return metric to capture a relation between credit risk determinants and changes in credit risk. For that purpose, break-even CDS spread changes are appropriate, as are the fully collateralized version of our approximated CDS return metric.

Both Acharya and Johnson (2007) and Hilscher, Pollet, and Wilson (2015) examine the lead-lag relation between equity and credit returns. We revisit their evidence using different metrics in Table 3.10. We report all results as in Tables 3 and 4 of Hilscher, Pollet, and Wilson (2015) (henceforth HPW), as those results are based on larger and more recent samples. Specifically, these regressions examine the lead-lag relation between credit and equity returns. In Panel A, we provide the regression results of daily CDS returns on contemporaneous and lagged equity returns as follows:

$$R_{t+T}^{i,CDS} = \beta_T^{i,0} + \beta_T^{i,EQ} R_t^{i,EQ} + \beta_T^{i,CDS} R_t^{i,CDS} + \epsilon_{t+T}^{i,CDS},$$

where $R_{t+T}^{i,CDS}$ denotes firm i's CDS return over day t to T for T from 0 to 10 days, $R_t^{i,EQ}$ denotes firm i's equity return at time t. For horizons $T > 0$, the regressions control for the corresponding credit protection return. All regressions contain firm fixed effects, and standard errors are adjusted for heteroskedasticity and clustered by date. In Panel B, we provide the regression results of daily equity returns on contemporaneous equity and lagged CDS returns as follows:

$$R_{t+T}^{i,EQ} = \beta_T^{i,0} + \beta_T^{i,CDS} R_t^{i,CDS} + \beta_T^{i,EQ} R_t^{i,EQ} + \epsilon_{t+T}^{i,EQ}.$$

We source all Markit firms for which we can find both matching CDS price and equity information from CRSP during the same sample period as in HPW, which ranges from January 2001 until December 2007. We end up with a sample of 690 firms and run regressions by rating groups, as in HPW. We only report results for firms rated A and above, but results for other categories are qualitatively similar.

The findings in both Panels A and B of Table 3.10 echo those that we reported in Table 3.9. The first two rows in each panel report the coefficients from HPW and our replication using the percentage changes as a measure of CDS returns. Unconditionally, HPW find that the CDS returns are only contemporaneously related to equity returns, while lagged equity returns have information for future CDS returns.

The third row in each panel corresponds to the regressions with our approximated measure of cash flow based returns. In that instance, we find that none of the lead-lag regression coefficients is statistically significant. Again, stock returns reflect changes in fundamentals. On the other hand, the cash flow-based measure of CDS return depends heavily on the magnitude of the trade leverage which is detached from fundamentals. However, if we compute fully collateralized ($\phi = 1$) CDS returns, then the returns are again better aligned with fundamentals. Recall that $R_{t,t+1}^{CCDS,5} \geq 0$ if and only if $\Delta s_{t+1} \geq 0$. Then, since $s_t > 0$, we have that $\Delta s_{t+1} \geq 0$ if and only if $\frac{\Delta s_{t+1}}{s_t} \geq 0$ so that $R_{t,t+1}^{CCDS,5}$, Δs_{t+1} and $\frac{\Delta s_{t+1}}{s_t}$ each correlate positively with each other and therefore co-move in a qualitatively similar fashion with respect to fundamentals. As a result, we restore the lead-lag relation found with CDS returns computed as percentage changes of the break-even CDS spreads.

3.5.2 CDS Risk and Returns

In a final step, we implement a CDS trading strategy, for which accounting for cash flows and a trade's leverage is of significant importance for evaluating investment performance through Sharpe ratios. Our application is inspired by capital structure arbitrage (CSA) strategies studied in Duarte, Longstaff, and Yu (2007). CSA is a statistical arbitrage convergence trading strategy that capitalizes on deviations from model-based prices of credit and equity prices. Typically, the implementation of CSA is based on standard applications of structural credit risk models, the CreditGrades model being one example (Finger, 2002). The strategy tends to be implemented using break-even CDS spreads, as it is easier to take short credit positions through derivative contracts than through cash bonds (Asquith, Au, Covert, and Pathak, 2013; Nashikkar, Subrahmanyam, and Mahanti, 2011).

As in Duarte, Longstaff, and Yu (2007), we use the CreditGrades model to evaluate when break-even CDS spreads deviate from their model-based counterparts. For example, if the break-even CDS spread is too large relative to that implied by the model, a long credit risk position would be initiated by selling the CDS contract. When the break-even CDS spread converges to its model-based counterpart, the position is closed. The offsetting position involves a CDS contract of shorter maturity so that both contracts would bear the same termination date, and to avoid any residual credit exposure. In contrast to Duarte, Longstaff, and Yu (2007), we do not hedge the credit exposure with an equity position, financed through initial capital, as our goal is to emphasize the impact on Sharpe ratios from the leverage associated with CDS trades.

For the trade to be worth the while, the deviation between observed and model-implied spreads must be sufficiently large, i.e., $c_t > c_t'$, where c_t and c_t' refer to market and model-implied spreads, respectively. Thus, the trade is initiated if $c_t > (1+\alpha)\, c_t'$, and we evaluate this strategy using three different trading trigger levels $\alpha = 1,\ 1.5,\ 2$. The positions are liquidated when the market spread and the model spread converge or after 180 days, whichever occurs first. We consider mid prices, but apply a bid ask spread equivalent to 5% of the CDS break-even spread when we open and close a position. Accounting for transaction costs lowers the strategy's realized returns uniformly across the different return metrics, while having little impact on volatility. At each date, we compute the equally-weighted return for all open trades as the trading strategy's return index, and then compound the daily returns to a monthly frequency. We subtract the Fama-French risk free rate from the monthly return to get the trading strategy's index excess return. For months in which there are no open trades, the monthly excess return is set to zero. We focus on investment grade companies during the same sample period as in Duarte, Longstaff, and Yu (2007), that is January 2001 to December 2004 (2004Q4). We source all firms with a minimum of 252 consecutive daily observations, and exclude financial and utility firms. This leaves us with a sample of 219 firms.

We report the results in Table 3.11. For each strategy, we provide standard metrics, such as Sharpe ratios and return volatilities for each return metric that we consider. Our results indicate that, when using standard metrics, these trading strategies produce relatively high Sharpe ratios. Nonetheless, when using cash flow-based CDS returns, which account for a trade's leverage, the return volatilities become significantly larger, and the Sharpe ratios fall correspondingly. These results thus highlight that it is important to consider cash flow-based CDS returns to evaluate trading strategies. Failure to do so may lead to inflated Sharpe ratios, and could therefore overstate the risk-return profiles of such trading strategies.

3.6 Conclusion

We show that commonly used metrics of CDS returns poorly approximate cash flow-based measures of CDS returns. Based on both simulations and actual data, we show that time-series correlations between CDS return series based on actual CDS returns and their approximations are often below 20%. We propose a simple formula for CDS returns, which is easy to implement and relies only on easily available information. This simple approximation bears a correlation with true CDS returns of no less than 99%. Moreover, we show that the relation between CDS and equity returns largely depends on the choice of CDS return metric. The discrepancies we emphasize have become particularly important since the CDS regulatory overhaul that occurred in 2009, which changed the cash flow structure of CDS transactions.

Our work provides two important insights for academic and applied research. First, it is critical to distinguish between the notions of changes or percentage changes in CDS spreads, as opposed to true cash flow-based CDS returns. This is an important nuance that needs to be taken into account when evaluating the findings in empirical research applications. Moreover, as we point out, the nature of the CDS return metric may potentially affect the interpretation of academic research findings. Second, while the computation of simple or log returns of break-even CDS spreads may be acceptable to examine a change in the relation with other empirical covariates, computing the cash flow-based measure of a CDS return is necessary for evaluations of predictive return regressions and investment strategies, as these rely on the correct evaluation of cash flow streams. Failing to do so may lead to erroneous conclusions regarding the factor structure of CDS returns and investment alpha.

Bibliography

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Asquith, Paul, Andrea S Au, Thomas Covert, and Parag A Pathak, 2013, The market for borrowing corporate bonds, *Journal of Financial Economics* 107, 155–182.

Augustin, Patrick, Marti G Subrahmanyam, Dragon Y Tang, and Sarah Q Wang, 2014, Credit Default Swaps: A Survey, *Foundations and Trends in Finance* 9, 1–196.

Berndt, Antje, and Iulian Obreja, 2010, Decomposing European CDS returns, *Review of Finance* 14, 189–233.

Bongaerts, Dion, Frank De Jong, and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* 66, 203–240.

Capponi, Agostino, W Allen Cheng, Stefano Giglio, and Richard Haynes, 2019, The Collateral Rule: An Empirical Analysis of the CDS Market, *Working Paper CFTC*.

Chernov, Mikhail, Alexander S. Gorbenko, and Igor Makarov, 2013, CDS Auctions, *Review of Financial Studies* 26, 768–805.

Cochrane, John H., 2009, Asset pricing, *Princeton University Press.*

Collin-Dufresne, Pierre, Robert S Goldstein, and J Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Du, Songzi, and Haoxiang Zhu, 2017, Are CDS Auctions Biased and Inefficient?, *Journal of Finance* 72, 2589–2628.

Du, Wenxin, Michael B Gordy, S Gadgil, and Clara Vega, 2016, Counterparty Risk and Counterparty Choice in the Credit Default Swap Market, *Working Paper Federal Reserve Board*.

Duarte, Jefferson, Francis A Longstaff, and Fan Yu, 2007, Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller?, *Review of Financial Studies* 20, 769–811.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2009, The Determinants of Credit Default Swap Premia, *Journal of Financial and Quantitative Analysis* 44, 109–132.

Finger, Christopher C., 2002, CreditGrades - Technical Document, *RiskMetrics Group, Inc.* pp. 1–52.

Gourieroux, Christian, and Joann Jasiak, 2006, Autoregressive gamma processes, *Journal of Forecasting* 25, 129–152.

Gupta, Sudip, and Rangarajan K. Sundaram, 2015, Inventory effects, the winner's curse, and bid shading in credit default swap auction outcomes, *Journal of Derivatives* 23, 36–52.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Hilscher, Jens, Joshua M Pollet, and Mungo Wilson, 2015, Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets, *Journal of Financial and Quantitative Analysis* 50, 543–567.

Kelly, Bryan, Gerardo Manzo, and Diogo Palhares, 2019, Credit-Implied Volatility, *Working Paper*.

Lando, David, 2004, *Credit Risk Modeling*. (Princeton University Press).

Loon, Yee Cheng, and Zhaodong Ken Zhong, 2014, The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market, *Journal of Financial Economics* 112, 91–115.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *The Journal of Finance* 29, 449–470.

Nashikkar, Amrut, Marti G Subrahmanyam, and Sriketan Mahanti, 2011, Liquidity and Arbitrage in the Market for Credit Risk, *Journal of Financial and Quantitative Analysis* 46, 627–656.

Palhares, D, 2014, Cash-flow maturity and risk premia in cds markets, *Working Paper*.

Schaefer, Stephen M, and Ilya A Strebulaev, 2008, Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* 90, 1–19.

Table 3.1: Investment Grade Sample Statistics

This table provides summary statistics for a sample of 25 USD denominated 5-year U.S. investment grade CDS spreads, based on the contract with the no-restructuring credit event clause. We report each reference entity's ticker, the company name, the number of observations N, the average sample CDS spread $\overline{s}$ (in bps), the estimated CDS spread volatility $\widehat{\sigma}_s$ (in bps) measured as the sample standard deviation of CDS spreads, the estimated cum-dividend equity volatility $\widehat{\sigma}_E$ (%, computed quarterly) measured as the annualized sample standard deviation of quarterly cum-dividend equity returns, the average sample leverage $\overline{LVG}$ (%, computed quarterly) measured as the the average book assets to book liabilities ratio, the Standard & Poor's long-term issuer credit rating $S\&P$ as of September 30, 2016. Unless otherwise stated, all data pertains to the period from May 2009 (2009Q2) until September 2016 (2016Q3). Sources: Markit, Center for Research in Security Prices, Compustat.

Ticker	**Company Name**	**N**	$\overline{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_E$	$\overline{LVG}$	**S&P**
AXP	American Express Co	1823	78	43	25%	88%	BBB+
BA	Boeing Co	1818	59	23	25%	93%	A
CAT	Caterpillar Inc	1821	77	31	34%	81%	A
CSCO	Cisco Systems Inc	1820	55	20	24%	45%	AA-
CVX	Chevron Corp	1822	30	13	19%	42%	AA-
DD	E. I. Du Pont de Nemours & Co	1823	52	13	28%	75%	A-
DIS	Walt Disney Co	1822	31	13	21%	44%	A
GS	Goldman Sachs Group Inc	1817	145	66	30%	91%	BBB+
HD	Home Depot Inc	1821	48	19	19%	65%	A
IBM	Intl. Business Machines Corp	1819	38	7	16%	84%	AA-
INTC	Intel Corp	1819	41	10	20%	33%	A+
JNJ	Johnson & Johnson	1823	30	11	12%	45%	AAA
JPM	JPMorgan Chase & Co	1816	86	26	27%	91%	A-
KO	Coca-Cola Co	1823	37	10	24%	61%	AA-
MCD	McDonalds Corp	1820	27	10	14%	63%	BBB+
MKCINC	Merck & Co Inc	1687	47	13	15%	50%	AA
MSFT	Microsoft Corp	1814	37	5	23%	48%	AAA
NKE	Nike Inc	1823	45	12	34%	36%	AA-
PFE	Pfizer Inc	1820	46	17	20%	56%	AA
PG	Procter & Gamble Co	1822	40	12	13%	52%	AA-
TRV	Travelers Cos Inc	1815	68	30	18%	76%	A
UNH	UnitedHealth Group Inc	1816	85	45	19%	61%	A+
VZW	Verizon Wireless Inc	1653	61	16	16%	73%	BBB+
WMT	Wal-Mart Stores Inc	1819	36	13	18%	61%	AA
XOM	Exxon Mobil Corp	1822	24	10	18%	49%	AA+

Table 3.2: CDS Return Correlations - Investment Grade Sample

This table reports correlations between cash flow-based CDS returns and various approximated CDS return metrics. The data is taken from Markit for the time period between May 2009 and September 2016. $\rho_{i,j} = Corr(R^{CDS,i}_{t,t+1}, R^{CDS,j}_{t,t+1})$ defines the time series correlation between return times series i and j. $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R^{CDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{P_t}$, and $R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$. All figures are rounded to the nearest hundredth. Computations in Panels A and B (C and D) impose a coupon of 25bps (100bps). Panels A and C (B and D) report simple (absolute) correlations.

	Panel A: 25bps					**Panel B: 25bps**				
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\lvert\rho_{1,5}\rvert$	$\lvert\rho_{2,5}\rvert$	$\lvert\rho_{3,5}\rvert$	$\lvert\rho_{4,5}\rvert$	$\lvert\rho_{6,5}\rvert$
AXP	0.81	0.96	0.96	0.81	1.00	0.81	0.96	0.96	0.81	1.00
BA	0.74	0.89	0.89	0.74	1.00	0.74	0.89	0.89	0.74	1.00
CAT	0.80	0.96	0.96	0.80	1.00	0.80	0.96	0.96	0.80	1.00
CSCO	0.48	0.66	0.65	0.48	1.00	0.48	0.66	0.65	0.48	1.00
CVX	0.06	0.06	0.06	0.06	1.00	0.06	0.06	0.06	0.06	1.00
DD	0.06	0.11	0.10	0.07	1.00	0.06	0.11	0.10	0.07	1.00
DIS	0.00	-0.00	-0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
GS	0.86	0.99	0.98	0.86	1.00	0.86	0.99	0.98	0.86	1.00
HD	0.00	0.00	0.00	0.01	1.00	0.00	0.00	0.00	0.01	1.00
IBM	0.09	0.12	0.11	0.10	1.00	0.09	0.12	0.11	0.10	1.00
INTC	0.72	0.92	0.81	0.72	1.00	0.72	0.92	0.81	0.72	1.00
JNJ	0.15	0.16	0.17	0.15	1.00	0.15	0.16	0.17	0.15	1.00
JPM	0.89	0.98	0.98	0.89	1.00	0.89	0.98	0.98	0.89	1.00
KO	0.09	0.10	0.10	0.09	1.00	0.09	0.10	0.10	0.09	1.00
MCD	0.01	-0.00	-0.00	0.01	1.00	0.01	0.00	0.00	0.01	1.00
MKCINC	0.33	0.34	0.34	0.33	1.00	0.33	0.34	0.34	0.33	1.00
MSFT	0.02	0.00	0.01	0.02	1.00	0.02	0.00	0.01	0.02	1.00
NKE	0.83	0.91	0.89	0.83	1.00	0.83	0.91	0.89	0.83	1.00
PFE	-0.01	-0.03	-0.03	-0.01	1.00	0.01	0.03	0.03	0.01	1.00
PG	0.16	0.19	0.19	0.16	1.00	0.16	0.19	0.19	0.16	1.00
TRV	0.75	0.89	0.89	0.75	1.00	0.75	0.89	0.89	0.75	1.00
UNH	0.79	0.93	0.93	0.79	1.00	0.79	0.93	0.93	0.79	1.00
VZW	0.81	0.95	0.90	0.81	1.00	0.81	0.95	0.90	0.81	1.00
WMT	0.07	0.05	0.05	0.07	1.00	0.07	0.05	0.05	0.07	1.00
XOM	0.19	0.20	0.20	0.19	1.00	0.19	0.20	0.20	0.19	1.00

	Panel C: 100bps					**Panel D: 100bps**				
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\lvert\rho_{1,5}\rvert$	$\lvert\rho_{2,5}\rvert$	$\lvert\rho_{3,5}\rvert$	$\lvert\rho_{4,5}\rvert$	$\lvert\rho_{6,5}\rvert$
AXP	-0.08	-0.10	-0.10	-0.08	1.00	0.08	0.10	0.10	0.08	1.00
BA	0.07	0.05	0.05	0.07	1.00	0.07	0.05	0.05	0.07	1.00
CAT	-0.04	-0.05	-0.05	-0.04	1.00	0.04	0.05	0.05	0.04	1.00
CSCO	-0.05	-0.06	-0.06	-0.05	1.00	0.05	0.06	0.06	0.05	1.00
CVX	-0.93	-0.81	-0.81	-0.93	1.00	0.93	0.81	0.81	0.93	1.00
DD	-0.06	-0.09	-0.09	-0.06	1.00	0.06	0.09	0.09	0.06	1.00
DIS	-0.94	-0.81	-0.82	-0.94	1.00	0.94	0.81	0.82	0.94	1.00
GS	-0.02	-0.04	-0.04	-0.02	1.00	0.02	0.04	0.04	0.02	1.00
HD	-0.08	-0.06	-0.06	-0.08	1.00	0.08	0.06	0.06	0.08	1.00
IBM	-0.94	-0.87	-0.88	-0.94	1.00	0.94	0.87	0.88	0.94	1.00
INTC	-0.84	-0.59	-0.77	-0.84	1.00	0.84	0.59	0.77	0.84	1.00
JNJ	-0.89	-0.82	-0.81	-0.89	0.99	0.89	0.82	0.81	0.89	0.99
JPM	-0.04	-0.04	-0.04	-0.04	1.00	0.04	0.04	0.04	0.04	1.00
KO	-0.91	-0.87	-0.88	-0.91	0.99	0.91	0.87	0.88	0.91	0.99
MCD	-0.90	-0.80	-0.80	-0.90	0.99	0.90	0.80	0.80	0.90	0.99
MKCINC	-0.93	-0.86	-0.86	-0.93	1.00	0.93	0.86	0.86	0.93	1.00
MSFT	-0.93	-0.90	-0.91	-0.93	0.99	0.93	0.90	0.91	0.93	0.99
NKE	-0.91	-0.79	-0.84	-0.90	1.00	0.91	0.79	0.84	0.90	1.00
PFE	-0.89	-0.74	-0.74	-0.89	1.00	0.89	0.74	0.74	0.89	1.00
PG	-0.87	-0.77	-0.77	-0.87	1.00	0.87	0.77	0.77	0.87	1.00
TRV	0.01	0.00	0.00	0.01	1.00	0.01	0.00	0.00	0.01	1.00
UNH	0.14	0.13	0.13	0.14	1.00	0.14	0.13	0.13	0.14	1.00
VZW	0.04	-0.01	0.00	0.04	1.00	0.04	0.01	0.00	0.04	1.00
WMT	-0.91	-0.78	-0.79	-0.91	1.00	0.91	0.78	0.79	0.91	1.00
XOM	-0.93	-0.84	-0.84	-0.93	0.99	0.93	0.84	0.84	0.93	0.99

Table 3.3: High Yield Sample Statistics

This table provides summary statistics for a sample of 25 USD denominated 5-year U.S. high yield CDS spreads, based on the contract with the no-restructuring credit event clause. We report each reference entity's ticker, the company name, the number of observations N, the average sample CDS spread $\overline{s}$ (in bps), the estimated CDS spread volatility $\widehat{\sigma}_s$ (in bps) measured as the sample standard deviation of CDS spreads, the estimated cum-dividend equity volatility $\widehat{\sigma}_E$ (%, computed quarterly) measured as the annualized sample standard deviation of quarterly cum-dividend equity returns, the average sample leverage $\overline{LVG}$ (%, computed quarterly) measured as the the average book assets to book liabilities ratio, the Standard & Poor's long-term issuer credit rating $S\&P$ as of September 30, 2016. Unless otherwise stated, all data pertains to the period from May 2009 (2009Q2) until September 2016 (2016Q3). We choose 25 firms with the largest market capitalization among the universe of HY (credit rating BB+ or lower) Markit firms with less than 10% of missing data during our sample period. Sources: Markit, Center for Research in Security Prices, Compustat.

Ticker	**Company Name**	**N**	$\overline{s}$	$\widehat{\sigma}_s$	$\widehat{\sigma}_E$	$\overline{LVG}$	**S&P**
AES	Aes Corp	1863	349	125	45%	79%	BB
ASH	Ashland Global Holdings Inc	1863	197	71	68%	65%	BB
AVP	Avon Products Inc	1863	336	296	46%	89%	B
BLL	Ball Corp	1862	163	32	18%	81%	BB+
BTU	Peabody Energy Corp	1740	1371	3509	56%	69%	D
CHK	Chesapeake Energy Corp	1863	696	975	42%	63%	CCC+
CTL	Centurylink Inc	1863	222	91	22%	64%	BB
CVC	Cablevision Systems Corp	1794	409	111	34%	175%	BB-
DISH	Dish Network Corporation	1863	302	66	30%	100%	B+
DVA	Davita Inc	1701	264	56	20%	68%	BB
FTR	Frontier Communications Corp	1862	428	151	28%	79%	BB-
GPS	Gap Inc	1863	138	85	34%	57%	BB+
GT	Goodyear Tire & Rubber Co	1862	412	185	50%	85%	BB
LB	L Brands Inc	1843	191	40	32%	98%	BB+
LEN	Lennar Corp	1863	284	96	36%	61%	BB
LVLT	Level 3 Communications Inc	1862	619	443	51%	86%	BB
MGM	MGM Resorts International	1863	598	355	76%	72%	BB-
MU	Micron Technology Inc	1804	313	38	56%	42%	BB
NFX	Newfield Exploration CO	1862	192	75	40%	61%	BB+
OKE	Oneok Inc	1863	150	112	39%	73%	BB+
PHM	Pulte Group Inc	1863	241	103	43%	60%	BB+
TSO	Tesoro Corp	1863	294	109	43%	59%	BB+
UHS	Universal Health Services Inc	1863	149	61	25%	57%	BB+
WMB	Williams Cos	1863	175	131	46%	67%	BB
YUM	Yum Brands Inc	1863	88	52	19%	81%	BB

Table 3.4: CDS Return Correlations - High Yield Sample

This table reports correlations between cash flow-based CDS returns and various approximated CDS return metrics. The data is taken from Markit for the time period between May 2009 and September 2016. $\rho_{i,j} = Corr(R^{CDS,i}_{t,t+1}, R^{CDS,j}_{t,t+1})$ defines the time series correlation between return times series i and j. $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R^{CDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{P_t}$, and $R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$. All figures are rounded to the nearest hundredth. Computations in Panels A and B (C and D) impose a coupon of 100bps (500bps). Panels A and C (B and D) report simple (absolute) correlations.

	Panel A: 100bps					Panel B: 100bps					Panel C: 500bps					Panel D: 500bps				
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\lvert\rho_{1,5}\rvert$	$\lvert\rho_{2,5}\rvert$	$\lvert\rho_{3,5}\rvert$	$\lvert\rho_{4,5}\rvert$	$\lvert\rho_{6,5}\rvert$	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\lvert\rho_{1,5}\rvert$	$\lvert\rho_{2,5}\rvert$	$\lvert\rho_{3,5}\rvert$	$\lvert\rho_{4,5}\rvert$	$\lvert\rho_{6,5}\rvert$
AES	0.84	0.96	0.96	0.84	1.00	0.84	0.96	0.96	0.84	1.00	-0.06	-0.05	-0.05	-0.06	1.00	0.06	0.05	0.05	0.06	1.00
ASH	0.64	0.90	0.90	0.64	1.00	0.64	0.90	0.90	0.64	1.00	-0.11	-0.19	-0.19	-0.11	1.00	0.11	0.19	0.19	0.11	1.00
AVP	0.06	0.20	0.18	0.06	1.00	0.06	0.20	0.18	0.06	1.00	0.04	0.03	0.03	0.04	1.00	0.04	0.03	0.03	0.04	1.00
BLL	0.05	0.06	0.06	0.05	1.00	0.05	0.06	0.06	0.05	1.00	-0.85	-0.81	-0.82	-0.85	0.99	0.85	0.81	0.82	0.85	0.99
BTU	0.09	0.46	0.53	0.10	1.00	0.09	0.46	0.53	0.10	1.00	0.05	0.00	-0.01	0.05	1.00	0.05	0.00	0.01	0.05	1.00
CHK	0.21	0.83	0.85	0.23	1.00	0.21	0.83	0.85	0.23	1.00	0.02	0.04	0.05	0.02	1.00	0.02	0.04	0.05	0.02	1.00
CTL	0.08	0.03	0.03	0.08	1.00	0.08	0.03	0.03	0.08	1.00	-0.10	-0.06	-0.06	-0.10	1.00	0.10	0.06	0.06	0.10	1.00
CVC	0.90	0.97	0.97	0.90	1.00	0.90	0.97	0.97	0.90	1.00	-0.03	-0.02	-0.03	-0.03	1.00	0.03	0.02	0.03	0.03	1.00
DISH	0.92	0.97	0.97	0.92	1.00	0.92	0.97	0.97	0.92	1.00	-0.12	-0.10	-0.10	-0.12	1.00	0.12	0.10	0.10	0.12	1.00
DVA	0.42	0.48	0.47	0.42	1.00	0.42	0.48	0.47	0.42	1.00	-0.96	-0.90	-0.94	-0.96	1.00	0.96	0.90	0.94	0.96	1.00
FTR	0.87	0.97	0.97	0.87	1.00	0.87	0.97	0.97	0.87	1.00	0.03	0.03	0.03	0.04	1.00	0.03	0.03	0.03	0.04	1.00
GPS	0.04	0.02	0.02	0.04	1.00	0.04	0.02	0.02	0.04	1.00	-0.89	-0.63	-0.63	-0.89	1.00	0.89	0.63	0.63	0.89	1.00
GT	0.69	0.88	0.88	0.69	1.00	0.69	0.88	0.88	0.69	1.00	-0.02	-0.02	-0.02	-0.02	1.00	0.02	0.02	0.02	0.02	1.00
LB	0.89	0.96	0.96	0.89	1.00	0.89	0.96	0.96	0.89	1.00	-0.95	-0.88	-0.89	-0.95	1.00	0.95	0.88	0.89	0.95	1.00
LEN	0.85	0.97	0.97	0.86	1.00	0.85	0.97	0.97	0.86	1.00	-0.19	-0.15	-0.15	-0.19	1.00	0.19	0.15	0.15	0.19	1.00
LVLT	0.50	0.85	0.85	0.51	1.00	0.50	0.85	0.85	0.51	1.00	0.04	0.04	0.04	0.04	1.00	0.04	0.04	0.04	0.04	1.00
MGM	0.66	0.92	0.92	0.67	1.00	0.66	0.92	0.92	0.67	1.00	0.11	0.08	0.08	0.11	1.00	0.11	0.08	0.08	0.11	1.00
MU	0.98	1.00	0.99	0.98	1.00	0.98	1.00	0.99	0.98	1.00	-0.92	-0.89	-0.91	-0.92	0.99	0.92	0.89	0.91	0.92	0.99
NFX	0.27	0.31	0.34	0.27	1.00	0.27	0.31	0.34	0.27	1.00	-0.40	-0.31	-0.32	-0.40	1.00	0.40	0.31	0.32	0.40	1.00
OKE	0.03	0.02	0.02	0.03	1.00	0.03	0.02	0.02	0.03	1.00	-0.04	-0.02	-0.02	-0.04	1.00	0.04	0.02	0.02	0.04	1.00
PHM	0.76	0.94	0.94	0.76	1.00	0.76	0.94	0.94	0.76	1.00	-0.11	-0.10	-0.10	-0.11	1.00	0.11	0.10	0.10	0.11	1.00
TSO	0.82	0.96	0.96	0.83	1.00	0.82	0.96	0.96	0.83	1.00	0.05	0.02	0.02	0.05	1.00	0.05	0.02	0.02	0.05	1.00
UHS	0.06	0.06	0.06	0.06	1.00	0.06	0.06	0.06	0.06	1.00	-0.92	-0.76	-0.76	-0.92	0.99	0.92	0.76	0.76	0.92	0.99
WMB	-0.03	-0.06	-0.06	-0.03	1.00	0.03	0.06	0.06	0.03	1.00	0.20	0.04	0.04	0.19	1.00	0.20	0.04	0.04	0.19	1.00
YUM	-0.11	-0.17	-0.18	-0.11	1.00	0.11	0.17	0.18	0.11	1.00	-0.88	-0.70	-0.68	-0.88	0.99	0.88	0.70	0.68	0.88	0.99

Table 3.5: Collateralized CDS Return Correlations - Investment Grade Sample

This table reports correlations between cash flow-based CDS returns and various approximated CDS return metrics when we account for collateralization through initial margins. The data is taken from Markit for the time period of May 2009 and September 2016. $\rho_{i,j} = Corr(R_{t,t+1}^{CCDS,i}, R_{t,t+1}^{CCDS,j})$ defines the time series correlation between return times series i and j. $R_{t,t+1}^{CCDS,1} \equiv s_{t+1} - s_t$, $R_{t,t+1}^{CCDS,2} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R_{t,t+1}^{CCDS,3} \equiv \log \frac{s_{t+1}}{s_t}$, $R_{t,t+1}^{CCDS,4} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R_{t,t+1}^{CCDS,5} = \frac{P_{t+1} - P_t}{\phi}$, and $R_{t,t+1}^{CCDS,6} = \frac{\widetilde{P}_{t+1} - \widetilde{P}_t}{\phi}$. We set $\phi = 1$ for our calculations but the results are identical for all $\phi > 0$. All figures are rounded to the nearest hundredth. Computations in Panels A and B (C and D) impose a coupon of 25bps (100bps). Panels A and C (B and D) report simple (absolute) correlations.

	Panel A: 25bps					Panel B: 25bps					Panel C: 100bps					Panel D: 100bps				
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\|\rho_{1,5}\|$	$\|\rho_{2,5}\|$	$\|\rho_{3,5}\|$	$\|\rho_{4,5}\|$	$\|\rho_{6,5}\|$	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\|\rho_{1,5}\|$	$\|\rho_{2,5}\|$	$\|\rho_{3,5}\|$	$\|\rho_{4,5}\|$	$\|\rho_{6,5}\|$
AXP	0.99	0.93	0.93	0.99	1.00	0.99	0.93	0.93	0.99	1.00	1.00	0.93	0.93	1.00	1.00	1.00	0.93	0.93	1.00	1.00
BA	0.99	0.93	0.94	0.99	1.00	0.99	0.93	0.94	0.99	1.00	0.99	0.93	0.93	0.99	1.00	0.99	0.93	0.93	0.99	1.00
CAT	0.99	0.91	0.92	0.99	1.00	0.99	0.91	0.92	0.99	1.00	1.00	0.92	0.93	1.00	1.00	1.00	0.92	0.93	1.00	1.00
CSCO	0.99	0.92	0.92	0.99	1.00	0.99	0.92	0.92	0.99	1.00	0.99	0.92	0.91	0.99	1.00	0.99	0.92	0.91	0.99	1.00
CVX	1.00	0.94	0.94	1.00	1.00	1.00	0.94	0.94	1.00	1.00	0.93	0.86	0.86	0.93	0.99	0.93	0.86	0.86	0.93	0.99
DD	0.99	0.95	0.96	0.99	1.00	0.99	0.95	0.96	0.99	1.00	0.99	0.93	0.94	0.99	1.00	0.99	0.93	0.94	0.99	1.00
DIS	1.00	0.94	0.94	1.00	1.00	1.00	0.94	0.94	1.00	1.00	0.94	0.88	0.88	0.94	1.00	0.94	0.88	0.88	0.94	1.00
GS	0.99	0.93	0.94	0.99	1.00	0.99	0.93	0.94	0.99	1.00	1.00	0.94	0.94	1.00	1.00	1.00	0.94	0.94	1.00	1.00
HD	0.99	0.95	0.95	0.99	1.00	0.99	0.95	0.95	0.99	1.00	0.98	0.93	0.93	0.98	1.00	0.98	0.93	0.93	0.98	1.00
IBM	1.00	0.97	0.97	1.00	1.00	1.00	0.97	0.97	1.00	1.00	0.95	0.92	0.93	0.95	1.00	0.95	0.92	0.93	0.95	1.00
INTC	1.00	0.91	0.98	1.00	1.00	1.00	0.91	0.98	1.00	1.00	0.99	0.90	0.97	0.99	1.00	0.99	0.90	0.97	0.99	1.00
JNJ	1.00	0.95	0.95	1.00	1.00	1.00	0.95	0.95	1.00	1.00	0.88	0.83	0.83	0.88	0.99	0.88	0.83	0.83	0.88	0.99
JPM	0.99	0.95	0.96	0.99	1.00	0.99	0.95	0.96	0.99	1.00	1.00	0.96	0.96	1.00	1.00	1.00	0.96	0.96	1.00	1.00
KO	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00	0.91	0.89	0.89	0.91	0.99	0.91	0.89	0.89	0.91	0.99
MCD	1.00	0.95	0.95	1.00	1.00	1.00	0.95	0.95	1.00	1.00	0.89	0.83	0.83	0.89	0.99	0.89	0.83	0.83	0.89	0.99
MKCINC	0.98	0.96	0.96	0.98	1.00	0.98	0.96	0.96	0.98	1.00	0.95	0.93	0.93	0.95	1.00	0.95	0.93	0.93	0.95	1.00
MSFT	1.00	0.98	0.98	1.00	1.00	1.00	0.98	0.98	1.00	1.00	0.94	0.93	0.93	0.94	0.99	0.94	0.93	0.93	0.94	0.99
NKE	0.99	0.97	0.98	0.99	1.00	0.99	0.97	0.98	0.99	1.00	0.97	0.95	0.96	0.98	1.00	0.97	0.95	0.96	0.98	1.00
PFE	0.99	0.93	0.94	0.99	1.00	0.99	0.93	0.94	0.99	1.00	0.97	0.90	0.90	0.97	1.00	0.97	0.90	0.90	0.97	1.00
PG	0.99	0.97	0.97	0.99	1.00	0.99	0.97	0.97	0.99	1.00	0.95	0.92	0.92	0.95	1.00	0.95	0.92	0.92	0.95	1.00
TRV	0.99	0.94	0.94	0.99	1.00	0.99	0.94	0.94	0.99	1.00	1.00	0.94	0.94	1.00	1.00	1.00	0.94	0.94	1.00	1.00
UNH	0.98	0.93	0.94	0.98	1.00	0.98	0.93	0.94	0.98	1.00	0.99	0.94	0.94	0.99	1.00	0.99	0.94	0.94	0.99	1.00
VZW	1.00	0.95	0.97	1.00	1.00	1.00	0.95	0.97	1.00	1.00	1.00	0.95	0.97	1.00	1.00	1.00	0.95	0.97	1.00	1.00
WMT	0.99	0.95	0.95	0.99	1.00	0.99	0.95	0.95	0.99	1.00	0.94	0.89	0.89	0.94	1.00	0.94	0.89	0.89	0.94	1.00
XOM	1.00	0.95	0.95	1.00	1.00	1.00	0.95	0.95	1.00	1.00	0.92	0.87	0.87	0.92	0.99	0.92	0.87	0.87	0.92	0.99

Table 3.6: Collateralized CDS Return Correlations - High Yield Sample

This table reports correlations between cash flow-based CDS returns and various approximated CDS return metrics when we account for collateralization through initial margins. The data is taken from Markit for the time period of May 2009 to September 2016. $\rho_{i,j} = Corr(R^{CCDS,i}_{t,t+1}, R^{CCDS,j}_{t,t+1})$ defines the time series correlation between return times series i and j. $R^{CCDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CCDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CCDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CCDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R^{CCDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{\phi}$, and $R^{CCDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\phi}$. We set $\phi = 1$ for our calculations but the results are identical for all $\phi > 0$. All figures are rounded to the nearest hundredth. Computations in Panels A and B (C and D) impose a coupon of 100bps (500bps). Panels A and C (B and D) report simple (absolute) correlations.

	Panel A: 100bps					Panel B: 100bps					Panel C: 500bps					Panel D: 500bps				
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\|\rho_{1,5}\|$	$\|\rho_{2,5}\|$	$\|\rho_{3,5}\|$	$\|\rho_{4,5}\|$	$\|\rho_{6,5}\|$	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$	$\|\rho_{1,5}\|$	$\|\rho_{2,5}\|$	$\|\rho_{3,5}\|$	$\|\rho_{4,5}\|$	$\|\rho_{6,5}\|$
AES	0.98	0.96	0.96	0.98	1.00	0.98	0.96	0.96	0.98	1.00	0.99	0.96	0.96	0.99	1.00	0.99	0.96	0.96	0.99	1.00
ASH	0.97	0.92	0.92	0.98	1.00	0.97	0.92	0.92	0.98	1.00	0.92	0.86	0.87	0.92	0.99	0.92	0.86	0.87	0.92	0.99
AVP	0.95	0.79	0.79	0.95	1.00	0.95	0.79	0.79	0.95	1.00	0.96	0.78	0.79	0.97	1.00	0.96	0.78	0.79	0.97	1.00
BLL	0.99	0.97	0.98	0.99	1.00	0.99	0.97	0.98	0.99	1.00	0.82	0.80	0.81	0.82	0.98	0.82	0.80	0.81	0.82	0.98
BTU	0.53	0.77	0.80	0.59	1.00	0.53	0.77	0.80	0.59	1.00	0.59	0.82	0.85	0.65	1.00	0.59	0.82	0.85	0.65	1.00
CHK	0.55	0.87	0.88	0.58	1.00	0.55	0.87	0.88	0.58	1.00	0.60	0.90	0.91	0.62	1.00	0.60	0.90	0.91	0.62	1.00
CTL	0.99	0.92	0.92	0.99	1.00	0.99	0.92	0.92	0.99	1.00	0.97	0.90	0.90	0.97	1.00	0.97	0.90	0.90	0.97	1.00
CVC	0.98	0.97	0.97	0.98	1.00	0.98	0.97	0.97	0.98	1.00	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00
DISH	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00
DVA	0.99	0.97	0.98	0.99	1.00	0.99	0.97	0.98	0.99	1.00	0.99	0.97	0.98	0.99	1.00	0.99	0.97	0.98	0.99	1.00
FTR	0.98	0.97	0.96	0.98	1.00	0.98	0.97	0.96	0.98	1.00	0.99	0.97	0.97	0.99	1.00	0.99	0.97	0.97	0.99	1.00
GPS	0.99	0.87	0.86	0.99	1.00	0.99	0.87	0.86	0.99	1.00	0.92	0.78	0.78	0.92	0.99	0.92	0.78	0.78	0.92	0.99
GT	0.98	0.95	0.95	0.98	1.00	0.98	0.95	0.95	0.98	1.00	0.99	0.95	0.95	0.99	1.00	0.99	0.95	0.95	0.99	1.00
LB	0.99	0.98	0.98	0.99	1.00	0.99	0.98	0.98	0.99	1.00	0.95	0.92	0.93	0.95	1.00	0.95	0.92	0.93	0.95	1.00
LEN	0.98	0.97	0.97	0.98	1.00	0.98	0.97	0.97	0.98	1.00	0.98	0.95	0.96	0.98	1.00	0.98	0.95	0.96	0.98	1.00
LVLT	0.86	0.85	0.85	0.87	1.00	0.86	0.85	0.85	0.87	1.00	0.94	0.90	0.90	0.94	1.00	0.94	0.90	0.90	0.94	1.00
MGM	0.94	0.94	0.94	0.94	1.00	0.94	0.94	0.94	0.94	1.00	0.96	0.95	0.95	0.97	1.00	0.96	0.95	0.95	0.97	1.00
MU	0.98	0.97	0.98	0.98	1.00	0.98	0.97	0.98	0.98	1.00	0.98	0.98	0.98	0.98	1.00	0.98	0.98	0.98	0.98	1.00
NFX	0.99	0.97	0.93	0.99	1.00	0.99	0.97	0.93	0.99	1.00	0.98	0.96	0.91	0.98	1.00	0.98	0.96	0.91	0.98	1.00
OKE	0.98	0.83	0.80	0.98	1.00	0.98	0.83	0.80	0.98	1.00	0.91	0.77	0.74	0.91	0.99	0.91	0.77	0.74	0.91	0.99
PHM	0.98	0.95	0.95	0.98	1.00	0.98	0.95	0.95	0.98	1.00	0.97	0.92	0.92	0.97	1.00	0.97	0.92	0.92	0.97	1.00
TSO	0.99	0.96	0.96	0.99	1.00	0.99	0.96	0.96	0.99	1.00	0.99	0.95	0.95	0.99	1.00	0.99	0.95	0.95	0.99	1.00
UHS	0.99	0.91	0.91	0.99	1.00	0.99	0.91	0.91	0.99	1.00	0.90	0.82	0.81	0.90	0.99	0.90	0.82	0.81	0.90	0.99
WMB	0.97	0.89	0.89	0.98	1.00	0.97	0.89	0.89	0.98	1.00	0.92	0.82	0.82	0.92	0.99	0.92	0.82	0.82	0.92	0.99
YUM	1.00	0.90	0.89	1.00	1.00	1.00	0.90	0.89	1.00	1.00	0.83	0.72	0.70	0.83	0.99	0.83	0.72	0.70	0.83	0.99

Table 3.7: Relation between CDS Correlations and CDS Volatility

This table provides the regression results from a projection of the CDS return correlations with the true collateralized CDS return metric $R^{CCDS,4}_{t,t+1}$ and CDS volatility σ_s. We define $\rho_{i,j} = Corr(R^{CCDS,i}_{t,t+1}, R^{CCDS,j}_{t,t+1})$ as the time series correlation between the CDS return times series i and j. $R^{CCDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CCDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CCDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CCDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R^{CCDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{\phi}$, $R^{CCDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\phi}$. Volatility is reported in basis points and measured as the sample standard deviation of CDS spreads. We use information from the sample of 25 U.S. investment grade and high yield reference names. All data pertains to the period from May 2009 (2009Q2) to September 2016 (2016Q3). We report t-statistics in parentheses. Sources: Markit, authors' computations.

	(1)	(2)	(3)	(4)	(5)
	$\rho_{1,5}$	$\rho_{2,5}$	$\rho_{3,5}$	$\rho_{4,5}$	$\rho_{6,5}$
σ_s	-1.453***	-0.463***	-0.383***	-1.275***	0.007
	(-9.79)	(-3.73)	(-2.94)	(-8.80)	(0.94)

Table 3.8: CDS-Equity Return Correlations

This table reports sensitivities of CDS returns to equity returns in the Merton (1974) model for a range of leverage and asset volatility values. To estimate the sensitivities, for each value of volatility and leverage, we estimate a thousand 25-month CDS and equity return simulations, similar to Schaefer and Strebulaev (2008), and run time-series regressions for each reference entity, which is defined in terms of leverage and asset volatility. The table reports the average hedge ratios with their corresponding t-statistics (in parentheses). Leverage is defined as the ratio of the quasi-market value of debt to the market value of assets. The quasi-market value of debt is defined as the face value of debt, which we discount at the constant riskless interest rate. σ_A defines the annual asset volatility. Leverage and asset volatility are reported in percent. We use a riskless rate of 5% and a time to maturity of the debt contract of 10 years. The hedge ratios are reported in basis points (0.01%). $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{P_t}$, $R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$. The CDS spread s_t is computed as a zero-coupon bond spread under Merton's model. Source: Authors' computations.

L/σ_A	20	25	30	35	40	45	50	20	25	30	35	40	45	50
	Panel A: $R^{Bond}_{t,t+1}$							**Panel B:** $R^{CDS,1}_{t,t+1}$						
50	0.09	0.14	0.18	0.22	0.25	0.28	0.30	−0.01	−0.01	−0.02	−0.02	−0.02	−0.03	−0.03
	(24.62)	(28.06)	(30.19)	(31.53)	(32.36)	(32.85)	(33.09)	(−23.96)	(−26.33)	(−27.17)	(−27.19)	(−26.74)	(−26.02)	(−25.18)
60	0.12	0.17	0.20	0.24	0.27	0.30	0.32	−0.01	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03
	(28.73)	(31.30)	(32.77)	(33.63)	(34.10)	(34.32)	(34.36)	(−27.22)	(−28.40)	(−28.46)	(−27.96)	(−27.17)	(−26.26)	(−25.31)
70	0.15	0.19	0.22	0.26	0.28	0.31	0.33	−0.01	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03
	(32.18)	(33.86)	(34.76)	(35.24)	(35.44)	(35.45)	(35.34)	(−29.57)	(−29.74)	(−29.22)	(−28.36)	(−27.38)	(−26.36)	(−25.35)
80	0.16	0.20	0.24	0.27	0.30	0.32	0.34	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03
	(34.85)	(35.80)	(36.26)	(36.44)	(36.45)	(36.33)	(36.12)	(−31.05)	(−30.51)	(−29.59)	(−28.53)	(−27.45)	(−26.38)	(−25.33)
90	0.18	0.22	0.25	0.28	0.31	0.33	0.35	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.04
	(36.73)	(37.18)	(37.35)	(37.34)	(37.22)	(37.01)	(36.75)	(−31.86)	(−30.87)	(−29.73)	(−28.57)	(−27.43)	(−26.33)	(−25.27)
	Panel C: $R^{CDS,2}_{t,t+1}$							**Panel D:** $R^{CDS,3}_{t,t+1}$						
50	−1.59	−1.20	−0.96	−0.80	−0.69	−0.60	−0.53	−1.60	−1.20	−0.96	−0.80	−0.69	−0.60	−0.53
	(−18.30)	(−18.49)	(−18.50)	(−18.42)	(−18.26)	(−18.04)	(−17.79)	(−31.83)	(−30.29)	(−29.07)	(−28.00)	(−26.98)	(−26.02)	(−25.10)
60	−1.30	−1.02	−0.84	−0.72	−0.63	−0.55	−0.49	−1.31	−1.02	−0.85	−0.72	−0.63	−0.56	−0.50
	(−18.47)	(−18.57)	(−18.53)	(−18.41)	(−18.24)	(−18.02)	(−17.76)	(−29.78)	(−28.80)	(−27.93)	(−27.09)	(−26.25)	(−25.42)	(−24.62)
70	−1.08	−0.89	−0.75	−0.66	−0.58	−0.52	−0.47	−1.09	−0.89	−0.76	−0.66	−0.58	−0.52	−0.47
	(−18.53)	(−18.57)	(−18.51)	(−18.38)	(−18.20)	(−17.98)	(−17.73)	(−28.27)	(−27.66)	(−27.03)	(−26.36)	(−25.65)	(−24.93)	(−24.21)
80	−0.93	−0.78	−0.68	−0.61	−0.54	−0.49	−0.44	−0.93	−0.79	−0.69	−0.61	−0.54	−0.49	−0.45
	(−18.52)	(−18.53)	(−18.46)	(−18.33)	(−18.15)	(−17.93)	(−17.68)	(−27.10)	(−26.74)	(−26.28)	(−25.74)	(−25.14)	(−24.51)	(−23.85)
90	−0.80	−0.70	−0.63	−0.56	−0.51	−0.46	−0.43	−0.81	−0.71	−0.63	−0.57	−0.51	−0.47	−0.43
	(−18.47)	(−18.47)	(−18.40)	(−18.26)	(−18.09)	(−17.88)	(−17.63)	(−26.14)	(−25.97)	(−25.65)	(−25.22)	(−24.70)	(−24.14)	(−23.54)
	Panel E: $R^{CDS,5}_{t,t+1}$							**Panel F:** $R^{CDS,6}_{t,t+1}$						
50	−1.21	−0.67	−0.47	−0.35	−0.28	−0.22	−0.18	−1.07	−0.59	−0.42	−0.33	−0.27	−0.23	−0.20
	(−1.67)	(−1.68)	(−1.68)	(−1.68)	(−1.67)	(−1.67)	(−1.66)	(−1.69)	(−1.69)	(−1.70)	(−1.69)	(−1.68)	(−1.67)	(−1.66)
60	−0.75	−0.50	−0.38	−0.29	−0.24	−0.19	−0.16	−0.65	−0.44	−0.34	−0.28	−0.23	−0.20	−0.18
	(−1.66)	(−1.67)	(−1.67)	(−1.67)	(−1.67)	(−1.66)	(−1.66)	(−1.68)	(−1.69)	(−1.69)	(−1.69)	(−1.68)	(−1.67)	(−1.65)
70	−0.55	−0.40	−0.31	−0.25	−0.20	−0.17	−0.14	−0.46	−0.35	−0.28	−0.24	−0.21	−0.18	−0.16
	(−1.65)	(−1.66)	(−1.67)	(−1.67)	(−1.67)	(−1.66)	(−1.66)	(−1.67)	(−1.68)	(−1.69)	(−1.69)	(−1.68)	(−1.66)	(−1.65)
80	−0.42	−0.33	−0.27	−0.22	−0.18	−0.15	−0.12	−0.35	−0.28	−0.24	−0.21	−0.18	−0.16	−0.14
	(−1.64)	(−1.66)	(−1.66)	(−1.66)	(−1.66)	(−1.66)	(−1.66)	(−1.66)	(−1.68)	(−1.69)	(−1.68)	(−1.67)	(−1.66)	(−1.64)
90	−0.34	−0.28	−0.23	−0.19	−0.16	−0.14	−0.11	−0.28	−0.24	−0.21	−0.18	−0.16	−0.15	−0.13
	(−1.64)	(−1.65)	(−1.66)	(−1.66)	(−1.66)	(−1.66)	(−1.65)	(−1.66)	(−1.68)	(−1.68)	(−1.68)	(−1.67)	(−1.66)	(−1.64)

Table 3.9: Ericsson, Jacobs, and Oviedo (2009) Merton Model Regressions

This table provides the Merton model regression results following Table 2 in Ericsson, Jacobs, and Oviedo (2009), henceforth EJO. For each of the N firms in our sample, we project each CDS return metric on the firm's leverage ratio (Leverage), the firm's realized annualized equity volatility computed using daily stock returns within the previous month, and the 10 year constant maturity treasury rate (10-year yield). As in EJO, we report the cross-sectional averages of the coefficient estimates and R^2 values. The t-statistics are calculated from the cross-sectional averages of the coefficient estimates divided by the standard deviation of the N estimates and scaled by $\sqrt{N}$. The CDS return metrics are $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,6}_{t,t+1} = \frac{\tilde{P}_{t+1} - \tilde{P}_t}{\tilde{P}_t}$, and $R^{CCDS,6}_{t,t+1} \equiv \tilde{P}_{t+1} - \tilde{P}_t$. The upfront payment is computed based on a $1 notional. We use the universe of Markit CDS firms, excluding financial and utility firms following EJO. The sample consists of senior unsecured USD denominated 5-year CDS with the XR restructuring clause. We drop firms with less than 25 observations. After matching with stock and balance sheet data, we have a sample of 499 firms. Leverage is defined as the ratio of the sum of book value of debt and the value of preferred equity to the sum of market value of equity, book value of debt, and book value of preferred equity. Volatility is computed as the annualized standard deviation of daily equity returns of the previous month. The data period ranges from Jan 2002 (2002Q1) until September 2016 (2016Q3). We report t-statistics in parentheses. Sources: Markit, Center for Research in Security Prices, Compustat, FRED, and authors' computations.

	(1) EJO	(2) $R^{CDS,1}_{t,t+1}$	(3) $R^{CDS,6}_{t,t+1}$	(4) $R^{CCDS,6}_{t,t+1}$
Constant	0.005	0.000***	1.966**	0.000***
	(0.87)	(5.68)	(2.14)	(5.38)
Leverage	0.056***	0.041***	-64.410	0.163***
	(6.0)	(17.54)	(-1.48)	(16.67)
Equity volatility	0.008***	0.002***	-12.089	0.008***
	(4.58)	(11.83)	(-1.22)	(10.31)
10-year yield	-0.212***	-0.090***	-1358.511	-0.401***
	(-4.49)	(-10.36)	(-1.26)	(-8.71)
R^2	22.30%	10.90%	2.70%	11.30%
No. of companies	78	499	499	499
Avg. no. of obs.	60	451	440	440

Table 3.10: CDS and Equity Returns Lead-Lag Relation – Acharya and Johnson (2007) & Hilscher, Pollet, and Wilson (2015)

Panel A (Panel B) in this table provides the regression results of daily CDS (equity) returns on contemporaneous (lag = 0) and lagged (lag = 1 to lag = 10) daily equity (CDS) returns. We report the results as in Tables 3 and 4 in Hilscher, Pollet, and Wilson (2015), henceforth HPW. The CDS return metrics are $R_{t,t+1}^{CDS,2} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R_{t,t+1}^{CDS,6} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$, and $R_{t,t+1}^{CCDS,6} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\phi}$, where $\phi = 1$. The upfront payment is computed based on a $1 notional. We use all Markit firms for which we can find both reliable CDS and matching equity price information during the same sample period as HPW, which ranges from January 2001 until December 2007. The total sample has 690 firms. We only report results for firms rated A and above. All variables are winsorized at the 0.1% and the 99.9% level. Regressions control for autocorrelation in the credit (equity) protection return by including the lagged credit (equity) return. The standard errors are adjusted for heteroscedasticity and are clustered by date. All regressions contain firm fixed effects. Sources: Markit, Center for Research in Security Prices, Compustat, FRED, and authors' computations.

Panel A	$R_{t+T}^{i,CDS}$	Time Period										
Rating Group	Return Metrics	0	1	2	3	4	5	6	7	8	9	10
A and above	HPW	-0.18***	-0.16***	-0.09***	-0.07***	-0.05***	-0.04***	-0.02	-0.02	-0.01	-0.01	-0.03**
		(9.04)	(12.29)	(7.09)	(5.73)	(4.45)	(3.41)	(1.49)	(1.64)	(0.90)	(1.29)	(2.40)
	$R_{t,t+1}^{CDS,2}$	-0.18***	-0.16***	-0.10***	-0.07***	-0.05***	-0.04***	-0.02	-0.01	-0.01	-0.01	-0.02*
		(-10.70)	(-11.46)	(-6.76)	(-5.61)	(-3.96)	(-3.15)	(-1.35)	(-0.47)	(-0.82)	(-0.73)	(-1.87)
	$R_{t,t+1}^{CDS,6}$	0.02	0.02	0.01	-0.02	-0.02	0.00	0.02	0.04	-0.01	-0.01	-0.02
		(0.69)	(0.85)	(0.22)	(-0.61)	(-0.83)	(0.06)	(0.75)	(1.51)	(-0.29)	(-0.29)	(-0.92)
	$R_{t,t+1}^{CCDS,6}$	-0.01***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00**	-0.00**	-0.00	0.00	0.00	-0.00*
		(-10.70)	(-8.43)	(-5.09)	(-4.36)	(-3.27)	(-2.19)	(-2.52)	(-0.72)	(0.42)	(0.44)	(-1.82)

Panel B	$R_{t+T}^{i,EQ}$	Time Period										
Rating Group	Return Metrics	0	1	2	3	4	5	6	7	8	9	10
A and above	HPW	-0.033***	0.001	0.000	0.002	0.001	0.006**	0.001	0.001	0.002	-0.001	-0.004
		(9.45)	(0.44)	(0.18)	(0.88)	(0.41)	(2.01)	(0.25)	(0.26)	(1.05)	(0.47)	(1.46)
	$R_{t,t+1}^{CDS,2}$	-0.038***	-0.001	0.001	0.004	0.002	0.002	-0.000	0.000	-0.003	-0.004	-0.003
		(-11.50)	(-0.45)	(0.33)	(1.31)	(0.69)	(0.75)	(-0.07)	(0.13)	(-1.38)	(-1.57)	(-1.18)
	$R_{t,t+1}^{CDS,6}$	-0.000*	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000*
		(-1.68)	(-0.87)	(-0.50)	(0.47)	(-0.91)	(-0.37)	(1.00)	(-0.29)	(-0.73)	(-1.33)	(1.78)
	$R_{t,t+1}^{CCDS,6}$	-0.848***	-0.088	-0.011	0.051	0.019	0.032	-0.004	-0.037	-0.061	-0.038	-0.011
		(-12.36)	(-1.31)	(-0.16)	(0.78)	(0.32)	(0.50)	(-0.07)	(-0.64)	(-1.00)	(-0.59)	(-0.16)

Table 3.11: CDS Trading Strategy Based on CreditGrades Model

This table provides the summary statistics for the monthly CDS trading strategy's index excess return based on different CDS return metrics. $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, and $R^{CDS,5}_{t,t+1} = \frac{\widetilde{P}_{t+1} - \widetilde{P}_t}{\widetilde{P}_t}$. n denotes the number of observations for the capital structure arbitrage return index. Trigger (α) denotes the ratio of the difference between the market spread and the CreditGrades model spread divided by the model spread, above which the strategy is implemented. We implement the following trading strategy for all obligors: if $c_t > (1+\alpha)c'_t$, where c_t and c'_t are the market and model spreads respectively, we short the CDS with a notional amount of \$1. The positions are liquidated when the market spread and the model spread become equal or after 180 days, whichever occurs first. At each date, we compute the equally-weighted return for all open trades as the trading strategy's return index. We introduce 5% CDS bid ask spreads in calculating the returns for the open and close positions only. We then compound the daily return to a monthly frequency and subtract the Fama-French risk free rate from the monthly return to get the trading strategy's index excess return. For months in which there are no open trades, the excess return is set to zero. The data period ranges from January 2001 (2001Q1) to December 2004 (2004Q4). We drop financial firms and utility firms. For each firm, we search for the longest string of more than 252 daily spreads that were no more than 14 calendar days apart and for which we also have the associated equity and balance sheet information. This provides us with a sample of 219 firms. The strategy is implemented on IG firms only. The t-statistics for the means are corrected for the serial correlation of excess returns using Newey West with 2 lags. All returns are in %. Sources: Markit, Center for Research in Security Prices, Compustat, FRED, and authors' computations.

CDS Trading Strategy – 219 firms											
Strategy	Return Metrics	Trigger	n	Mean	t-Stat	Std.	Min	Max	Skew	Kurtosis	SR
CS1	$R^{CDS,1}_{t,t+1}$	1.000	48	0.059	2.916	0.125	-0.155	0.554	1.936	4.307	1.626
	$R^{CDS,2}_{t,t+1}$	1.000	48	3.904	2.231	12.211	-19.167	59.139	2.156	7.289	1.108
	$R^{CDS,3}_{t,t+1}$	1.000	48	6.782	2.873	17.137	-12.630	102.695	3.859	18.671	1.371
	$R^{CDS,4}_{t,t+1}$	1.000	48	0.305	3.415	0.537	-0.607	2.373	1.813	3.668	1.969
	$R^{CDS,6}_{t,t+1}$	1.000	48	94.315	1.042	631.288	-70.902	4370.592	6.679	42.752	0.518
CS2	$R^{CDS,1}_{t,t+1}$	1.500	48	0.025	0.786	0.190	-0.594	0.767	0.544	6.646	0.463
	$R^{CDS,2}_{t,t+1}$	1.500	48	0.968	0.691	8.020	-20.397	28.571	0.992	3.058	0.418
	$R^{CDS,3}_{t,t+1}$	1.500	48	2.034	1.387	8.367	-19.634	30.284	1.154	2.932	0.842
	$R^{CDS,4}_{t,t+1}$	1.500	48	0.152	1.167	0.736	-1.890	3.063	0.951	6.090	0.714
	$R^{CDS,6}_{t,t+1}$	1.500	48	0.591	0.150	31.364	-87.875	121.941	1.263	5.512	0.065
CS3	$R^{CDS,1}_{t,t+1}$	2.000	48	0.019	0.944	0.133	-0.571	0.555	-0.049	12.013	0.501
	$R^{CDS,2}_{t,t+1}$	2.000	48	1.308	0.935	8.686	-17.588	33.841	1.254	3.479	0.521
	$R^{CDS,3}_{t,t+1}$	2.000	48	2.375	1.644	8.886	-16.117	35.275	1.335	3.231	0.926
	$R^{CDS,4}_{t,t+1}$	2.000	48	0.121	1.363	0.548	-1.984	2.454	0.992	10.368	0.766
	$R^{CDS,6}_{t,t+1}$	2.000	48	4.892	0.663	56.662	-87.545	335.747	4.532	23.532	0.299

Figure 3.1: Scatterplot of CDS Return Correlations (Investment Grade)

These figures illustrate scatter-plots for realized daily CDS returns based on the true cash flow based CDS return calculations on the x-axis, against realized daily CDS returns computed using various approximated CDS return metrics on the y-axis. These figures are based on simulations of 50 years of daily data. It is assumed that the CDS spread s_t at time t follows the process $\Delta s_t = \theta(\mu - s_t) + \sigma\sqrt{s_t}\varepsilon_t$, where $\varepsilon_t \sim \mathcal{N}(0,1)$. For the simulation, we use the parameter values $\theta = 0.005$, $\mu = .0125$, $\sigma = 0.002$. The fixed coupon c is assumed to be 100 bps. Each panel in Figure 3.1 compares the simulated time series of cash flow based CDS returns with a time series of returns computed using an approximated CDS return metric. Panel (a) uses simple changes in CDS spreads; Panel (b) uses simple percentage changes in CDS spreads; Panel (c) uses changes in the natural logarithms of CDS spreads; Panel (d) uses the CDS return metric from He, Kelly, and Manela (2017); Panel (e) uses our suggested approximation of CDS returns described in Equation (3.14). Source: Authors' computations.

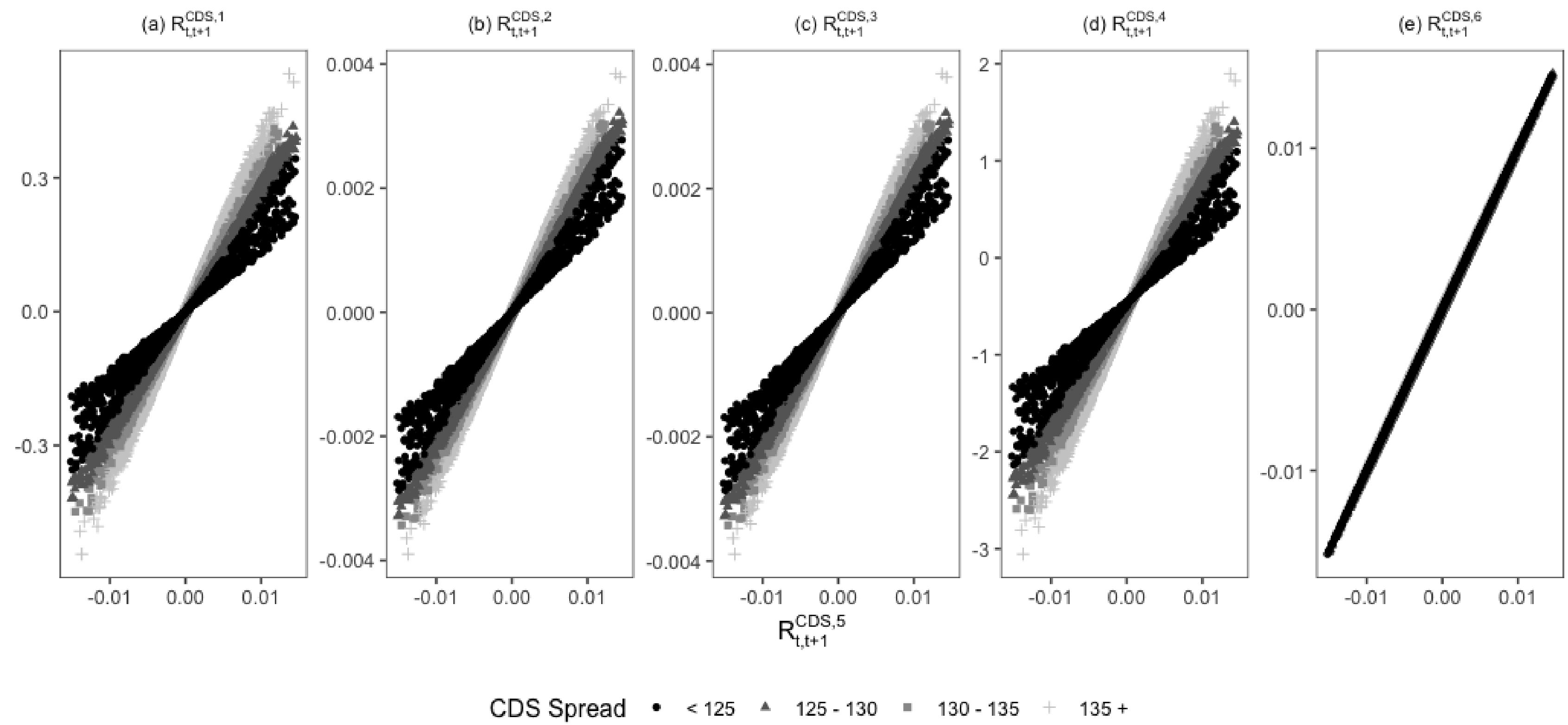


Figure 3.2: Scatterplot of CDS Return Correlations (High Yield)

These figures illustrate scatter-plots for realized daily CDS returns based on the true cash flow based CDS return calculations on the x-axis, against realized daily CDS returns computed using various approximated CDS return metrics on the y-axis. These figures are based on simulations of 50 years of daily data. It is assumed that the CDS spread s_t at time t follows the process $\Delta s_t = \theta(\mu - s_t) + \sigma\sqrt{s_t}\varepsilon_t$, where $\varepsilon_t \sim \mathcal{N}(0,1)$. For the simulation, we use the parameter values $\theta = .013$, $\mu = .06$, $\sigma = .004$. The fixed coupon c is assumed to be 500 bps. Each panel in Figure 3.2 compares the simulated time series of cash flow based CDS returns with a time series of returns computed using an approximated CDS return metric. Panel (a) uses simple changes in CDS spreads; Panel (b) uses simple percentage changes in CDS spreads; Panel (c) uses changes in the natural logarithms of CDS spreads; Panel (d) uses the CDS return metric from He, Kelly, and Manela (2017); Panel (e) uses our suggested approximation of CDS returns described in Equation (3.14). Source: Authors' computations.

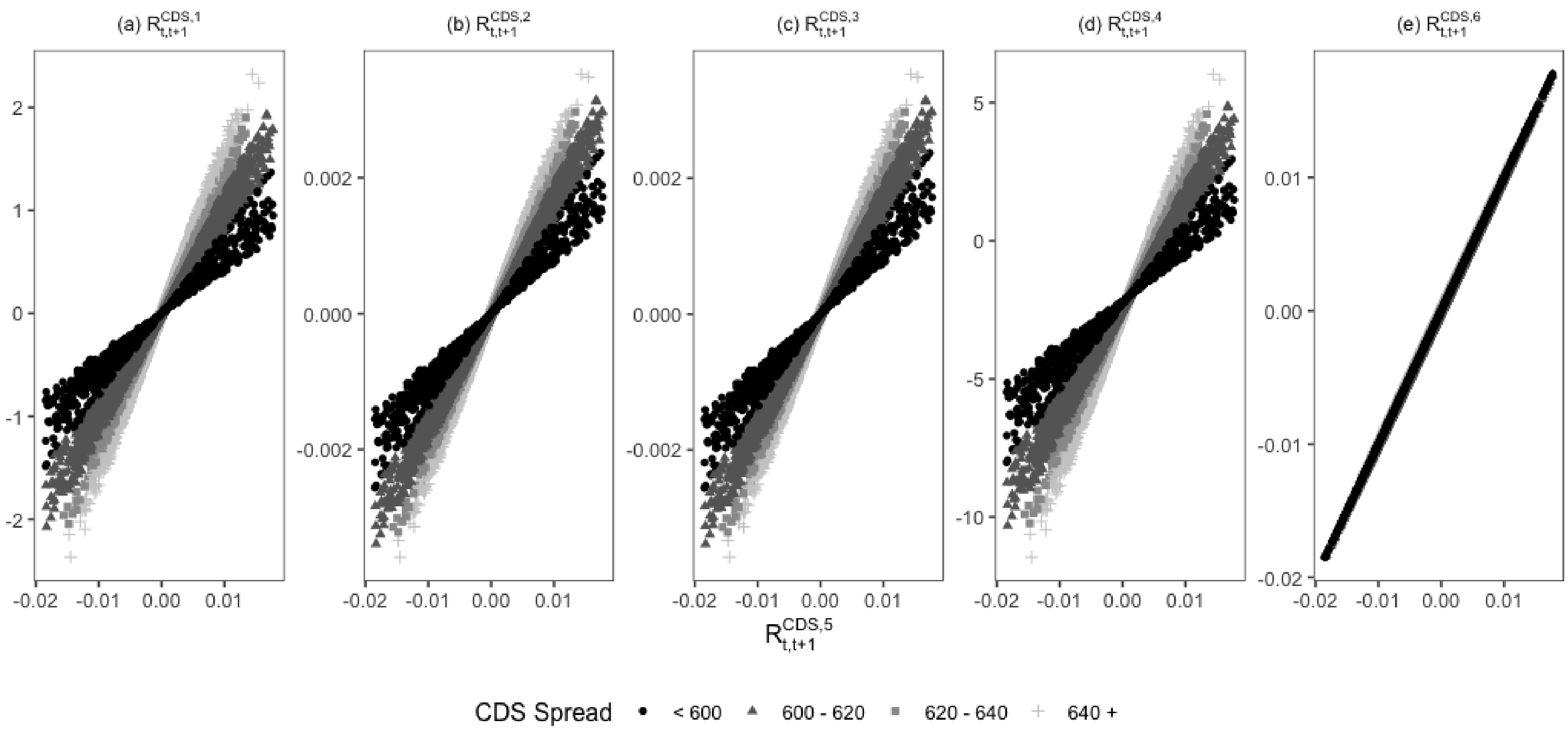


Figure 3.3: Scatterplot of CDS Return Correlations (Robustness)

These figures illustrate scatter-plots for realized daily CDS returns based on the cash flow-based CDS return calculations on the x-axis, against realized daily CDS returns computed using various approximated CDS return metrics on the y-axis. These figures are based on simulations of 50 years of daily data. It is assumed that the CDS spread s_t follows the ARG(1) process of Gourieroux and Jasiak (2006). Hence, we assume that the CDS spread follows the autoregressive process $s_{t+1} = \nu \cdot c + \phi s_t + \eta_{t+1}$, where η_{t+1} represents a martingale difference sequence. We use $\phi = 0.9998$, $c = 5e - 8$, and $\nu = 50$. We set the fixed coupon, c, to 100 bps. Each panel in Figure 3.1 compares the simulated time series of cash flow-based CDS returns with a time series of returns computed using some approximated CDS return metric discussed in the body of the paper. Panel (a) uses simple changes in CDS spreads; Panel (b) uses simple percentage changes in CDS spreads; Panel (c) uses changes in the natural logarithms of CDS spreads; Panel (d) uses the CDS return metric from He, Kelly, and Manela (2017); Panel (e) uses our suggested approximation of CDS returns described in Equation (3.14). Source: Authors' computations.

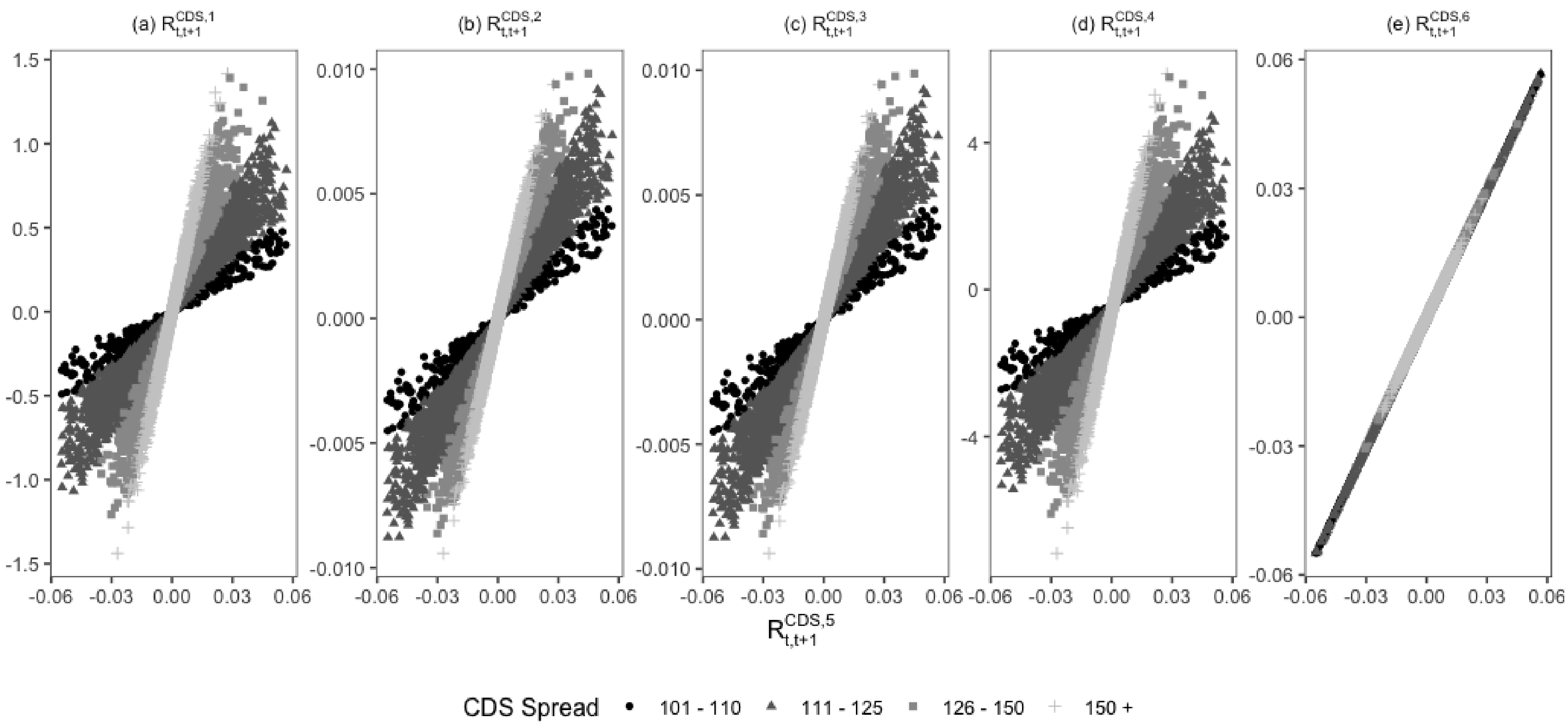
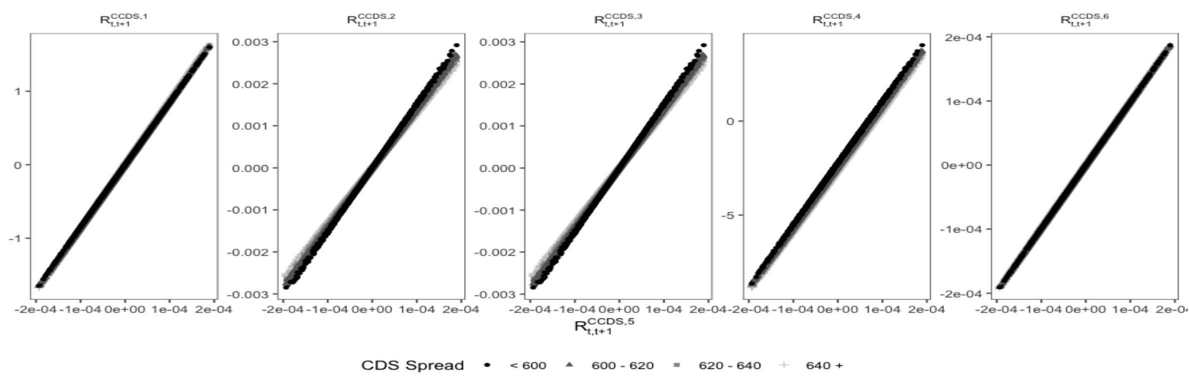


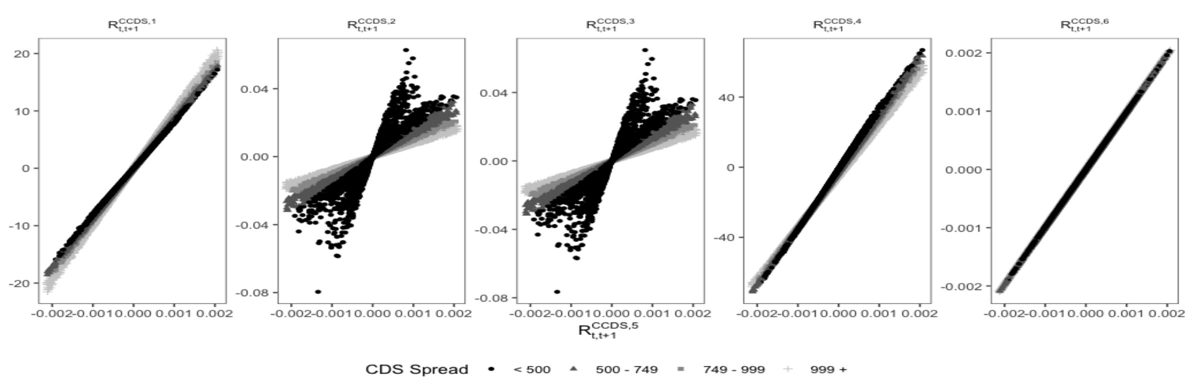
Figure 3.4: Scatterplot of Fully Collateralized CDS Return Correlations ($\phi = 1$)

These figures illustrate, using scatter-plots, the relation between daily cash flow based CDS returns on the x-axis and realized daily CDS returns computed using various approximated CDS return metrics on the y-axis. These figures are based on simulations of 50 years of daily data. It is assumed that the CDS spread s_t at time t follows the process $\Delta s_t = \theta(\mu - s_t) + \sigma\sqrt{s_t}\varepsilon_t$, where $\varepsilon_t \sim \mathcal{N}(0,1)$. For the simulations in Panel (a), we use the parameter values $\theta = 0.013$, $\mu = 0.06$, $\sigma = 0.004$. For the simulations in Panel (b), we increase the volatility parameter to $\sigma = 0.04$. The fixed coupon c is chosen to be 500 bps. Each panel compares the simulated time series of cash flow based CDS returns, defined as $P_{t+1} - P_t$, with a time series of returns computed using an approximated CDS return metric. The left-most panel uses simple changes in CDS spreads; the second panel uses simple percentage changes in CDS spreads; the third panel uses changes in the natural logarithms of CDS spreads; the fourth panel uses the CDS return metric from He, Kelly, and Manela (2017); the right-most panel uses our suggested approximation of CDS returns $\widetilde{P}_{t+1} - \widetilde{P}_t$. Source: Authors' computations.

(a) Low Volatility



(b) High Volatility



Appendix

A CDS Price Approximation

We prove Proposition 3.3.1 in two steps. First, we establish coherence of λ_t, which in turn ensures that P_t, defined in Equation (3.11), is well-defined. Then, we establish Lemmas A.1 and A.2. Proposition 3.3.1 follows as a corollary of Lemma A.2.

A.1 Coherence of λ_t

We assume that credit spreads, interest rates, and recovery are non-negative (i.e. $s_t > 0, \forall \tau : r_t(\tau) \geq 0$ and $R \geq 0$). We also assume that $R < 1$. Further, we define the function $f_t(x)$ as:

$$\begin{aligned} f_t(x) \equiv \quad & (1-R)\sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{t_i-t} r_t(u)du}\right]\left[e^{-x(t_{i-1}-t)} - e^{-x(t_i-t)}\right] \\ & -s_t \sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{t_i-t} r_t(u)du}\right] e^{-x(t_i-t)}\Delta_i. \end{aligned} \tag{A.1}$$

The fact that $s_t \geq 0$ implies Equation (A.2):

$$f_t(0) = -s_t \sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{t_i-t} r_t(u)du}\right]\Delta_i \leq 0. \tag{A.2}$$

Moreover, the fact that $\forall\tau : r_t(\tau) \geq 0$ and $R \leq 1$ implies Equation (A.3):

$$f_t\left(\frac{s_t}{1-R}\right) \geq 0. \tag{A.3}$$

Equations (A.2) and (A.3) imply the existence of a default intensity $\lambda_t \in [0, \frac{s_t}{1-R}]$ that satisfies Equation (A.4) by the Intermediate Value Theorem. Moreover, $s_t > 0$ implies that $\lambda_t > 0$. All references to λ_t are thus consistent with values that satisfy Equation (A.4).

$$s_t \sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{t_i-t} r_t(u)du}\right] e^{-\lambda_t(t_i-t)}\Delta_i = (1-R)\sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{t_i-t} r_t(u)du}\right]\left[e^{-\lambda_t(t_{i-1}-t)} - e^{-\lambda_t(t_i-t)}\right]. \tag{A.4}$$

A.2 Proofs

Lemma A.1. $\lim\limits_{\Delta\to 0^+} \lambda_t = \frac{s_t}{1-R}$.

Consider any sequence of partitions $\{\Pi_k\}_{k=1}^{\infty} \equiv \{\bigcup\limits_{i=0}^{n_k}\{t_{k,i}\}\}_{k=1}^{\infty}$ of $[t, T]$, such that $\lim\limits_{k\to\infty} \Delta(\Pi_k) = 0$, with $\Delta(\Pi_k) \equiv \max\limits_i \Delta(\Pi_k)_i$, and $\forall i \in \{1, ..., n_k\} : \Delta(\Pi_k)_i \equiv t_{k,i} - t_{k,i-1} \geq 0$. In the following proof, we show that any convergent sub-sequence of $\{\lambda_t(\Pi_k)\}_{k=1}^{\infty} \subseteq \left[0, \frac{s_t}{1-R}\right]$ must converge to $\frac{s_t}{1-R}$, which implies the desired result.

Let $g : \mathbb{N} \mapsto \mathbb{N}$ be a strictly increasing function such that $\{\lambda_t\left(\Pi_{g(k)}\right)\}_{k=1}^{\infty}$ denotes an arbitrary convergent sub-sequence of $\{\lambda_t(\Pi_k)\}_{k=1}^{\infty}$. For exposition, we define $L \equiv \lim\limits_{k\to\infty} \lambda_t(\Pi_{g(k)})$. We start with Equation (A.4) and then take limits on both sides. Applying the assumed conditions yields Equation (A.5):

$$s_t \int\limits_0^{T-t} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{z} r_t(u)du}\right] e^{-Lz}dz = (1-R)\, L \int\limits_0^{T-t} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{z} r_t(u)du}\right] e^{-Lz}dz, \tag{A.5}$$

which in turn implies that $\lim\limits_{k\to\infty} \lambda_t\left(\Pi_{g(k)}\right) = \frac{s_t}{1-R}$, thereby completing the proof.

Lemma A.2. $\lim\limits_{\Delta\to 0^+} P_t = (s_t - c) \int\limits_0^{T-t} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int\limits_0^{z} r_t(u)du}\right] e^{-\frac{s_t}{1-R}z}dz.$

Using $DF_t(z) = \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^z r_t(u)du}\right]$ and taking limits on both sides of Equation (3.11) yields Equation (A.6):

$$\lim_{\Delta \to 0^+} P_t = \lim_{\Delta \to 0^+} (s_t - c) \sum_{i=1}^{n} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_0^{t_i - t} r_t(u)du}\right] e^{-\lambda_t (t_i - t)} \Delta_i. \tag{A.6}$$

Then, invoking Lemma A.1 and $e^{-x} \in \mathcal{C}^1$ delivers the desired result.

B Simulating CDS-Equity Return Regression Coefficients

This section describes the detailed steps for the simulation of hedge ratios between equity and bond prices, approximated using CDS return metrics.

B.1 Simulation

We assume that the annualized interest rate $r = 5\%$, the time to maturity is $M = 10$ years, the level of outstanding debt is equal to $D = 1$ (normalization), and the coupon is $c = 25$ bps. For the simulation parameters, we choose $N = 1000$ as the number of simulation paths, and $T = 25$ (months) as the number of time steps per path. Across the different paths, we vary initial leverage in the range $L_0 \in \{50\%, 60\%, 70\%, 80\%, 90\%\}$, and annualized asset volatility in the range $\sigma_A \in \{20\%, 25\%, 30\%, 35\%, 40\%, 45\%, 50\%\}$.

For the simulation procedure, we describe the initialization and the iterations. We initialize each simulation path n for some fixed value of asset volatility, σ_A, and leverage, L_0. The initial asset value is then computed as $A_0^n = L_0^{-1} e^{-rM}$, which derives from the fact that $L_0 = PV(1) / PV(A_T^n) \Leftrightarrow L_0 = e^{-rM} / A_0^n$. The Value of equity at time t, E_t^n, is initialized by the equation $E_0^n = Call(A_0^n, 1, r, M, \sigma_A)$, where $Call(A, D, R, \tau, \sigma)$ denotes the Black-Scholes-Merton implied price for a European call option with underlying asset value A, strike price D, interest rate R, expiration τ, and underlying volatility σ. The value of debt at time t, D_t^n, is initialized by the equation, $D_0^n = A_0^n - E_0^n$. The implied spread at time t, s_t^n, is initialized by the equation, $s_0^n = -M^{-1} \log(D_0^n) - r$. Assuming a fixed coupon of c bps and a fixed recovery rate of 40%, the approximate upfront cash-amount to be paid when trading a CDS contract at time t, $\widetilde{P}_{s,t}^n$ is initialized by the equation

$$\widetilde{CDS}_0^n = (s_0^n - c) \frac{\left(1 - exp\left[-\left(r + \frac{s_0^n}{0.6}\right) M\right]\right)}{r + \frac{s_0^n}{0.6}}. \tag{B.1}$$

The true upfront cash-amount at time t, $P_{s,t}^n$ is initialized by the equation $P_{s,0}^n = P(s_0^n, c, r, M)$, where $P(s, k, R, \tau)$ is the ISDA up-front price for a CDS contract with spread s, coupon k, time to maturity τ, and assuming a flat term structure of interest rates with level R. This computation is based on the publicly available ISDA code (http://www.cdsmodel.com/cdsmodel/).

For the iterations, from $t = 0$ to $T - 1$, we compute

$$A_{t+1}^n = A_t^n \exp\left[\frac{r - \frac{1}{2}\sigma_A^2}{12} + \sigma_A \varepsilon_{t,t+1}^{\sigma_A, L_0, n}\sqrt{\frac{1}{12}}\right], \tag{B.2}$$

where $\forall \sigma_A, L_0, n \in \{1, ..., N\}, t \in \{0, ..., T-1\} : \varepsilon_{t,t+1}^{\sigma_A, L_0, n} \stackrel{d}{=} N(0,1)$. We note that the various subscripts and superscripts indicate that a new innovation is drawn for each combination of time-step ($t \in \{0, ..., T-1\}$), simulated path ($n \in \{1, ..., N\}$), asset volatility level (σ_A), and initial leverage value (L_0). For each simulation step, we compute

$$
\begin{aligned}
E_t^n &= Call\left(A_t, 1, r, M, \sigma_A\right) && \text{(B.3)}\\
D_t^n &= A_t^n - E_t^n && \text{(B.4)}\\
s_t^n &= -\frac{1}{M}\log\left(D_t^n\right) - r && \text{(B.5)}\\
\widetilde{P}_{s,t}^n &= \left(s_t^n - c\right)\frac{\left(1 - exp\left[-\left(r + \frac{s_t^n}{0.6}\right)M\right]\right)}{r + \frac{s_t^n}{0.6}} && \text{(B.6)}\\
P_{s,t}^n &= P(s_t^n, c, r, M). && \text{(B.7)}
\end{aligned}
$$

Given the constant maturity nature of CDS contracts, we keep the debt maturity constant throughout the simulations. We also do not change the notional of the debt maturity. For each iteration, we compute the equity return, the spread change, the spread return, the log spread change, the CDS return, and the approximate CDS return, defined as:

$$
\begin{aligned}
P_{t,t+1}^{E,n} &\equiv \frac{P_{t+1}^{E,n} - P_t^{E,n}}{P_t^{E,n}} && \text{(B.8)}\\
R_{t,t+1}^{1,n} &\equiv s_{t+1}^n - s_t^n && \text{(B.9)}\\
R_{t,t+1}^{2,n} &\equiv \frac{s_{t+1}^n - s_t^n}{s_t^n} && \text{(B.10)}\\
R_{t,t+1}^{3,n} &\equiv \log(s_{t+1}^n) - \log(s_t^n) && \text{(B.11)}\\
R_{t,t+1}^{4,n} &\equiv \frac{P_{s,t+1}^n - P_{s,t}^n}{P_{s,t}^n} && \text{(B.12)}\\
R_{t,t+1}^{5,n} &\equiv \frac{\widetilde{P}_{s,t+1}^n - \widetilde{P}_{s,t}^n}{\widetilde{P}_{s,t}^n}. && \text{(B.13)}
\end{aligned}
$$

B.2 Regression

For each path and for each metric, $\{R^{i,n}_{t,t+1}\}^{T-1}_{t=0}$, we estimate the model

$$R^{i,n}_{t,t+1} = \alpha^{i,n}_0 + \alpha^{i,n}_1 R^{E,n}_{t,t+1} + u^{i,n}_{t,t+1} \tag{B.14}$$

using simple OLS regressions and retrieve a point estimate, $\widehat{\alpha}^{i,n}_1$, and the associated asymptotic z-statistic, $z_{\alpha^{i,n}_1}$. For a given σ_A and L_0, we average across all simulation paths to obtain a single point estimate, $\widehat{\alpha}^i_1 \equiv \frac{1}{N}\sum_{n=1}^{N} \widehat{\alpha}^{i,n}_1$ and a single asymptotic z-statistic, $z_{\alpha^i_1} \equiv \frac{1}{N}\sum_{n=1}^{N} z_{\alpha^{i,n}_1}$.

C Summary Statistics of CDS Returns

Table C.1: Summary Statistics of CDS Returns - Investment Grade

This table provides summary statistics for a sample of 25 U.S. investment-grade daily CDS spread return series computed using different return metrics. We use USD denominated 5-year CDS contracts with the no-restructuring credit event clause. We report each reference entity's ticker, the mean (in bps) and standard deviation (in bps) for 5 CDS return metrics. $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1 + s/4(1-R))$, $R^{CDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{P_t}$, $R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$, $R^{CCDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{\phi}$, $R^{CCDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\phi}$, where $\phi = 1$. $R^{CDS,5}_{t,t+1}$, $R^{CCDS,5}_{t,t+1}$, $R^{CDS,6}_{t,t+1}$, and $R^{CCDS,6}_{t,t+1}$ are computed using a coupon of 100 bps. All data pertain to the period from May 2009 (2009Q2) to September 2016 (2016Q3). Sources: Markit and authors' computation.

Investment Grade																
Ticker	$R^{CDS,1}_{t,t+1}$		$R^{CDS,2}_{t,t+1}$		$R^{CDS,3}_{t,t+1}$		$R^{CDS,4}_{t,t+1}$		$R^{CDS,5}_{t,t+1}$		$R^{CDS,6}_{t,t+1}$		$R^{CCDS,5}_{t,t+1}$		$R^{CCDS,6}_{t,t+1}$	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
AXP	-0.26	4.02	-10.70	337.40	-16.33	334.88	-1.58	19.29	1.27e+3	6.48e+4	1.26e+3	6.48e+4	-1.10	18.22	-1.08	17.74
BA	-0.10	1.86	-9.92	225.61	-12.43	223.43	-0.74	8.98	36.61	1.66e+4	37.68	1.66e+4	-0.47	8.86	-0.46	8.64
CAT	-0.10	2.97	-6.99	271.38	-10.66	270.63	-0.78	14.24	1.37e+3	4.15e+4	1.37e+3	4.16e+4	-0.45	13.72	-0.43	13.35
CSCO	-0.02	1.51	-0.56	261.47	-3.98	261.76	-0.32	7.35	10.05	5.01e+3	10.12	5.02e+3	-0.09	7.41	-0.09	7.25
CVX	-0.03	0.92	-5.77	238.17	-8.58	236.63	-0.29	4.47	7.78	192.19	7.78	192.95	-0.16	4.88	-0.15	4.79
DD	-0.05	1.59	-2.92	275.44	-6.58	268.85	-0.44	7.72	-12.07	2.69e+3	-11.86	2.69e+3	-0.22	7.83	-0.21	7.65
DIS	-0.03	1.06	-3.91	271.41	-7.58	270.92	-0.27	5.12	7.28	215.97	7.31	217.50	-0.14	5.42	-0.13	5.32
GS	-0.11	7.59	0.07	410.97	-8.11	401.97	-1.17	36.74	1.43e+5	5.39e+6	1.43e+5	5.37e+6	-0.51	32.84	-0.50	32.07
HD	-0.06	1.56	-7.83	240.72	-10.66	236.57	-0.50	7.50	75.73	1.33e+4	75.21	1.33e+4	-0.29	7.53	-0.29	7.35
IBM	-0.01	1.08	0.90	274.79	-2.84	272.90	-0.22	5.23	4.67	204.48	4.70	206.94	-0.07	5.46	-0.06	5.37
INTC	-0.02	1.91	3.74	413.39	-3.18	363.76	-0.25	9.16	25.14	923.82	25.29	928.64	-0.09	9.38	-0.08	9.16
JNJ	-0.03	0.72	-6.27	211.21	-8.51	212.39	-0.25	3.49	4.82	129.57	4.84	131.24	-0.13	3.89	-0.12	3.83
JPM	-0.08	3.74	-1.40	375.71	-8.30	369.47	-0.76	18.14	-3.11e+14	1.17e+16	2.24e+5	9.32e+6	-0.39	17.76	-0.38	17.35
KO	-0.03	0.75	-5.27	177.55	-6.83	176.90	-0.28	3.61	5.55	144.37	5.57	146.22	-0.13	3.88	-0.12	3.83
MCD	-0.02	0.81	-1.82	259.07	-5.11	255.68	-0.20	3.90	3.46	138.83	3.50	140.39	-0.08	4.30	-0.08	4.24
MKCINC	-0.03	0.88	-6.02	163.16	-7.35	162.83	-0.35	4.27	8.24	237.58	8.28	238.37	-0.14	4.47	-0.14	4.37
MSFT	-0.00	0.95	3.37	285.38	-0.57	279.17	-0.16	4.62	1.58	162.35	1.59	163.67	-0.01	5.09	-0.01	4.99
NKE	-0.03	1.27	-3.29	220.18	-5.88	232.77	-0.32	6.15	13.05	468.97	13.04	468.42	-0.13	6.45	-0.13	6.30
PFE	-0.04	1.11	-5.83	223.18	-8.31	222.33	-0.38	5.35	14.16	344.19	14.19	345.13	-0.18	5.50	-0.18	5.38
PG	-0.05	1.04	-6.59	228.73	-9.19	227.21	-0.40	5.06	18.18	266.99	18.20	268.23	-0.23	5.29	-0.22	5.17
TRV	-0.06	2.29	-6.84	238.93	-9.65	236.08	-0.60	11.11	378.56	2.42e+4	378.53	2.42e+4	-0.29	10.89	-0.28	10.63
UNH	-0.12	2.38	-10.55	192.97	-12.42	192.79	-0.95	11.41	-82.64	5.15e+3	-82.72	5.14e+3	-0.54	10.96	-0.53	10.67
VZW	-0.03	3.30	6.20	507.42	-5.88	487.01	-0.41	16.04	-366.59	9.99e+3	-365.76	9.98e+3	-0.17	16.26	-0.16	15.85
WMT	-0.04	0.99	-7.87	226.84	-10.44	226.00	-0.36	4.78	11.43	237.07	11.46	238.09	-0.20	5.05	-0.20	4.95
XOM	-0.02	0.93	-4.16	303.33	-8.70	300.72	-0.22	4.50	4.62	160.50	4.63	161.31	-0.11	5.09	-0.11	4.99

Table C.2: Summary Statistics of CDS Returns - High Yield

This table provides summary statistics for a sample of 25 U.S. high-yield daily CDS spread return series computed using different return metrics. We choose 25 firms with the largest market capitalization among the universe of HY (credit rating BB+ or lower) Markit firms with less than 10% of missing data during our sample period. We use USD denominated 5-year CDS contracts with the no-restructuring credit event clause. We report each reference entity's ticker, the mean (in bps) and standard deviation (in bps) for 5 CDS return metrics. $R^{CDS,1}_{t,t+1} \equiv s_{t+1} - s_t$, $R^{CDS,2}_{t,t+1} \equiv \frac{\Delta s_{t+1}}{s_t}$, $R^{CDS,3}_{t,t+1} \equiv \log \frac{s_{t+1}}{s_t}$, $R^{CDS,4}_{t,t+1} = -\frac{s_t}{250} + \Delta s_{t+1} RD_t$, where $RD_t = \frac{1}{4}\sum_{j=1}^{4(T-t)} e^{-j\gamma/4} e^{-jr_f/4}$, $\gamma = 4\log(1+s/4(1-R))$, $R^{CDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{P_t}$, $R^{CDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\widetilde{P}_t}$, $R^{CCDS,5}_{t,t+1} = \frac{P_{t+1}-P_t}{\phi}$, $R^{CCDS,6}_{t,t+1} = \frac{\widetilde{P}_{t+1}-\widetilde{P}_t}{\phi}$, where $\phi = 1$. $R^{CDS,5}_{t,t+1}$, $R^{CCDS,5}_{t,t+1}$, $R^{CDS,6}_{t,t+1}$, and $R^{CCDS,6}_{t,t+1}$ are computed using a coupon of 100bps (500bps) if the average sample CDS spread is 300bps or lower (higher). All data pertain to the period from May 2009 (2009Q2) to September 2016 (2016Q3). Sources: Markit and authors' computation.

High Yield																
Ticker	$R^{CDS,1}_{t,t+1}$		$R^{CDS,2}_{t,t+1}$		$R^{CDS,3}_{t,t+1}$		$R^{CDS,4}_{t,t+1}$		$R^{CDS,5}_{t,t+1}$		$R^{CDS,6}_{t,t+1}$		$R^{CCDS,5}_{t,t+1}$		$R^{CCDS,6}_{t,t+1}$	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
AES	-0.28	9.95	-3.12	251.27	-6.27	250.94	-2.72	47.36	-6.95e+14	3.96e+16	4.01e+3	1.60e+5	-1.23	42.20	-1.18	41.17
ASH	-0.34	4.65	-8.19	157.97	-9.44	157.80	-2.40	22.10	-6.65	380.48	-7.08	379.86	-1.19	17.48	-1.18	17.04
AVP	0.35	13.29	18.00	314.63	13.17	308.56	0.34	62.68	-2.49e+3	9.51e+4	-2.49e+3	9.52e+4	1.52	47.78	1.52	46.93
BLL	-0.07	2.59	-2.51	142.24	-3.49	139.62	-0.97	12.37	-153.11	6.26e+3	-153.83	6.27e+3	-0.27	11.84	-0.27	11.58
BTU	28.49	447.13	40.05	540.65	30.43	401.64	96.11	1659.37	44.84	1.03e+3	44.62	1.03e+3	5.95	69.09	5.96	68.85
CHK	0.99	115.71	12.14	406.95	4.20	395.73	1.96	483.85	-487.54	9.58e+3	-487.75	9.58e+3	1.07	91.06	1.05	90.40
CTL	0.13	6.41	11.43	274.95	7.70	271.99	-0.27	30.93	-51.41	3.47e+3	-51.69	3.47e+3	0.62	27.23	0.59	26.71
CVC	0.17	11.24	6.16	261.43	2.91	252.28	-0.81	53.59	-5.87e+3	2.60e+5	-5.87e+3	2.60e+5	0.63	46.44	0.63	45.43
DISH	-0.00	8.53	3.60	268.60	0.05	265.88	-1.21	40.94	-88.03	7.72e+3	-88.47	7.72e+3	-0.09	39.48	-0.05	38.62
DVA	-0.19	8.83	-2.46	337.30	-7.94	330.66	-1.94	42.75	11.93	1.11e+3	11.56	1.11e+3	-0.73	37.38	-0.74	36.66
FTR	0.12	11.56	5.54	252.85	2.32	254.73	-1.12	55.22	-4.28e+3	1.40e+5	-4.29e+3	1.40e+5	0.46	46.64	0.46	45.69
GPS	0.15	4.75	14.48	284.53	10.50	280.67	0.17	22.97	-77.82	6.41e+3	-78.20	6.41e+3	0.70	20.83	0.68	20.48
GT	-0.33	13.16	-4.73	265.76	-8.22	263.74	-3.20	62.56	-1.53e+4	6.30e+5	-1.53e+4	6.30e+5	-1.48	51.40	-1.43	50.24
LB	-0.05	4.90	0.56	225.92	-1.97	224.45	-0.98	23.51	8.89	480.52	8.51	481.19	-0.15	21.61	-0.16	21.07
LEN	-0.13	8.20	-1.16	254.96	-4.36	252.43	-1.74	39.33	2.12	398.76	1.77	399.76	-0.43	32.12	-0.45	31.42
LVLT	-0.79	22.94	-10.74	248.15	-13.84	249.32	-6.16	105.66	220.65	8.17e+3	219.94	8.16e+3	-2.84	61.76	-2.78	60.37
MGM	-1.07	24.98	-8.18	267.67	-11.75	267.31	-7.28	115.43	41.99	2.94e+3	41.64	2.94e+3	-2.99	67.56	-2.94	66.29
MU	-0.00	1.07	-0.02	36.40	-0.08	35.91	-1.26	5.20	1.50	80.58	1.07	82.64	-0.10	7.02	-0.06	7.02
NFX	-0.02	10.05	8.70	507.05	-0.52	407.26	-0.82	48.50	-50.57	3.87e+3	-50.84	3.87e+3	-0.02	40.54	-0.03	39.80
OKE	0.14	5.10	10.34	240.84	7.62	229.84	0.08	24.41	-83.81	8.04e+3	-84.22	8.03e+3	0.65	19.37	0.63	19.10
PHM	-0.03	6.97	2.39	263.68	-1.04	261.24	-1.10	33.54	13.42	553.07	13.06	553.77	-0.06	28.06	-0.08	27.43
TSO	-0.10	8.91	1.40	276.90	-2.37	273.65	-1.65	42.64	8.36	450.79	8.01	451.77	-0.28	34.89	-0.30	34.13
UHS	-0.02	3.93	0.93	231.12	-1.65	225.26	-0.69	18.96	288.57	1.05e+4	287.80	1.05e+4	-0.07	17.36	-0.07	16.95
WMB	0.06	5.29	6.16	242.12	3.42	230.90	-0.42	25.27	-2.69e+3	9.34e+4	-2.69e+3	9.35e+4	0.30	20.43	0.28	20.08
YUM	0.06	3.38	7.85	275.53	4.33	260.84	-0.08	16.31	-99.26	8.74e+3	-99.80	8.74e+3	0.26	15.42	0.26	15.12

Chapter 4

Why does the CDS Term Structure Predict Equity Returns?

4.1 Introduction

Structural models of credit risk (Merton, 1974) suggest that equity and credit claims are driven by the same underlying firm's values. In the absence of frictions, these claims should be tightly linked to each other and should not contain superior information.

However, recent studies find that information is not revealed in these markets at the same time. There has been a debate in the literature on whether the credit market or the equity market is more informative (e.g. Acharya and Johnson, 2007; Hilscher, Pollet, and Wilson, 2015, Lee, Naranjo, and Velioglu (2018)).

Despite the debate on whether the equity or credit market contains superior information, most of these studies examine the relation between the equity and credit markets focusing on the level of the credit spreads. Nevertheless, this inference omits a significant amount of information embedded in the term structure of the credit spreads. To see this, Figure 4.1 plots the credit spreads term structure of three different firms on 2008-04-04. While the three firms have the same 5-year credit spread level (125 bps), they have completely different shapes of the term structure.

To fill this gap in the literature, this paper revisits the predictability between equity and credit markets by focusing on the term structure of the credit spreads. We find that the credit spread slope, defined as 10-year credit spread minus 1-year credit spread, has stronger predictive power than the credit spread level in predicting cross-section of the equity returns, consistent with the findings in Han, Subrahmanyam, and Zhou (2017).

Motivated by Figure 4.1, we further examine whether the credit spread slope has significant predictive power on the equity returns conditional on the CDS level. We conduct a double-sort analysis to form stock portfolios by sorting on the level of the credit spreads and the slope. A long short portfolio formed on the CDS slope for the high (low) credit quality firms category earns significant positive (negative) returns, indicating that the CDS slope positively (negatively) predicts the equity returns for high (low) credit quality firms.

Furthermore, we conduct a panel regression by projecting the future equity returns on the current CDS slope and its interaction with CDS spread level, as well as the high or low CDS spread level indicator variables. We find that the CDS slope has a significant positive (negative) effect on the future equity returns when interacting with low (high) credit spread levels.

To check whether such predictability is generated by informed trading in the CDS market, we perform the same panel regression by controlling for the firm's transparency proxies, such as CDS depth, idiosyncratic risk, size, institutional ownership, and analyst coverage, since the informed trading is likely to affect the equity predictability when the firm is less transparent. We show that the predictive power of the CDS slope is still significant conditional on CDS spread level, indicating that the predictive relation between the CDS slope and equity returns conditional on the CDS level, is not driven by the informed trading channel in the CDS market.

To understand the superior predictive power of the CDS slope compared to the CDS spread level, we adopt the classic stuctural credit risk framework (Leland, 1994) to examine the determinants of the equity returns and credit spread slope. Based on the Leland (1994) model, a firm's underlying dynamics can be characterized by the firm's default boundary and the asset volatility. We study whether the credit spread slope reflects information on the default boundary and the asset volatility by keeping the credit spread level constant.

First, since both the asset volatility and default boundary increases the firm credit risk, to produce the same credit spread level, an increase in the asset volatility corresponds to a decrease in the default boundary and vice versa. These two forces have different impacts on the long and short term credit spreads. For the long (short) term credit spreads, the impact of the changes of the asset volatility (default bounday) dominates that of the changes of the default boudnary (asset volatility), constrained on the same 5-year credit spread level. Therefore, the steeper the term structure is, the higher the asset volatility and the lower the default boundary is.

The cross-sectional difference of the default boundary and the asset volatility implied by the credit spread term structure are informative on the equity risk premium. To see this, we decompose the equity risk premium into the equity beta component and asset risk premium component. We show that these two components have different impacts on the equity risk premium conditional on firms with high (low) credit spread level, henceforth low (high) credit quality firms.

On the one hand, the equity risk premium of the high credit quality firm is mainly driven by the asset risk premium. The high credit quality firm is likely to be far away from default. In this case, the equity value is very close to the asset value, and the equity beta is relatively much more stable than the asset risk premium. Since the asset risk premium is crucially dependent on the asset volatility, the credit spread slope positively predicts the equity returns.

On the other hand, the equity risk premium of the low credit quality firm is mainly driven by the equity beta. The low credit quality firm is likely to be close to default. Under this circumstance, the equity value is close to zero and the equity beta is much more volatile than the asset risk premium. The higher (lower) the default boundary (asset volatility) is, the smaller the equity value and the larger the equity beta is. Therefore, the credit spread slope negatively predicts the equity returns.

To further justify that the economic channel in the model is responsible for the different predictability between CDS slope and equity returns conditional on different types of firms, we simulate the Leland (1994) model to generate a panel data. By replicating the same double-sort and panel regression exercise as the empirical analysis, we find qualitatively similar results as the results based on the market data. This again supports our conjecture that the predictive power of the CDS slope arises because the CDS slope reflects the additional information on the default boundary and asset volatility.

Our work contributes to the debate on the predictability between equity and credit markets, by showing two different predictive relations between the credit spread term structure and equity returns, conditional on high and low credit spread level. It highlights the importance of focusing on the credit spread term structure in studying the relation between these two markets.

This paper is organized as follows. Section 4.2 presents a preliminary analysis of the predictability between the equity and credit markets. Section 4.3 documents the empirical evidence on the predictive power of credit spread term structure conditional on the credit spread level. In section 4.4, we provides a theoretical framework in understanding the information content of the credit spread term structure and how it is related to the equity risk premium. Section 5.7 concludes.

4.2 Preliminary analysis

In this section, we conduct preliminary analysis to understand the predictive relation between the equity and credit market. First, we provide a data description. Second, we study the predictability between the equity and credit market by focusing on both the credit spread level and term structure.

4.2.1 Data

We obtain CDS quotes from MARKIT. Our sample period covers from January 2001 to March 2018. We restrict our sample to consist only of US entities and non government sectors. We keep only the US dollar-denominated CDS and the CDS observations belonging to the senior unsecured tier. Furthermore we drop any observations with missing values of the CDS for the following maturities: 1, 2, 3, 5, 7, and 10 years.

We obtain stock monthly data from CRSP. We manually match the CRSP "PERMCO" and MARKIT "REDCODE" company identifiers by checking the company names of the two datasets. We also manually filter out the matchings such as parent-subsidiary matching. For example, if the AT&T Inc. matches with AT&T Corp, we drop such matchings.

Table 5.1 documents the sample cross-sectional descriptive statistics. We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics. Our sample contains 733 firms with 74,770 firm-month observations from January 2001 to March 2018. The cross-sectional average 5-year CDS spreads is 260 bps and the average of CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, is 80 bps. The median firm in the sample has a leverage of 18.5%, equity volatility of 0.3, log market capitalization of 8.7, and BBB rating. This is consistent with the total Compustat sample median documented in the previous literature (e.g. Feldhütter and Schaefer, 2018), indicating that our sample is representative of the Compustat universe.

4.2.2 The predictability between equity and credit markets

In this section, we revisit the predictability between the credit and equity market, using the credit spread term structure in contrast to the credit spread level. As a first step, we examine the unconditional relation between the credit spread slopes[1] and equity future returns.

To study the cross-sectional predictability between the credit spread level (slope) and equity returns, we document the stock portfolio one month ahead returns sorted by the CDS spread level or slope. We first sort the stocks into 10 deciles based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Second, for each decile, we

[1] Although the CDS spread contains illiquidity component, Bongaerts, De Jong, and Driessen (2011) find that such component is economically insignificant. Hence, we omit such effect for simplicity and introduce CDS depth as a control variable for regressions. Nevertheless, the illiquidity might impact the long and short term CDS spreads differently. It will be interesting to exclude the illiquidity noise embedded in the CDS spread level and slope in a, e.g. reduced form manner, and to use this clean measure to study the predictability between the equity and credit market. We leave this for future work.

compute the equal weighted equity one month ahead return. Lastly, we compute the low slope - high slope long short portfolio return.

Table 4.2 reports the empirical results. We find that higher credit spread level (slope) deciles have higher (lower) equity future returns than lower credit spread level (slope) deciles on average. The low - high portfolio return is not significant for the portfolio sorted by CDS spread level, but significantly positive at 10% confidence level without being corrected by the Newey West method, for the portfolio sorted by CDS spread slope. However, it is not significant after being corrected by the Newey west method. In this exercise, we provide weak evidence that the credit spread slope negatively predicts the equity returns, consistent with the findings in Han, Subrahmanyam, and Zhou (2017). Furthermore, the credit spread slope exhibits more accurate predictive effect compared to the credit spread level.

As an alternative test, we perform the following panel regression by projecting the one month ahead equity returns on the CDS spread level and slope.

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta Var_t + Y_{i,t}'\beta_Y + \epsilon_{i,t} \tag{4.1}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, Var_t denotes either the CDS spread level or slope, which is defined as 10-year CDS spreads minus 1-year CDS spreads, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, and stock daily return.

Table 4.3 reports the regression results. Columns (3) and (7) reports the results of the same regression by substituting the year-month fixed effect into quarterly fixed effect with additional macroeconomic controls. The macroeconomic control variables include CBOE VIX index, 10-year treasury yield, treasury yield slope, defined as 10-year yield minus 2-year yield, default spread, and TED spread.

The CDS spread level is not significant in predicting the equity returns while the CDS spread slope is significant at 10% confidence level for all regression specifications. Furthermore, the encompassing regression (9) shows that the predictive effect of the credit spread slope survives after controlling for the credit spread level. This again suggests that the information set for the predictability between the credit and equity market improves by incorporating the term structure information of the CDS spreads.

To understand why the credit spread slope has a more accurate prediction on the equity return as documented in the previous section, we examine the credit spread term structures of three different firms with the same 5-year credit spread level at a given day. Figure 4.1 shows that firms could have very different shapes of the term structure even if they have the same credit spread level. These shapes might contain important information on the equity risk premium. In the following section, we provide a theoretical analysis on the information content of the CDS slope and how it relates to the equity returns.

4.3 The predictive power of CDS slopes conditional on CDS levels

To further justify that the CDS slope contains larger information set than the CDS level, first, we perform both the double sort exercise and the panel regression analysis to study the predictive power of the slope on the equity returns conditionl on the level. Second, we perform several robustness checks to rule out the possible explanation of the predictive relaion between the equity returns and CDS term structure.

4.3.1 Stock portfolios sorted on CDS levels and slopes

To examine the relation between CDS slopes and future equity returns conditional on CDS levels, we perform a bivariate dependent-sort portfolio analysis (Engle, Bali, and Murray, 2016).

At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each three terciles, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, into five quintiles. Third, for each group, we compute the equal-weighted one-month ahead portfolio's returns. Fourth, within each CDS tercile, we compute the low slope quintile minue high slope quintile portfolio return. Finally, we compute the time series averages of these portfolio returns and compute the t-statistics corrected under the Newey West method.

Figure 4.2 presents a visual summary of the double sort exercise and Table 4.4 reports the statistical results. Visually, we see that conditional on low (high) credit spread level, the future equity returns are increasing (decreasing) with the CDS slope. These patterns are statistically significant. The long short portfolio, defined as low slope portfolio minus high slope portfoilo, earns significantly negative (positive) returns, for the low (high) CDS spread level tercile. This evidence suggests that the credit spread term structure contains additional information beyond the credit spread level. The sign of the predictability between the CDS slope and equity returns are different conditional on high and low credit spread level.

To further justify this pattern, we perform a panel regression by projecting the future equity returns on the CDS slope and its interaction with high and low credit spread levels. The regression specification is described below:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t \times Slope_t + \beta_l Level_t + Y_{i,t}'\beta_Y + \epsilon_{i,t} \tag{4.2}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 500 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively. α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads.

Table 4.5 reports the regression results. The coefficients of $Level_t \times Slope_t$ under the 3 different specifications of $Level_t$ are significant. This indicates that the credit spread slopes have significantly different predictive effects on the equity returns, conditional on different credit spread levels. In particular, the coefficients of $D_{highCDS,avg} \times Slope$ ($D_{lowCDS,avg} \times Slope$), $D_{highCDS,500bp} \times Slope$ ($D_{lowCDS,50bp} \times Slope$), and $CDS_{5y} \times Slope$ are significantly negative (positive). This suggests that conditional on high (low) credit spread level, the predictive effect of the CDS slope becomes more negative (positive). Furthermore, $\beta_u + \beta_c$ is positive (negative) for firms with low (high) CDS spread level. This again supports that the CDS slope positively (negatively) predicts the equity returns for firms with low (high) CDS spread level.

Given such interesting patterns in the data, we discuss several economic mechanisms which might give rise to such results. To begin with, CDS spreads are affected by variance risk, which can be influenced by growth opportunities of a firm. Intuitively speaking, the more idiosyncratic the firm is, the lower the credit spread slope is (Augustin, 2018). A firm that possesses many growth opportunities is usually more idiosyncratic and hence subject to lower equity risk premium. This can create a positive relation between the credit spread slope and equity future returns for low credit spread firms. To account for such channel, we incorporate firm size as a control variable to proxy growth opportunities, since a small firm is likely to have more growth opportunities.[2] The relation between the CDS slope and equity return still remains.

Another potential channel for the result is that the CDS slope contains forward-looking information about the downside risk of the equity market. Furthermore, equity returns can be skewed based on its P-measure. This might also show up in the CDS slope information content. To control these channels, we first incorporate a time fixed effect, which will absorb any market risk. We then incorporate a number of firm specific controls such as leverage, equity volatility, size, rating, etc, which proxy the equity P-distribution property. Our result is robust given such controls.

[2]In an unreported result, we also introduce idiosyncratic risk as a control variable. The result remains.

Furthermore, these results are not driven by the financial crisis period. During the financial crisis, the Securities and Exchange Commission (SEC) issued an emergency ban on short sale for all financial stocks. Literature documents that this can induce the informed traders choosing the derivatives market to exercise their trades (Ni and Pan, 2020, etc.), resulting in CDS slope predicting equity returns. Our similar empirical evidence reported with and without financial crisis indicates that these predictive patterns are not likely to be driven by stock short selling.

In sum, we find strong empirical evidence that the CDS slope has additional predictive power on the equity returns conditional on the credit spread level. It positively predicts the equity returns for high credit quality firms but negatively predicts the equity returns for low credit quality firms. Not surprisingly, due to these two opposite signs of predictability, unconditionally, we find a weak predictabitive relation between the CDS slope and equity returns documented in section 4.2.

4.3.2 Different slope definitions

The computation of credit spread slope is crucially dependent on our selection of the maturity. To examine whether the empirical results are robust across different credit spread slope definitions, we conduct the double-sort and panel regression exercises using the CDS slope defined as 10-year CDS spread minus 2-year CDS spread, and 5-year CDS spread minus 1-year CDS spread.

Table 4.10 reports the double-sort results and Table 4.11 reports the results of the panel regression following Equation (4.2), based on the different credit spread slope definition. We find robust results that the CDS slope positively (negatively) predicts the equity returns conditional on firms with low (high) credit spread level. The results are highly significant across different slope definitions. This suggests that the predictive relation between the CDS slope and equity returns is not affected by the credit spread slope definition.

4.3.3 The impact of informed trading

Acharya and Johnson (2007) shows that the CDS market is more informative than the equity market, since the banks acquire non-public information through the lending relationship with debtors and use it in the trading of CDSs. Han, Subrahmanyam, and Zhou (2017) documents that the predictive power of the CDS slope on the equity market can also come from the informed trading behaviour in the CDS market. In particular, they show that the predictive effect of the slope are stronger conditional on the firms with low visibility. To examine whether the predictive power of the slope conditional on different credit spread level is purely driven by the informed trading channel, we perform the same regression following Equation (4.2) with an additional term by interacting the CDS slope with the firm's transparency proxies, such as the firm's CDS depth, idiosyncratic risk (Idiosyn), institutional ownership (IO), analyst coverage (# Analyst), and market capitalization

Table 4.12 documents the regression results. Both the coefficients of $D_{\text{highCDS}} \times Slope$ and $CDS_{5y} \times Slope$ are significantly negative across different firm's transparency proxies. The coefficient of $D_{lowCDS} \times Slope$ is significantly negative. This indicates that controlling for the informed trading proxies, the CDS slope still has significantly more negative (positive) predictive effect on the equity returns, conditional on high (low) credit spread levels. Furthermore, the economic magnitudes of the coefficients are similar across all regressions and similar to the regressions in Table 4.5. This suggests that the predictive effect of the CDS slope conditional on different CDS levels is not completely driven by the CDS informed trading.

4.3.4 The impact of industry effect

The CDS slope might contain not only the firm fundamental information content, but also industry-wide effects, since an industry wide shock - related, for example, to technology, collateral, supply chain, Covid led demand shocks etc. - can have diffused effects on all firms. These industry-wide effects can also impact the equity risk premium. Hence, it is possible that the predictability of the equity returns comes from the industry wide information content embedded in the CDS slope.

To rule out such explanation, we re-perform Regression (4.2) by introducing an additional industry fixed effect, where the industry definitions are based on Fama-French definition. Table 4.13 reports the results. All interaction variable coefficients have the same signs and similar magnitude as those in Table 4.5. Furthermore, almost all interaction variables are significant at 5% confidence level. Therefore, industry-wide effects are not likely to be the main drivers of the predictive patterns between the CDS slope and equity returns.

4.3.5 Corporate bond market

To examine whether the predictive relation between the credit spread slope and equity returns only exists in the CDS market, we also perform the main analysis using the corporate bond data.

We obtain the corporate bond yield data from WRDS Bond Returns. We interpolate the yield curve to generate bond yields with 2, 5, and 10 years to maturity.[3] Figure G.1 plots the time series of the aggregate CDS spreads and bond credit spreads for maturities of 1, 5, and 10 years. Quantitatively, the 2-year, 5-year, and 10-year bond credit spreads have a correlation of 87%, 84%, and 90% with the CDS spreads, respectively. This indicates that the credit spreads observed from the corporate bond market are similar to those observed in the CDS market. We remove observations with missing values of bond yield with 2, 5, 10 years to maturity. This leaves us with an unbalanced panel data of 5,570 firm-month observations with 153 firms. We define the credit spread slope as 10-year bond yield minus 2-year bond yield. The results are qualitatively similar using other maturities.

Table 4.14 documents the double-sort results and Table 4.15 reports the panel regression results following Equation (4.2). Due to data limitation, we sort the firms into tercile rather than quintile based on the slope. Qualitatively, the implication is consistent with the empirical results in the previous sections. Not surprisingly, the results are statistically

[3]Since the corporate bond data is very illiquid for maturity below 1 year, we interpolate to generate 2-year bond yield instead of 1-year.

weaker compared to the results based on the CDS data, since the corporate bond data is much noisier than the CDS data. The long-short portfolio returns sorted by the bond yield slope for the low credit quality firms are significant, but the long-short portfolio returns for the high credit quality firms are not significant. Furthermore, the coefficients of the $D_{\text{lowYield}} \times Slope$ and $D_{\text{highYield}} \times Slope$ are weakly significant across most of the regression specifications. This suggests that the two different predictive relations between the credit spread slope and equity returns conditional on high and low credit quality firms are weakly supported by the corporate bond data.

4.4 Theoretical framework

In this section, we apply the classic Leland (1994) framework[4] to understand 1) the predictive power of the credit spread slope on equity returns, conditional on the credit spread level; 2) the different signs of the predictability conditional on high and low credit spread level.

Following Leland (1994), we assume that the firm value is assumed to follow the following Geometric Brownian Motion:

$$\begin{aligned} \frac{dV_t}{V_t} &= \mu^P dt + \sigma dW_t^P \\ &= r dt + \sigma dW_t^Q, \end{aligned} \tag{4.3}$$

under the physical and risk neutral measure, respectively. $\mu^P = r + \lambda\sigma$, where λ is the market price of risk. Suppose that the firm issues a perpetual debt that pays a coupon C per instant of time if the firm is solvent. The firm defaults when the asset value V_t falls below the default boundary V_d for the first time. The firm enjoys tax benefits but is subject to bankruptcy cost α at default. We denote the tax rate to be τ. Following Leland (1994),

[4] Although the Leland (1994) model does not provide finite maturity debt, one can think of finite maturity bonds as STRIPS issued by an investment bank. Several papers study finite maturity credit claims using Leland (1994) type of model (Du, Elkamhi, and Ericsson, 2019). Ultimately, the main goal of this paper is to provide intuition on the mechanism behind the equity predictability. Hence we stick to the Leland (1994) to provide more tractability. Additionally, the Merton (1974) model is a simpler form of the Leland (1994) model which delivers similar intuition. However, the assumption that bonds can only default at maturity is problematic in understanding the drivers of the term structure of the credit spread.

the value matching and smooth pasting conditions imply that

$$V_d = \frac{(1-\tau)C}{r}\frac{\xi}{\xi - 1}, \tag{4.4}$$

where $\xi = -\frac{2r}{\sigma^2}$ is the negative root of the characteristic polynomial.

The equity value can be expressed as

$$E = V - \frac{(1-\tau)C}{r} + \left(\frac{(1-\tau)C}{r} - V_d\right)\left(\frac{V}{V_d}\right)^{\xi} \tag{4.5}$$

where the first part $V - \frac{(1-\tau)C}{r}$ is the firm value net of the debt value with additional tax benefits from the debt, had there been no default. $\left(\frac{V}{V_d}\right)^{\xi}$ is the Arrow Debreu price of default. The second part of the equation can be interpreted as the payoff received by the equity holder at default. It loses the firm value V_d but is no longer required to pay for the debt $\frac{(1-\tau)C}{r}$ at default.

Applying Ito's lemma to the asset dynamic, we can express the equity risk premium as

$$ERP_t = \frac{\partial E_t}{\partial V_t}\frac{V_t}{E_t}\sigma\lambda. \tag{4.6}$$

Equation (B.4) shows that the equity risk premium can be decomposed into equity beta and asset risk premium. The equity beta can be further expressed as the interaction between the equity delta and leverage effect. On the one hand, when equity delta is high, the equity is more correlated with the firm's risk, indicating a high equity beta. On the other hand, when leverage is large, the equity value is small and it becomes riskier, leading to a high equity beta.

Next, we derive the credit spread expression. Under the assumption that the creditor get a fraction of the price of the equivalent remaining maturity Treasury at default ("Reovery of Treasury"), the price of a zero coupon bond with τ maturity can be expressed as

$$\begin{aligned} B_{t,\tau} &= e^{-r\tau}\mathbb{E}^Q[\mathbb{I}_{V_\tau > F} + \mathbb{I}_{V_\tau < F}(1-L)] \\ &= e^{-r\tau}(1 - L\pi^Q_{t,\tau}), \end{aligned} \tag{4.7}$$

where L is the loss given default which is assumed to be constant, and $\pi^Q_{t,\tau}$ denotes the risk neutral default probability. Therefore, the credit spread of this bond can be expressed as

$$s_{t,\tau} = -\frac{1}{\tau}\log(1 - L\pi^Q_{t,\tau}). \tag{4.8}$$

Based on reflection principle, we have the following lemma:

Lemma 4.4.1. *Suppose $F(T) = \mathbb{P}(\tau < T)$, where $\tau \in \inf\{t \geq 0 : W_t + mt = b\}$ with $m > 0$ and $b < 0$,*

$$F(T) = e^{2mb}N(\frac{b}{\sqrt{\tau}} + m\sqrt{\tau}) + N(\frac{b}{\sqrt{\tau}} - m\sqrt{\tau}), \tag{4.9}$$

where $N(\cdot)$ denotes the standard normal cumulative distribution function.

According to Lemma 4.4.1, $\pi^Q_{t,\tau}$ can be expressed as

$$\pi^Q_{t,\tau} = e^{2mb}N(\frac{b}{\sqrt{\tau}} + m\sqrt{\tau}) + N(\frac{b}{\sqrt{\tau}} - m\sqrt{\tau}), \tag{4.10}$$

where $m = \frac{r-\frac{\sigma^2}{2}}{\sigma}$, and $b = \log\left(\frac{V_d}{V}\right)/\sigma$.

4.4.1 Discussion

Fixing the credit spread level, the firm can have completely different underlying dynamics. For instance, both the default boundary and asset volatility have positive impacts on the credit risk of the firm. For firms with the same credit spread level, they can have a high default boundary (asset volatility) but low asset volatility (default boundary). Simply focusing on the level of the credit spread, one cannot infer the cross-sectional variations of the firm's default boundary and asset volatility. Next, we discuss that the shape of the term structure contains this useful information.

In the spirit of Merton (1974) and Leland (1994), the bond price is negatively related to the value of the put option on the firm value. Therefore, the credit spread is positively related to this put option value. The option value is crucially dependent on the asset volatility and the option moneyness, henceforth default boundary. Intuitively, conditional on the same credit spread level, a higher volatility and a lower default boundary are likely to increase the long term credit spread. This is because the long maturity is likely to dampen the impact of the default boundary due to the possibility of getting out of the distress region over time. In the special case of Merton (1974), the bond price is a function of the European put option on the firm value. Even if the firm value is lower than the default bounday today, the default can only happen at maturity. For long maturity bond, the firm has a long time to get out of the default region. This dampens the impact of the default boundary. Therefore, the impact of the decrease in default boundary will be dominated by the increase in asset volatility on the credit spread.

In the meantime, conditional on the same credit spread level, a higher default boundary and a lower volatility are likely to increase the short term credit spread. This is because the short maturity reduces the impact of the volatility. If the maturity is 0, the total option value is driven by the intrinsic value, which is tightly related to the moneyness of the option. Based on this intuition, the steeper the slope is, the larger (smaller) the long (short) term credit spread is, indicating the larger the asset volatility and the smaller the default boundary is.

This information is especially important in understanding the equity risk premium. According to Equation (4.5), the equity risk premium can be decomposed into the equity beta $\frac{\partial E}{\partial V}\frac{V}{E}$ and the asset risk premium $\sigma\lambda$. If we increase the asset volatility and decrease the default boundary to keep the credit spread level constant, the asset risk premium increases. However, the equity beta is likely to decrease. Intuitively, since the equity is a call option on the asset value, when the asset volatility (default boundary) increases (decreases), the equity value increases. This implies a decrease in the leverage $\frac{V}{E}$, resulting in a decrease in equity beta. Even though the equity beta also consists of the equity delta $\frac{\partial E}{\partial V}$, the delta is likely to be much more stable than the leverage, since the equity delta $\frac{\partial E}{\partial V}$ is only able to vary between 0.5 to 1,[5] approximately. Changes in the firm fundamentals are not likely to cause the equity delta to vary much in percentage term. However, they can cause the leverage $\frac{V}{E}$ to vary a lot, especially when the firm is close to default and equity value is close to 0. Hence, the equity beta is likely to be mainly driven by the leverage.

[5]The lower bound should be larger for perpetual option.

Based on the above argument, the equity beta and asset risk premium counteract with each other as the firm's default boundary and volatility vary to keep the credit spread level constant. The net effect depends on the credit worthiness of the firm. When the firm is far away from default (henceforth, high credit quality firm), the equity beta is not sensitive to the changes of the firm fundamentals, since the equity value is very close to the asset value. Therefore, the equity risk premium is mainly driven by the asset volatility (asset risk premium). A higher credit spread slope implies a higher asset volatility. This indicates a positive relation between the credit spread slope and the equity risk premium. When the firm is close to default (henceforth, low credit quality firm), the equity beta is very sensitive to the leverage component, since the equity value is very small. Hence, the equity risk premium is mainly driven by the equity beta. A higher credit spread slope implies a smaller default boundary and a larger asset volatility, both resulting in a larger equity value and smaller leverage ratio. This indicates a negative relation between the credit spread slope and the equity risk premium.

In the following section, we provide a numerical analysis to justify the above economic mechanism, which generates the predictability patterns between the credit spread slope and equity returns, consistent with the data.

4.4.2 Numerical analysis

For either of the high or low credit quality firms, we first calibrate the Leland (1994) model to match the same credit spread level. In particular, as shown in Table 4.7, we set the credit spread level to be 50 (700) bps and the asset volatility ranges from 0.2 to 0.4 for the high (low) credit quality firms according to Feldhütter and Schaefer (2018). The sharpe ratio of the firm value is set to be 0.2 (0.1) for the high (low) credit quality firms based on Chen, Collin-Dufresne, and Goldstein (2009) and our computation for the equity sharpe ratio based on our sample. The bond loss given default is set as 0.45 (0.55) for high (low) credit quality firms based on Elton, Gruber, Agrawal, and Mann (2001) and Huang and Huang (2012). Finally, we set the firm value to be 100 and the risk free rate to be 0.02.

Second, based on these parameters, for each group of firms, we vary the asset volatility and back out the debt coupon value based on the target credit spread level. We then compute the credit spread slope, the equity risk premium (ERP), and the default boundary.

Figure 4.4 reports these quantities against asset volatility σ. As is indicated in Panel (b), in order to produce the same level of credit spread, when the asset volatility σ increases, the firm's default boundary decreases. Based on these capital structures of the firms, panel (a) plots the credit spread slope variations. For both of the high and low credit quality firms, the credit spread slope becomes steeper as the volatility increases and the default boundary decreases. Figure 4.5 reports the 1-year and 10-year credit spread level for both the good and bad firms. The long (short) term credit spread is increasing (decreasing) with the asset volatility. This implies that the long (short) term credit spread is mainly driven by the asset volatility (default boundary). These figures demonstrate that a steep slope corresponds to a higher (lower) volatility (leverage), consistent with the conjecture in the previous section.

This information has important implications on the equity risk premium for the high or low credit quality firms. Panel (c) shows that the equity risk premium (henceforth ERP) is increasing with volatility for a high credit quality firm but decreasing with the volatility for a low credit quality firm. To understand the dynamic of the ERP, Panels (d) and (e) report the ERP components, namely the equity beta and the asset risk premium (henceforth ARP). For both firms, the ARP (equity beta) is increasing (decreasing) with asset volatility. However, the decrease in equity beta for a low credit quality firm is much more rapid than for a high credit quality firm. As a result, the equity risk premium is mainly driven by the asset risk premium for a high credit quality firm but driven by the equity beta for a low credit quality firm.

To understand the driver of the equity beta, Figure 4.6 reports the dynamics of equity beta components, namely equity delta ($\frac{\partial E}{\partial V}$) and leverage ($\frac{V}{E}$), against the asset volatility. Visually, the equity delta is very stable but the leverage is changing much more rapid than the equity delta. This implies that the equity beta is mainly driven by the leverage, which is crucially dependent on the equity value of the firm. An increase in asset volatility and a decrease in default boundary increase the equity value since it is a call option on the firm's asset.

Therefore, as we increase the volatility and decrease the default boundary to keep the credit spread level constant, the credit spread slopes becomes steeper and steeper. On the one hand, the equity risk premium is increasing for a high credit quality firm, because it is mainly driven by the asset risk premium, which is crucially dependent on the asset volatility. This generates a positive relation between the credit spread slope and the equity risk premium. On the other hand, the equity risk premium is decreasing for a low credit quality firm, because it is mainly driven by the equity beta, which is crucially dependent on the leverage and equity value of the firm. The equity value is increasing with volatility and decreasing with default boundary. This leads to a negative relation between the credit spread slope and equity risk premium.

4.4.3 Simulation

To further confirm the economic mechanism for the predictability between the credit spread slope and equity returns, we simulate a set of panel data based on the Leland (1994) model to perform the same empirical analysis as Section 4.3.

In particular, We set the initial firm value to be 100. We construct 900 firms with volatilities ranging between 0.2 to 0.4 and default boundaries ranging between 10 to 50. Based on the calibration in the previous section, we set the minimum default boundary to be 10 and the upper bound to be 70. We set risk free rate to be 0.02, loss-given-default to be 0.5, bankruptcy cost to be 0.15, tax rate to be 0.15, sharpe ratio to be 0.15. According to Chen, Collin-Dufresne, and Goldstein (2009), we set the market price of risk to be 0.4. We then compute the systematic volatility and idiosyncratic volatility based on the firm's sharpe ratio and the market price of risk. Finally, we simulate 10 years of daily data based on these parameters, and aggregate the sample into monthly data.

First, we perform the double sort analysis as Section 4.3. Figure 4.3 and Table 4.8 reports the double sort results. Visually, for firms with low 5-year CDS spread level, the future equity returns are higher for firms with larger CDS slope. On the contrary, for firms with high 5-year CDS spread level, the future equity returns are lower for firms with larger CDS slope. Statistically, the returns of the long-short portfolio, defined as the low slope portfolio minus the high slope portfolio, is significantly negative for the high credit quality firms but significantly positive for the low credit quality firms. This evidence is consistent with the empirical evidence in Section 4.3. It also supports the model intuition in the previous discussion.

Second, we perform the panel regression by projecting the future equity returns on the current CDS slopes. Since the volatility is not time varying at the Leland model, we discard the firm fixed effect in the panel regression to examine the cross-sectional patterns between credit spread slopes and future equity returns. Table 4.9 reports the regression results. When conditional on high (low) credit spread level, the conditional beta β_c is significantly negative (positive), indicating that firms with high and low credit spread levels have a distinct predictive relation between the credit spread slope and the equity returns. In addition, $\beta_u + \beta_c$ is negative (positive) for firms with high (low) credit spread level, indicating that for low (high) credit quality firms, the credit spread slope negatively (positively) predicts the equity returns. This is consistent with the previous empirical evidence and discussion.

In sum, the classic Leland (1994) model is able to replicate the empirical findings in the market data. Under the Leland (1994) framework, we show that by conditioning on the same credit spread level, the credit spread slope contains information on the relative magnitudes of the default boundary and asset volatility across firms, which is helpful in understanding the equity risk premium for both high and low credit quality firms.

4.5 Conclusion

There has been a debate in the literature on the predictability between the equity and credit markets. While most of these studies focus on the credit spread level, we revisit the predictability incorporating the term structure of the credit spread. We find that conditional on high (low) credit spread level, the CDS spread slope negatively (positively) predicts the equity returns.

To understand the superior predictive power of the term structure, we adopt the Leland (1994) framework in dissecting the credit spread slope and the equity risk premium and study the interplay among the different components. We find that in theory, the credit spread slope can reflect a different combination of the endogenous default boundary and asset volatility even though the credit spread level remains unchanged. This information is tightly related to the equity beta and the asset risk premium. For firms with high and low credit spread level, the equity risk premium is driven by the equity beta and the asset risk premium respectively. This results in different predictability between the CDS slope and equity returns, because the slope is positively (negatively) related to the asset risk premium (equity beta).

Our work highlights the importance of incorporating the credit spread term structure in studying the lead lag relation between the credit and equity markets. While we mainly focus on the cross-sectional predictability between the credit spread slope and equity returns, the time series predictability also deserves great attention. It would be interesting to extend the Leland (1994) and Du, Elkamhi, and Ericsson (2019) framework in jointly capturing both the cross-sectional and time series predictability. We leave this for future work.

Bibliography

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Armstrong, Christopher S., and Rahul Vashishtha, 2012, Executive stock options, differential risk-taking incentives, and firm value, *Journal of Financial Economics* 104, 70–88.

Augustin, Patrick, 2018, The term structure of CDS spreads and sovereign credit risk, *Journal of Monetary Economics* 96, 53–76.

Bongaerts, Dion, Frank De Jong, and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* 66, 203–240.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein, 2009, On the relation between the credit spread puzzle and the equity premium puzzle, *Review of Financial Studies* 22, 3367–3409.

Du, Du, Redouane Elkamhi, and Jan Ericsson, 2019, Time-Varying Asset Volatility and the Credit Spread Puzzle, *Journal of Finance* 74, 1841–1885.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, Explaining the rate spread on corporate bonds, *Journal of Finance* 56, 247–277.

Engle, Robert F., Turan G. Bali, and Scott Murray, 2016, (*Empirical Asset Pricing - The Cross Section of Stock Returns*).

Ericsson, Jan, and Joel Reneby, 2005, Estimating structural bond pricing models, *Journal of Business* 78, 707–735.

Feldhütter, Peter, and Stephen M. Schaefer, 2018, The myth of the credit spread puzzle, *Review of Financial Studies* 31, 2897–2942.

Han, Bing, Avanidhar Subrahmanyam, and Yi Zhou, 2017, The term structure of credit spreads, firm fundamentals, and expected stock returns, *Journal of Financial Economics* 124, 147–171.

Hilscher, Jens, Joshua M Pollet, and Mungo Wilson, 2015, Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets, *Journal of Financial and Quantitative Analysis* 50, 543–567.

Huang, Jing-Zhi, and Ming Huang, 2012, How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?, *Review of Asset Pricing Studies* 2, 153–202.

Lee, Jongsub, Andy Naranjo, and Guner Velioglu, 2018, When do CDS spreads lead? Rating events, private entities, and firm-specific information flows, *Journal of Financial Economics* 130, 556–578.

Leland, Hayne E, 1994, Corporate Debt Value, Bond Covenants, and Optimal Capital Structure, *The Journal of Finance* 49, 1213–1252.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *The Journal of Finance* 29, 449–470.

Ni, Sophie X., and Jun Pan, 2020, Trading Puts and CDS on Stocks with Short Sale Ban, *Workig Paper*.

Norden, Lars, and Martin Weber, 2009, The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis, *European Financial Management* 15, 529–562.

Figure 4.1: Credit spread term structures of Bear Stearns Cos Inc, Emulex Corp, and Sunoco Inc.

In this figure, we report the credit spread term structures of Bear Stearns Cos Inc (BSC), Emulex Corp (EMU), and Sunoco Inc (SUN) on 2008-04-04. Sources: Markit, authors' computation.

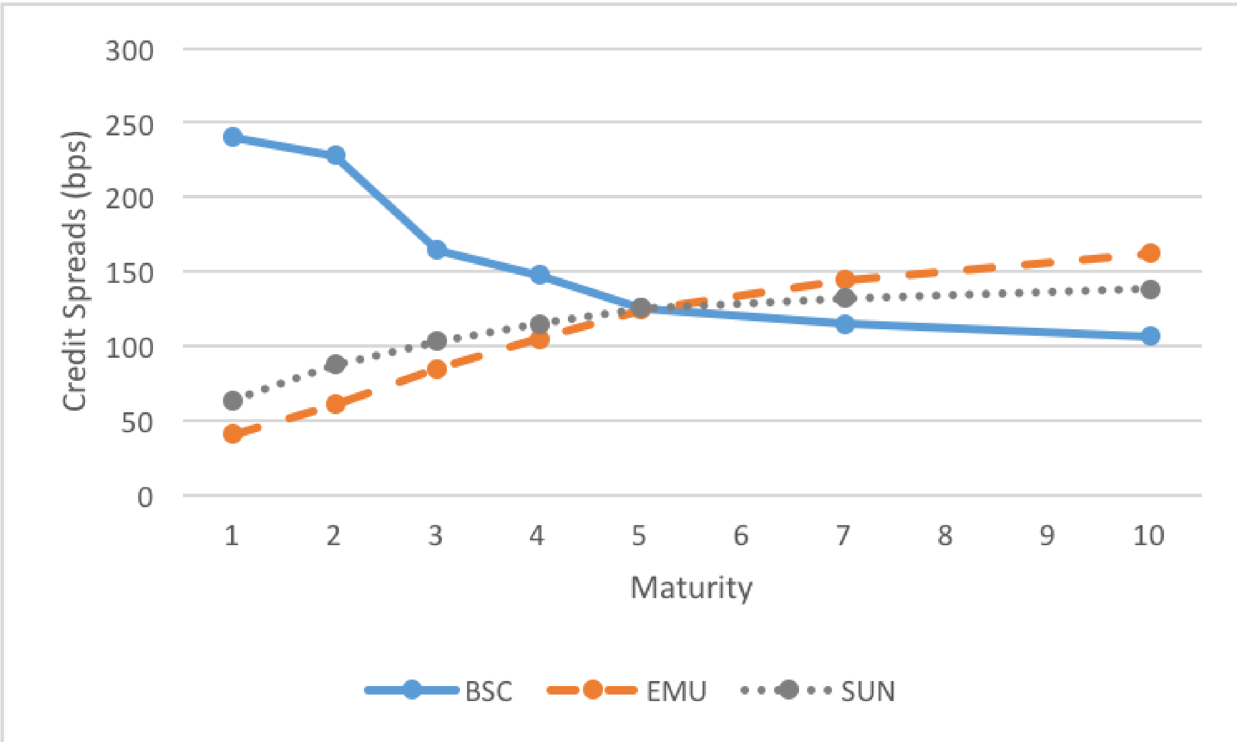


Figure 4.2: Returns on stock portfolios sorted by CDS spread level and CDS spread slope.

In this figure, we report the stock portfolio one month ahead returns sorted by the CDS spread level and slope. We first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Finally, we compute the time series averages of each portfolio returns. The data is at monthly frequency and the data period ranges from January 2002 until April 2018. Sources: Markit, CRSP, authors' computation.

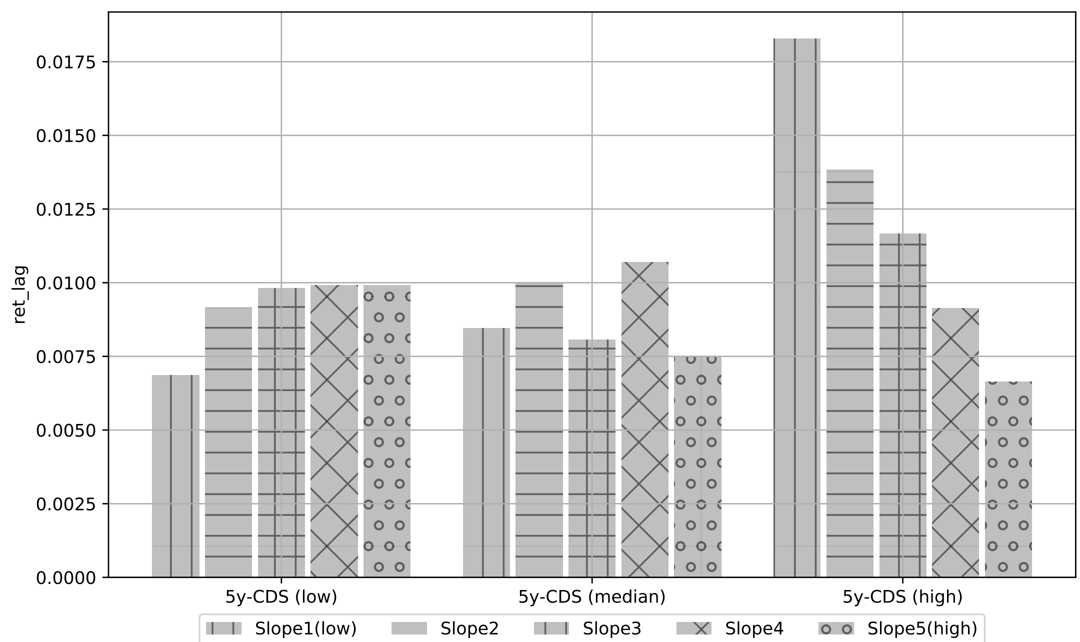


Figure 4.3: Returns on stock portfolios sorted by CDS spread level and CDS spread slope (Simulated Data).

In this figure, we report the stock portfolio one month ahead returns sorted by the CDS spread level and slope using the simulated data based on the Leland (1994) Model. The initial firm value is set to be 100. We simulate 10,000 firms with volatility ranging between 0.2 to 0.4 and default bounday ranging between 10 to 50. We set the minimum default boundary to be 10 and vary the upper bound such that the cross-sectional average of the 5-year credit spreads is around 150 bps. We set risk free rate to be 0.02, loss-given-default to be 0.5, bankruptcy cost to be 0.15, tax rate to be 0.15, sharpe ratio to be 0.15. According to Chen, Collin-Dufresne, and Goldstein (2009), we set the market price of risk to be 0.4. We then compute the systematic volatility and idiosyncratic volatility based on the firm's sharpe ratio and the market price of risk. Finally, we simulate 10 years of monthly data based on these parameters. At each month, we first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Finally, we compute the time series averages of each portfolio returns. The data is at monthly frequency and the data period ranges from January 2002 until April 2018. Sources: Authors' computation.

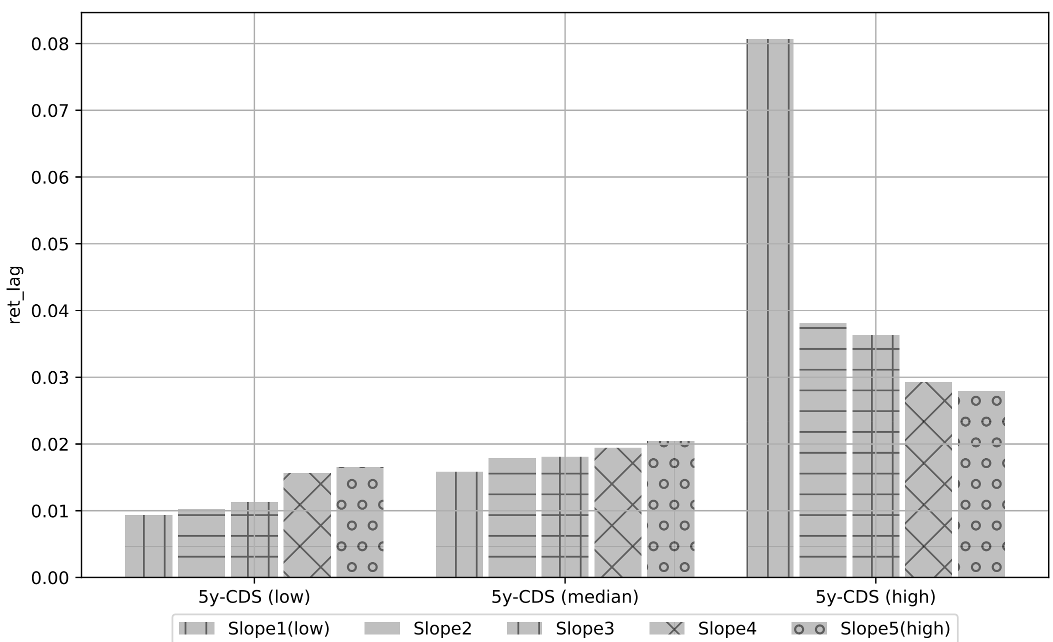
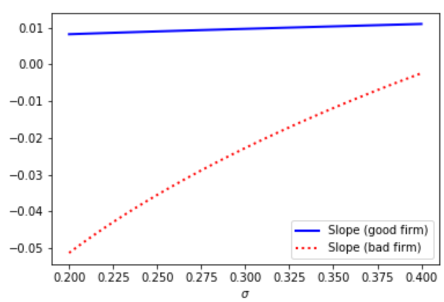


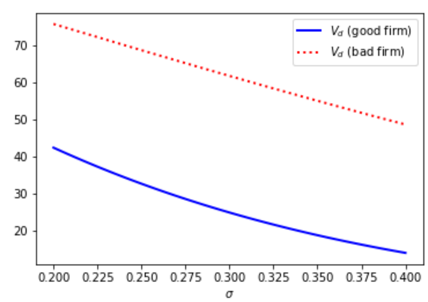
Figure 4.4: Credit spread slope and equity risk premium, and default boundary based on the Leland (1994) framework.

In these figures, we report the credit spread slope, equity risk premium, and default boundary, produced by the Leland (1994) framework, against asset volatility. We first calibrate the model to match the target credit spread of a high credit quality firm and a low credit quality firm. In particular, we set the firm's parameters based on Table 4.7, and we vary the asset volatility within the volatility range to back out the firm's coupon rate. We then compute the credit spread slope, the equity risk premium (ERP), the ERP components $\frac{\partial E}{\partial V}$ and $\frac{V}{E}$, as well as the default boundary. Sources: Authors' computation.

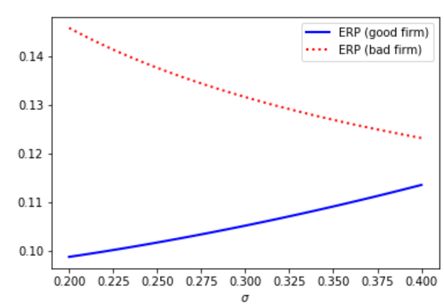
(a) Credit Spread Slope



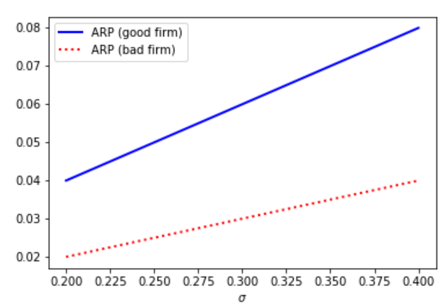
(b) Default Boundary



(c) ERP



(d) ARP



(e) Equity Beta

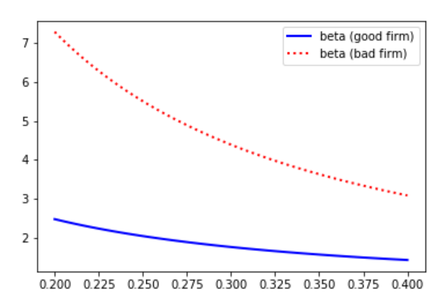
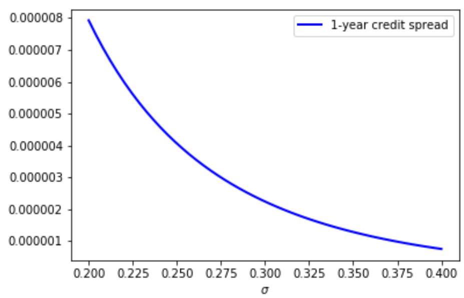


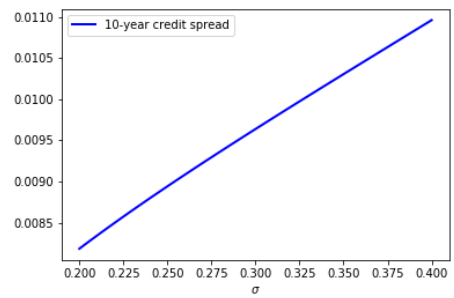
Figure 4.5: Long and short term Credit spread against asset volatility based on the Leland (1994) framework.

In these figures, we report the 10-year (long term) and 1-year (short term) credit spread, produced by the Leland (1994) framework, against asset volatility. We first calibrate the model to match the target credit spread of a high credit quality firm and a low credit quality firm. In particular, we set the firm's parameters based on Table 4.7, and we vary the asset volatility within the volatility range to back out the firm's coupon rate. We then compute the 10-year and 1-year credit spread levels. Sources: Authors' computation.

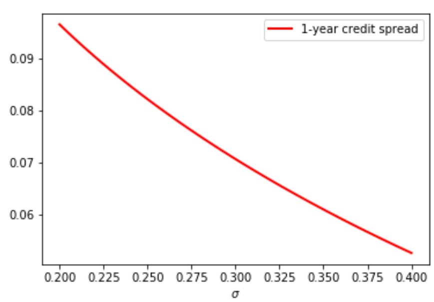
(a) Short Term Credit Spread (High Credit Quality)



(b) Long Term Credit Spread (High Credit Quality)



(c) Short Term Credit Spread (Low Credit Quality)



(d) Long Term Credit Spread (Low Credit Quality)

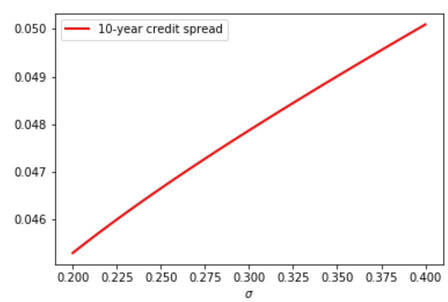
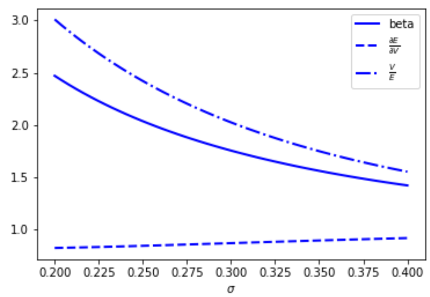


Figure 4.6: Equity beta components based on the Leland (1994) framework.

In these figures, we report the dynamics of equity beta components produced by the Leland (1994) framework, against asset volatility. We first calibrate the model to match the target credit spread of a high credit quality firm and a low credit quality firm. In particular, we set the firm's parameters based on Table 4.7, and we vary the asset volatility within the volatility range to back out the firm's coupon rate. We then compute the equity beta and its components, namely equity delta ($\frac{\partial E}{\partial V}$) and leverage ($\frac{V}{E}$). Sources: Authors' computation.

(a) Equity Beta (High Credit Quality Firm)



(b) Equity Beta (Low Credit Quality Firm)

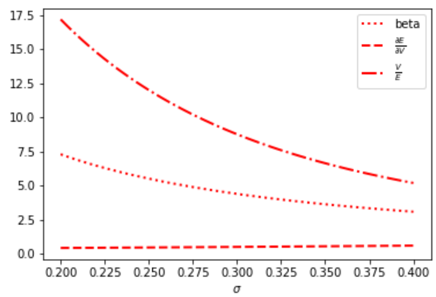


Table 4.1: Descriptive Statistics.

This table presents the cross-sectional descriptive statistics. We first compute the unconditional averages of the variables for each firm. We then generate the cross-sectional summary statistics of the CDS spreads, CDS spread slope, defined as 10-year CDS spreads minus 1-year CDS spreads, equity returns, leverage, equity volatility, log market capitalization (MC), and rating. The data period ranges from January 2001 until March 2018. The data frequency is monthly. Sources: CRSP, Compustat, Markit, and authors' computations.

	obs.	#firms	mean	std	min	25%	50%	75%	max
1y-CDS	74,770	733	0.020	0.070	0.000	0.003	0.006	0.016	1.203
5y-CDS	74,770	733	0.026	0.066	0.002	0.006	0.012	0.028	1.143
10y-CDS	74,770	733	0.028	0.065	0.002	0.008	0.015	0.031	1.132
Slope	74,770	733	0.008	0.013	-0.137	0.004	0.007	0.012	0.046
Equity Return	74,770	733	0.008	0.032	-0.299	0.005	0.010	0.016	0.202
Leverage	67,271	656	0.249	0.195	0.001	0.109	0.185	0.330	0.945
Equity Volatility	74,770	733	0.338	0.166	0.019	0.237	0.301	0.394	2.308
MktCap	74,770	733	8.733	1.455	2.689	7.834	8.669	9.699	13.327
Rating	66,746	632	4.165	1.046	1.000	3.471	4.000	5.000	7.000

Table 4.2: Returns on stock portfolios sorted by CDS spread level or slope. In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level (panel A and B) or slope (panel C and D). We first sort the stocks in to 10 deciles based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Second, for each decile, we compute the equal weighted equity one month ahead return. Lastly, we compute the low slope - high slope long short portfolio return. The returns are in percentage term. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

Panel A: Sorted by CDS spread level (standard error not corrected by Newey West method)											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	low - high
Average Return	0.63**	0.90***	0.96***	0.99***	0.94***	0.91**	0.86*	1.09**	1.08	1.04	-0.42
	t = 2.13	t = 2.93	t = 3.18	t = 2.72	t = 2.93	t = 2.14	t = 1.94	t = 2.03	t = 1.61	t = 1.22	t = -0.70
Panel B: Sorted by CDS spread level (standard error corrected by Newey West method)											
Average Return	0.63**	0.90***	0.96***	0.99***	0.94***	0.91**	0.86*	1.09**	1.08	1.04	-0.42
	t = 2.13	t = 2.93	t = 3.18	t = 2.72	t = 2.93	t = 2.14	t = 1.94	t = 2.03	t = 1.61	t = 1.22	t = -0.61
Panel C: Sorted by CDS spread slope (standard error not corrected by Newey West method)											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	low - high
Average Return	1.29*	0.99**	1.07***	1.07***	0.79**	0.93**	0.86**	0.82**	0.95*	0.61	0.68*
	t = 1.88	t = 2.11	t = 2.90	t = 3.29	t = 2.25	t = 2.52	t = 2.10	t = 1.99	t = 1.76	t = 0.95	t = 1.66
Panel D: Sorted by CDS spread slope (standard error corrected by Newey West method)											
Average Return	1.29*	0.99**	1.07***	1.07***	0.79**	0.93**	0.86**	0.82**	0.95*	0.61	0.68
	t = 1.88	t = 2.11	t = 2.90	t = 3.29	t = 2.25	t = 2.52	t = 2.10	t = 1.99	t = 1.76	t = 0.95	t = 1.55

Table 4.3: Predicting equity returns based on CDS spread levels and slopes.

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta Var_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, Var_t denotes either the CDS spread level or slope, which is defined as 10-year CDS spreads minus 1-year CDS spreads, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, and stock daily return. Columns (3) and (7) reports the same regression results by substituting the year-month fixed effect into year fixed effect with additional macroeconomic controls. The macroeconomic control variables include CBOE VIX index, 10-year treasury yield, treasury yield slope, defined as 10-year yield minus 2-year yield, default spread, and TED spread. The data period ranges from January 2001 until March 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$	$R^{Eqty}_{i,t+1}$
5y-CDS	0.134	0.075	-0.034	0.035					0.009
	(1.032)	(0.892)	(-0.246)	(0.269)					(0.073)
Slope					-0.231*	-0.329*	-0.432*	-0.433*	-0.433*
					(-1.896)	(-1.845)	(-1.815)	(-1.755)	(-1.783)
Leverage		-0.010*	0.022	0.014		-0.002	0.018	0.016	0.016
		(-1.715)	(1.143)	(0.730)		(-0.335)	(0.949)	(0.793)	(0.782)
Equity Volatility		0.000	0.000	0.000		0.000	0.000	0.000	0.000
		(0.704)	(0.632)	(0.393)		(0.743)	(0.371)	(0.107)	(0.099)
MC		-0.001**	-0.025***	-0.023***		-0.003***	-0.026***	-0.025***	-0.025***
		(-2.065)	(-8.546)	(-8.325)		(-3.813)	(-7.819)	(-7.645)	(-8.290)
BM		0.018	0.007	0.007		0.014	0.005	0.006	0.006
		(1.204)	(0.321)	(0.345)		(1.030)	(0.269)	(0.285)	(0.285)
Equity Return		-0.000	0.005	0.000		0.000	0.005	0.001	0.001
		(-0.002)	(0.198)	(0.000)		(0.013)	(0.219)	(0.047)	(0.045)
VIX			0.004***				0.004***		
			(2.802)				(2.872)		
10-year Yield			-7.834***				-7.763***		
			(-3.903)				(-3.868)		
Yield Slope			1.636				1.607		
			(0.631)				(0.621)		
DEF			128.734				125.952		
			(0.237)				(0.232)		
TED			-6.445*				-6.416*		
			(-1.825)				(-1.817)		
_cons	0.007***	0.018*	0.397***	0.216***	0.012***	0.032***	0.412***	0.238***	0.237***
	(3.199)	(1.744)	(3.831)	(8.042)	(10.264)	(4.954)	(3.803)	(8.257)	(8.715)
Observations	74562	59924	59908	59908	74562	59924	59908	59908	59908
R^2	0.239	0.242	0.124	0.260	0.239	0.243	0.125	0.261	0.261
Adjusted R^2	0.237	0.239	0.114	0.250	0.237	0.240	0.115	0.251	0.251
Firm FE			✓	✓			✓	✓	✓
Year-Month FE	✓	✓		✓	✓	✓		✓	✓
Quarter FE			✓				✓		

Table 4.4: Returns on stock portfolios sorted by CDS spread level and CDS spread slope. In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level and slope. We first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Third, for each group, we compute the equal weighted equity one month ahead return. Lastly, within each CDS tercile, we compute the low slope - high slope long short portfolio return. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.69^{**}	0.90^{***}	0.97^{***}	1.00^{***}	0.98^{***}	-0.29^{**}
	t = 2.57	t = 3.11	t = 3.24	t = 3.22	t = 2.95	t = -2.34
2	0.84^{**}	0.97^{**}	0.82^{*}	1.06^{***}	0.80^{*}	0.04
	t = 2.25	t = 2.59	t = 1.97	t = 2.67	t = 1.95	t = 0.23
3 (high CDS)	1.65^{**}	1.36^{*}	1.01	0.88	0.62	1.03^{**}
	t = 2.05	t = 1.93	t = 1.60	t = 1.43	t = 0.82	t = 2.19

Table 4.5: Predicting equity returns based on CDS slopes conditional on CDS spreads levels.

In this table, I report the results of the following predictive panel regression:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y_{i,t}'\beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 500 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	Full Sample					Ex. Crisis				
	(1) R_{t+1}^{Eqty}	(2) R_{t+1}^{Eqty}	(3) R_{t+1}^{Eqty}	(4) R_{t+1}^{Eqty}	(5) R_{t+1}^{Eqty}	(6) R_{t+1}^{Eqty}	(7) R_{t+1}^{Eqty}	(8) R_{t+1}^{Eqty}	(9) R_{t+1}^{Eqty}	(10) R_{t+1}^{Eqty}
Slope	-0.398	0.310	-0.343	-0.021	0.125	-0.523***	0.053	-0.474***	-0.222	-0.140
	(-1.444)	(1.053)	(-1.261)	(-0.114)	(0.545)	(-3.191)	(0.221)	(-2.939)	(-1.442)	(-0.740)
$D_{lowCDS,avg} \times Slope$	0.709***					0.577**				
	(2.787)					(2.299)				
$D_{highCDS,avg} \times Slope$		-0.709***					-0.577**			
		(-2.787)					(-2.299)			
$D_{lowCDS,50bp} \times Slope$			1.967*					2.262**		
			(1.688)					(2.202)		
$D_{highCDS,500bp} \times Slope$				-0.639*					-0.525**	
				(-1.940)					(-2.306)	
$CDS_{5y} \times Slope$					-9.604**					-7.182*
					(-2.069)					(-1.951)
Observations	59908	59908	59908	59908	59908	52776	52776	52776	52776	52776
R^2	0.261	0.261	0.261	0.262	0.261	0.226	0.226	0.226	0.227	0.226
Adjusted R^2	0.251	0.251	0.251	0.251	0.251	0.215	0.215	0.215	0.215	0.215
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4.6: The relation between the CDS slope and the firm fundamentals conditional on the same CDS spread level.

In this table, I report the relation between the CDS spread slope and the default boundary proxy, leverage, as well as the asset volatility. The asset volatility is computed as the volatility of the value-weighted portfolio return, whose individual asset return is the firm's operating industry's value-weighted equity return, following Armstrong and Vashishtha (2012). We first compute the unconditional averages of CDS spread level and slope, as well as the firm fundamentals for each firm. Second, we search for firms in the entire cross section with 5-year credit spreads that are no more than 1 bps away from each other. Third, for each of these groups of firms with very close credit spread level, we compute the Spearman's rank correlation coefficient (ρ) between the CDS slope and default boundary proxy as well as the asset volatility. Finally, we conduct a t-test on ρ to test whether it is significant different from 0, and we report the fraction of groups with negative correlation. Sources: Markit, CRSP, Compustat, authors' computation.

	Average ρ	T-Stats	N	$\frac{N_{negative}}{N_{total}}$
Leverage	-0.231***	-4.669	163	66.9%
Asset Volatility	0.100*	1.757	159	44.0%

Table 4.7: Model parameters.

In this table, I report the parameters for the Merton model simulation. The high (low) credit quality firms refer to firms that are far away (close) to default. Sources: authors' computation.

Parameters	High Credit Quality Firms	Low Credit Quality Firms	Sources
Target credit spread (5y)	50 bps	700 bps	Feldhütter and Schaefer (2018)
Asset volatility range $[\sigma_{min}, \sigma_{max}]$	$[0.2, 0.4]$	$[0.2, 0.4]$	Feldhütter and Schaefer (2018)
Sharpe ratio SR	0.2	0.1	Chen, Collin-Dufresne, and Goldstein (2009) and authors' computation
Loss given default L	0.45	0.55	Elton, Gruber, Agrawal, and Mann (2001) and Huang and Huang (2012)
Tax rate (τ)	0.15	0.15	Du, Elkamhi, and Ericsson (2019)
Bankruptcy cost (α)	0.15	0.15	Du, Elkamhi, and Ericsson (2019)
Firm value V	100	100	
Risk free rate r	0.02	0.02	

Table 4.8: Returns on stock portfolios sorted by CDS spread level and CDS spread slope based on simulated data. In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level and slope based on the simulated data generated by the Leland (1994) model. We first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads. Third, for each group, we compute the equal weighted equity one month ahead return. Lastly, within each CDS tercile, we compute the low slope - high slope long short portfolio return. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency with a 10-year length. Sources: Author's computation.

	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.93^{***}	1.02^{***}	1.13^{***}	1.56^{***}	1.65^{***}	-0.72^{***}
	t = 2.92	t = 3.06	t = 2.68	t = 3.45	t = 3.66	t = −3.01
2	1.58^{***}	1.79^{***}	1.81^{***}	1.94^{***}	2.04^{***}	−0.46
	t = 3.04	t = 3.43	t = 3.12	t = 3.13	t = 3.13	t = −1.50
3 (high CDS)	8.06^{***}	3.81^{***}	3.63^{***}	2.92^{***}	2.79^{***}	5.27^{***}
	t = 7.10	t = 3.88	t = 4.08	t = 3.55	t = 3.29	t = 8.97

Table 4.9: Predicting equity returns based on CDS slopes conditional on levels of CDS spreads using simulated data.

In this table, I report the results of the following predictive panel regression based on the simulated data generated by the Leland (1994) model:

$$R^{Eqty}_{i,t+1} = \gamma_t + \beta_u Slope_t + D_{highCDS} + \beta_c D_{highCDS} Slope_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $D_{highCDS}$ denotes the indicator variable which equals 1 if the CDS level belonging the the top half and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, and stock daily return. Columns (2) and (4) reports the same regression results by substituting the year-month fixed effect into macroeconomic control, namely the systematic Weiner process in the simulation. The data is at monthly frequency with a 10-year length. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Author's computation.

	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}
Slope	-0.329***	-0.333***	0.108	0.246
	(-11.037)	(-10.024)	(0.461)	(0.888)
$D_{lowCDS} \times Slope$	0.437*	0.579**		
	(1.825)	(2.036)		
$D_{highCDS} \times Slope$			-0.437*	-0.579**
			(-1.825)	(-2.036)
Observations	105836	105836	105836	105836
R^2	0.128	0.016	0.128	0.016
Adjusted R^2	0.127	0.016	0.127	0.016
Year-Month FE	✓		✓	
Firm Control	✓	✓	✓	✓
Macro Control		✓		✓

Table 4.10: Double sort results based on different CDS slope definitions. In this table, we reports the stock portfolio one month ahead returns sorted by the CDS spread level and slope. The CDS slope is defined as 10-year CDS spreads minus 2-year CDS spreads and 5-year CDS spreads minus 1-year CDS spreads. We first sort the stocks based on the 5-year CDS spread level into terciles. At each tercile, we then sort the stocks based on the CDS slope. Third, for each group, we compute the equal weighted equity one month ahead return. Lastly, within each CDS tercile, we compute the low slope - high slope long short portfolio return. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, CRSP, author's computation.

Panel A: $Slope = CDS_{10y} - CDS_{2y}$						
	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.72^{***} t = 2.62	0.90^{***} t = 3.13	0.95^{***} t = 3.28	0.97^{***} t = 3.12	1.00^{***} t = 2.98	-0.28^{**} t = -2.06
2	0.89^{**} t = 2.12	0.90^{***} t = 2.61	0.93^{**} t = 2.35	0.94^{**} t = 2.29	0.83^{**} t = 2.10	0.05 t = 0.34
3 (high CDS)	1.69^{**} t = 1.99	1.30^{*} t = 1.79	1.16^{*} t = 1.77	0.91 t = 1.43	0.46 t = 0.66	1.24^{***} t = 2.73
Panel B: $Slope = CDS_{5y} - CDS_{1y}$						
	1 (low slope)	2	3	4	5 (high slope)	low - high
1 (low CDS)	0.77^{***} t = 2.76	0.82^{***} t = 2.73	0.96^{***} t = 3.22	0.95^{***} t = 3.14	1.03^{***} t = 3.15	-0.26^{**} t = -2.12
2	0.90^{**} t = 2.26	0.84^{**} t = 2.36	0.98^{**} t = 2.49	0.95^{**} t = 2.37	0.81^{*} t = 1.90	0.09 t = 0.57
3 (high CDS)	1.71^{**} t = 2.01	1.18^{*} t = 1.70	1.03^{*} t = 1.85	0.94 t = 1.51	0.66 t = 0.83	1.05^{**} t = 2.21

Table 4.11: Panel regression based on different CDS slope definitions.

In this table, I report the results of the following predictive panel regression based on different CDS slope definitions:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c D_{highCDS} Slope_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 2-year CDS spreads, or 5-year CDS spreads minus 1-year CDS spreads, $D_{highCDS}$ denotes the indicator variable which equals 1 if the CDS level belonging the the top half and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. Columns (2) and (5) reports the same regression results by substituting the year-month fixed effect into quarterly fixed effect with additional macroeconomic controls. The macroeconomic control variables include CBOE VIX index, 10-year treasury yield, treasury yield slope, defined as 10-year yield minus 2-year yield, default spread, and TED spread. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	Full Sample		Ex. Crisis		Full Sample		Ex. Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}	R^{Eqty}_{t+1}
Panel A: $Slope = CDS_{10y} - CDS_{2y}$								
Slope	-0.471	-0.441	-0.727***	-0.663***	0.167	0.303	0.019	0.086
	(-1.534)	(-1.437)	(-3.950)	(-3.583)	(0.544)	(0.993)	(0.070)	(0.326)
$D\_lowCDS \times Slope$	0.638**	0.745**	0.746**	0.749**				
	(2.190)	(2.569)	(2.518)	(2.594)				
$D\_highCDS \times Slope$					-0.638**	-0.745**	-0.746**	-0.749**
					(-2.190)	(-2.569)	(-2.518)	(-2.594)
Observations	59908	59908	52776	52776	59908	59908	52776	52776
R^2	0.125	0.261	0.136	0.227	0.125	0.261	0.136	0.227
Adjusted R^2	0.115	0.251	0.125	0.215	0.115	0.251	0.125	0.215
Panel B: $Slope = CDS_{5y} - CDS_{1y}$								
Slope	-0.563*	-0.576*	-0.710***	-0.654***	0.301	0.258	-0.174	-0.189
	(-1.730)	(-1.754)	(-3.378)	(-3.100)	(0.696)	(0.594)	(-0.517)	(-0.573)
$D\_lowCDS \times Slope$	0.864***	0.834**	0.536*	0.465				
	(2.629)	(2.512)	(1.688)	(1.490)				
$D\_highCDS \times Slope$					-0.864***	-0.834**	-0.536*	-0.465
					(-2.629)	(-2.512)	(-1.688)	(-1.490)
Observations	59908	59908	52776	52776	59908	59908	52776	52776
R^2	0.126	0.261	0.135	0.226	0.126	0.261	0.135	0.226
Adjusted R^2	0.116	0.251	0.124	0.215	0.116	0.251	0.124	0.215
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE		✓		✓		✓		✓
Quarterly FE	✓		✓		✓		✓	
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓
Macro Control	✓		✓		✓		✓	

Table 4.12: Predicting equity returns based on CDS slopes conditional on levels of CDS spreads controlled for informed trading.

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ denotes $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), or 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}	(6) R^{Eqty}_{t+1}	(7) R^{Eqty}_{t+1}	(8) R^{Eqty}_{t+1}	(9) R^{Eqty}_{t+1}	(10) R^{Eqty}_{t+1}	(11) R^{Eqty}_{t+1}	(12) R^{Eqty}_{t+1}	(13) R^{Eqty}_{t+1}	(14) R^{Eqty}_{t+1}	(15) R^{Eqty}_{t+1}
Slope	-0.580*	-0.389	-0.835**	-0.242	-1.324	0.101	0.322	-0.163	0.512	-0.768	-0.064	0.135	-0.311	0.375	-0.709
	(-1.866)	(-1.397)	(-2.394)	(-0.698)	(-1.253)	(0.319)	(1.096)	(-0.466)	(1.330)	(-0.676)	(-0.194)	(0.588)	(-0.887)	(1.219)	(-0.674)
$D_{lowCDS} \times Slope$	0.681***	0.711***	0.672***	0.754***	0.556**										
	(2.696)	(2.784)	(2.641)	(2.941)	(2.220)										
$D_{highCDS} \times Slope$						-0.681***	-0.711***	-0.672***	-0.754***	-0.556**					
						(-2.696)	(-2.784)	(-2.641)	(-2.941)	(-2.220)					
$CDS_{5y} \times Slope$											-9.047*	-9.629**	-8.054*	-11.033**	-7.345*
											(-1.851)	(-2.071)	(-1.669)	(-2.378)	(-1.662)
$Depth \times Slope$	0.028					0.028					0.025				
	(0.854)					(0.854)					(0.729)				
$Idiosyn \times Slope$		-0.015					-0.015					-0.012			
		(-0.206)					(-0.206)					(-0.167)			
$IO \times Slope$			0.619*					0.619*					0.508		
			(1.737)					(1.737)					(1.372)		
$\#Analyst \times Slope$				-0.015					-0.015					-0.016	
				(-1.084)					(-1.084)					(-1.264)	
$MktCap \times Slope$					0.119					0.119					0.092
					(1.081)					(1.081)					(0.867)
Observations	59907	59908	59904	59761	59908	59907	59908	59904	59761	59908	59907	59908	59904	59761	59908
R^2	0.261	0.261	0.262	0.262	0.261	0.261	0.261	0.262	0.262	0.261	0.261	0.261	0.261	0.262	0.261
Adjusted R^2	0.251	0.251	0.251	0.252	0.251	0.251	0.251	0.251	0.252	0.251	0.251	0.251	0.251	0.252	0.251
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4.13: Predicting equity returns based on CDS slopes conditional on CDS spreads levels (control for industry effect).

In this table, I report the results of the following predictive panel regression:

$$R^{Eqty}_{i,t+1} = \alpha_i + \gamma_t + \delta_{ind} + \beta_u Slope_t + \beta_c Level_t Slope_t + \beta_l Level_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Eqty}_{i,t+1}$ denotes the equity one month ahead return, $Slope_t$ denotes the CDS slope, defined as 10-year CDS spreads minus 1-year CDS spreads, $Level_t \times Slope_t$ capture the CDS slope predictive effect conditional on the CDS spread level. We specify $Level_t$ in 3 different forms, $D_{highCDS,avg}$ ($D_{lowCDS,avg}$), $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$), and 5y-CDS spreads, where $D_{highCDS,avg}$ ($D_{lowCDS,avg}$) denotes the indicator variable which equals 1 if the firm's average CDS spreads level belonging to the top (bottom) half and 0 otherwise, and $D_{highCDS,500bp}$ ($D_{lowCDS,30bp}$) denotes the indicator variable which equals 1 if the firm's monthly CDS spreads are larger (smaller) than 500 (30) bps and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, δ_{ind} denotes the industry fixed effect, where the industry definitions are based on Fama-French definition, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, CRSP, and author's computation.

	Full Sample					Ex. Crisis				
	(1) R^{Eqty}_{t+1}	(2) R^{Eqty}_{t+1}	(3) R^{Eqty}_{t+1}	(4) R^{Eqty}_{t+1}	(5) R^{Eqty}_{t+1}	(6) R^{Eqty}_{t+1}	(7) R^{Eqty}_{t+1}	(8) R^{Eqty}_{t+1}	(9) R^{Eqty}_{t+1}	(10) R^{Eqty}_{t+1}
Slope	-0.385	0.324	-0.329	0.007	0.163	-0.502***	0.058	-0.452***	-0.191	-0.112
	(-1.383)	(1.094)	(-1.204)	(0.041)	(0.713)	(-3.073)	(0.235)	(-2.832)	(-1.242)	(-0.595)
$D_{lowCDS,avg} \times Slope$	0.709***					0.560**				
	(2.717)					(2.178)				
$D_{highCDS,avg} \times Slope$		-0.709***					-0.560**			
		(-2.717)					(-2.178)			
$D_{lowCDS,50bp} \times Slope$			1.769					2.108**		
			(1.547)					(2.100)		
$D_{highCDS,500bp} \times Slope$				-0.660**					-0.538**	
				(-2.013)					(-2.359)	
$CDS_{5y} \times Slope$					-10.043**					-7.271**
					(-2.189)					(-1.997)
Observations	59771	59771	59771	59771	59771	52640	52640	52640	52640	52640
R^2	0.262	0.262	0.262	0.263	0.262	0.228	0.228	0.228	0.228	0.228
Adjusted R^2	0.252	0.252	0.251	0.252	0.252	0.215	0.215	0.215	0.215	0.215
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4.14: Returns on stock portfolios sorted by bond yield level and bond yield slope. In this table, we reports the stock portfolio one month ahead returns sorted by the bond yield level and slope. We first sort the stocks based on the 5-year bond yield level into terciles. At each tercile, we then sort the stocks based on the bond yield slope, defined as 10-year bond yields minus 2-year bond yields. Third, for each group, we compute the equal weighted equity one month ahead return. Lastly, within each level tercile, we compute the low slope - high slope long short portfolio return. The returns are in percentage term. All the t-stats are corrected under the Newey West method. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The data is at monthly frequency and the data period ranges from January 2001 until March 2018. Sources: Markit, WRDS, author's computation.

	1 (low slope)	2	3 (high slope)	low - high
1 (low CDS)	0.54	0.74**	1.06**	−0.52
	t = 1.10	t = 2.07	t = 2.37	t = −1.14
2	1.23***	1.33**	0.99*	0.24
	t = 3.02	t = 2.27	t = 1.92	t = 0.51
3 (high CDS)	2.16**	0.34	0.64	1.53**
	t = 2.14	t = 0.35	t = 0.62	t = 2.02

Table 4.15: Predicting equity returns using bond yield slopes conditional on levels of bond yields.

In this table, I report the results of the following predictive panel regression:

$$R_{i,t+1}^{Eqty} = \alpha_i + \gamma_t + \beta_u Slope_t + \beta_c D_{highYield} Slope_t + Y_{i,t}'\beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Eqty}$ denotes the equity one month ahead return, $Slope_t$ denotes the bond yield slope, defined as 10-year bond yields minus 2-year bond yields, $D_{highYield}$ denotes the indicator variable which equals 1 if the bond yield level belonging the the top half and 0 otherwise. β_u and β_c denotes the unconditional and conditional effect of the CDS slope, respectively, α_i denotes the firm fixed effect, γ_t denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, and 5-year bond yields. Columns (2) and (5) reports the same regression results by substituting the year-month fixed effect into quarterly fixed effect with additional macroeconomic controls. The macroeconomic control variables include CBOE VIX index, 10-year treasury yield, treasury yield slope, defined as 10-year yield minus 2-year yield, default spread, and TED spread. The data period ranges from Jan 2002 until April 2018. The data frequency is monthly. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, WRDS, and author's computation.

	Full Sample		Ex. Crisis		Full Sample		Ex. Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}	R_{t+1}^{Eqty}
Slope	-0.828**	-0.898***	-1.050***	-0.992***	0.167	-0.306	-0.229	-0.161
	(-2.278)	(-2.794)	(-2.838)	(-2.731)	(0.479)	(-0.999)	(-0.720)	(-0.593)
$D_{lowYield} \times Slope$	0.996**	0.592	0.820*	0.831*				
	(2.121)	(1.399)	(1.740)	(1.877)				
$D_{highYield} \times Slope$					-0.996**	-0.592	-0.820*	-0.831*
					(-2.144)	(-1.399)	(-1.740)	(-1.877)
Observations	3976	3976	3687	3687	3976	3976	3687	3687
R^2	0.162	0.355	0.174	0.301	0.162	0.355	0.174	0.301
Adjusted R^2	0.119	0.300	0.130	0.241	0.119	0.300	0.130	0.241
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE		✓		✓		✓		✓
Quarterly FE	✓		✓		✓		✓	
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓
Macro Control	✓		✓		✓		✓	

Appendix

A Studies on credit market and its relation with equity market

Table A.1: Literature on the relation between credit and equity markets

	Type		Focus		Economic mechanism		
Study	Empirics	Theory	Level	Term Structure	Informed Trading	Market Imperfection	Rational Expectation
Acharya and Johnson (2007)	✓		✓		✓		
Hilscher, Pollet, and Wilson (2015)	✓		✓		✓	✓	
Ni and Pan (2020)	✓		✓			✓	
Lee, Naranjo, and Velioglu (2018)	✓		✓		✓		
Norden and Weber (2009)	✓		✓				
Han, Subrahmanyam, and Zhou (2017)	✓			✓	✓		
The present study	✓	✓		✓			✓

Notes. This table summarizes the main studies on the relation between equity and credit markets. We describe the type of study (empirical or theoretical), the focus of the paper (credit spread level or term structure), and the main economic mechanism proposed by each study.

B Merton (1974) model

We apply the Merton (1974) framework to understand the predictability between the credit spread slope and equity returns. The firm value is assumed to follow

$$
\begin{aligned}
\frac{dV_t}{V_t} &= \mu^P dt + \sigma dW_t^P \\
&= r dt + \sigma dW_t^Q,
\end{aligned}
\tag{B.1}
$$

under the physical and risk neutral measure, respectively. $\mu^P = r + \lambda\sigma$, where λ is the market price of risk. Suppose that the firm issues a zero coupon debt with face value F and maturity T. The firm pays the debt face value F at maturity and defaults when the asset value V_T at time T falls below the face value of the debt F. Based on this dynamic, the equity pays $\max(E_T - F, 0)$ at maturity T. This is equivalent to an European call option written on the firm value. We can thus express the equity value as

$$
E_t = V_t N(d_1) - F e^{-rT} N(d_2), \tag{B.2}
$$

where

$$
\begin{aligned}
d_1 &= \frac{\log\left(\frac{V_t}{F}\right) + \left(r + \frac{1}{2}\sigma^2\right) T}{\sigma\sqrt{T}} \\
d_2 &= d_1 - \sigma\sqrt{T}.
\end{aligned}
\tag{B.3}
$$

According to Ito's lemma, we can express the equity risk premium as

$$
ERP_t = \frac{\partial E_t}{\partial V_t}\frac{V_t}{E_t}\sigma\lambda = N(d_1)\frac{V_t}{E_t}\sigma\lambda, \tag{B.4}
$$

Next, we derive the credit spread expression. The price of the bond with τ maturity can be expressed as

$$
\begin{aligned}
B_{t,\tau} &= e^{-r\tau}\mathbb{E}^Q[\mathbb{I}_{V_\tau > F} + \mathbb{I}_{V_\tau < F}(1 - L)] \\
&= e^{-r\tau}(1 - L\pi_{t,\tau}^Q),
\end{aligned}
\tag{B.5}
$$

where L is the loss given default which is assumed to be constant, and $\pi_{t,\tau}^Q$ denotes the risk neutral default probability. Therefore, the credit spread of this bond can be expressed as

$$s_{t,\tau} = -\frac{1}{\tau}\log(1 - L\pi^Q_{t,\tau}). \tag{B.6}$$

Note that $\pi^Q_{t,\tau} = Prob\left(\log\left(\frac{V_\tau}{F_\tau}\right) < 0\right)$. Based on the firm value dynamic,

$$\log\left(\frac{V_\tau}{F}\right) \sim N^Q\left(\log\left(\frac{V_t}{F}\right) + \left(r - \frac{\sigma^2}{2}\right)\tau, \sigma^2\tau\right). \tag{B.7}$$

Therefore, $\pi^Q_{t,\tau}$ can be expressed as

$$\pi^Q_{t,\tau} = N\left(-\frac{\log\left(\frac{V_t}{F}\right) + \left(r - \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}\right). \tag{B.8}$$

C Leland (1994) model solution

Equity and debt are contingent claims written on the firm value V_t. We assume that the assets are traded and replicable following Ericsson and Reneby (2005). Since V_t follows a geometric brownian motion process, the equity claim satisfy the following PDE:

$$E_V rV + \frac{1}{2}E_{VV}\sigma^2V^2 - rE + V - (1-\tau)C = 0, \tag{C.1}$$

where $f(V)$ represents the equity or debt value. This PDE has a generic solution:

$$f(V_t) = a_0 + a_1V_t^\zeta + a_2V_t^\xi, \tag{C.2}$$

where ζ and ξ are the roots of the characteristic polynomial of the PDE: $\frac{1}{2}\sigma^2x(x-1) + rx - r = 0$. Therefore, without loss of generosity, let $\zeta = 1 > 0$ and $\xi = -\frac{2r}{\sigma^2} < 0$.

The debt value $E(V_t)$ is subject to boundary conditions $\lim_{V_t\to\infty} E(V_t) = V_t$, and $E(V_d) = 0$. Based on these two boundary conditions, we can solve for a_0, a_1, and a_2 to be $-\frac{(1-\tau)C}{r}$, 1, and $\frac{\frac{(1-\tau)C}{r} - V_t}{V_d^\xi}$. Therefore,

$$E(V_t) = V_t - \frac{(1-\tau)C}{r} + \left(\frac{(1-\tau)C}{r} - V_t\right)\left(\frac{V_t}{V_d}\right)^\xi. \tag{C.3}$$

To find the default boundary expression, we use the smooth pasting condition:

$$\left.\frac{\partial E(V_t)}{\partial V_t}\right|_{V_t=V_d} = 0, \tag{C.4}$$

which yields

$$V_d = \frac{(1-\tau)C}{r}\frac{\xi}{\xi-1}. \tag{C.5}$$

D Proof of Lemma 4.4.1

Proof. Define

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = \exp\left(-\frac{m^2}{2} - mW_t\right). \tag{D.1}$$

According to Girsanov theorem, $\widetilde{W_t} = W_t + mt$ is a Brownian motion under $\mathbb{Q}$. Applying the change of measure,

$$\begin{aligned} F(T) = \mathbb{P}(\tau < T) = \mathbb{E}_{\mathbb{P}}[\mathbb{I}_{\tau<T}] &= \mathbb{E}_{\mathbb{Q}}[\mathbb{I}_{\tau<T}e^{-\frac{m^2T}{2}+m\widetilde{W}_t}] \\ &= e^{-\frac{m^2T}{2}}\int_{-\infty}^{\infty} e^{mu}\mathbb{Q}(\widetilde{W_T} \in [u, u+du], \tau < T). \end{aligned} \tag{D.2}$$

The reflection principle suggests for $u > b$,

$$\mathbb{Q}(\widetilde{W_T} \in [u, u+du], \tau < T) = \mathbb{Q}(\widetilde{W_T} \in [2b-u-du, 2b-u], \tau < T) = \mathbb{Q}(\widetilde{W_T} \in [2b-u-du, 2b-u]). \tag{D.3}$$

Therefore,

$$\begin{aligned}
F(T) &= e^{-\frac{m^2T}{2}}\left(\int_{-\infty}^{b} e^{mu}\mathbb{Q}(\widetilde{W}_T\in[u,u+du]) + \int_{b}^{\infty} e^{mu}\mathbb{Q}(\widetilde{W}_T\in[2b-u-du,2b-u])\right)\\
&= e^{-\frac{m^2T}{2}}\left(\int_{-\infty}^{b} e^{mu}\frac{1}{\sqrt{2\pi T}}e^{-\frac{u^2}{2T}}du + \int_{b}^{\infty} e^{mu}\frac{1}{\sqrt{2\pi T}}e^{-\frac{(u-2b)^2}{2T}}du\right)\\
&= \int_{-\infty}^{b}\frac{1}{\sqrt{2\pi T}}e^{-\frac{(u-mT)^2}{2T}}du + e^{2mb}\int_{b}^{\infty}\frac{1}{\sqrt{2\pi T}}e^{-\frac{(u-mt-2b)^2}{2T}}du\\
&= \int_{-\infty}^{\frac{b-mT}{\sqrt{T}}}\frac{1}{\sqrt{2\pi}}e^{-\frac{y^2}{2}}dy + e^{2mb}\int_{\frac{b-mT-2b}{\sqrt{T}}}^{\infty}\frac{1}{\sqrt{2\pi}}e^{-\frac{y^2}{2T}}dy\\
&= e^{2mb}N\left(\frac{b}{\sqrt{T}}+m\sqrt{T}\right) + N\left(\frac{b}{\sqrt{T}}-m\sqrt{T}\right)
\end{aligned} \tag{D.4}$$

□

To compute the risk neutral default probability $\pi^{Q}_{t,tau}$, we first adopt Ito's Lemma to the firm value V_t and have

$$d\ln V_t = (r-\frac{1}{2}\sigma^2)dt + \sigma dW_t^Q. \tag{D.5}$$

Define the default time $t \in \{t \geq 0 : V_t = V_d\}$.

$$V_t = V_d \iff \ln V_t = \ln V_d \iff \left(r-\frac{1}{2}\sigma^2\right)t + \sigma W_t^Q = \ln V_d \iff W_t^Q + \left(\frac{r-\frac{1}{2}\sigma^2}{\sigma}\right)t = \frac{\ln V_d}{\sigma}. \tag{D.6}$$

Based on Lemma 4.4.1, setting $m = \frac{r-\frac{1}{2}\sigma^2}{\sigma}$ and $b = \frac{\ln V_d}{\sigma}$, we have Equation (4.10).

E Numerical analysis procedure

We first set the initial parameters for high and low credit quality firms based on Table 4.7. For both high and low credit quality firms, the initial asset value is set to be 100. We also set risk free rate to be 0.02, tax rate to be 0.15, and bankcrupcy cost to be 0.15. For the high (low) credit quality firm, we set the 5-year bond yield to be 0.025 (0.09), sharpe ratio 0.2 (0.1), and loss given default 0.45 (0.55).

Next, based on these parameters, we vary the asset volatility within the range of $[0.2, 0.4]$, and back out the coupon value of the firm based on the Leland (1994) model. In particular, we solve for the coupon by matching the 5-year credit spread of the bond.

Once we obtain the coupon value, we can then compute the equity value, equity beta, and credit spread slope, etc.

F Simulation procedure

We set the initial asset value, risk free rate, loss given default, tax rate, bankcrupcy cost, and sharpe ratio to be 100, 0.02, 0.5, 0.15, 0.15, and 0.15, respectively.

We construct a sample of firms with asset volatility taken from 30 evenly spaced numbers over $[0.2, 0.4]$, and default boundary taken from 30 evenly spaced numbers over $[10, 70]$. In particular, we construct firms with all the combinations between the 30 volatility values and 30 default boundary values. Hence, there are 900 firms in total.

Based on the total asset volatility, market sharpe ratio λ_M, and the firm i's sharpe ratio λ_i, we compute the systematic and idiosyncratic volatility as $\sigma_{sym} = \frac{\sigma_{total}\lambda_i}{\lambda_M}$, and $\sigma_{idio} = \sqrt{\sigma_{total}^2 - \sigma_{sym}^2}$. Based on the default boundary value, we obtain the coupon value as $V_d \frac{r(\xi-1)}{(1-\tau)\xi}$.

Next, we simulate 10 years of daily data. We set 360 days for a year, and 30 days each month, for simplicity. For each date, we update the newest firm value according to Equation (4.3). We then compute the equity value, and credit spreads based on the new firm value. The formula for the equity value is shown as Equation (4.5), and the formula for the credit spreads is shown as Equation (4.8).

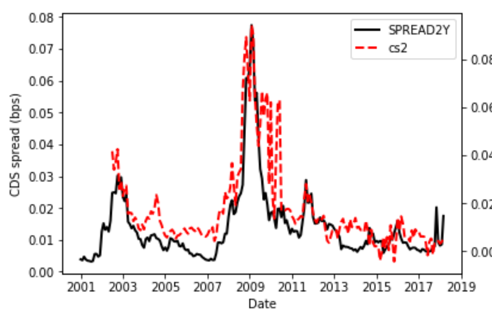
Once we have the simulated 10-year daily panel data, we pick the month end value to form a sample at the monthly frequency. We compute the one month ahead equity returns based on the equity values and winsorize them at 2.5%, and 97.5% levels.

G CDS spread and bond yield

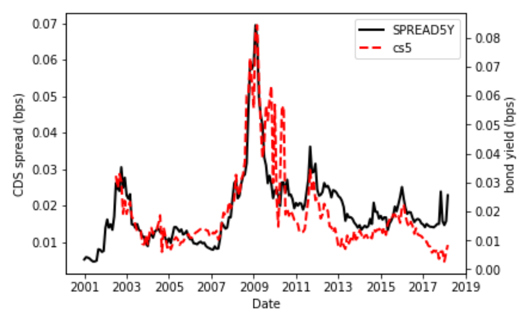
Figure G.1: Aggregate CDS Spreads and bond credit spread time series plot.

In this figure, I report the monthly time series of aggregate CDS spreads (black line, in bps), and the bond credit spreads (red line, in bps), with 2-year, 5-year, and 10-year maturity. The aggregate time series is computed as cross sectional averages of the CDS spread and the bond yields. The bond yield is interpolated based on the yield curve of each firm. The risk free rate is taken from the constant maturity treasury zero coupon yield. The data period ranges from January 2001 until March 2018. Sources: Markit, TRACE, FRED, authors' computation.

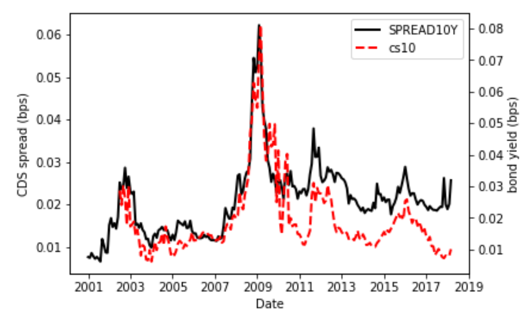
(a) 2-year



(b) 5-year



(c) 10-year



Chapter 5

Are Option and CDS Markets Integrated?

5.1 Introduction

Structural models of credit risk (Merton, 1974) suggest that equity, debt, and their derivatives are claims on their underlying firm value. In the absence of frictions, these claims should be closely related to each other, because they all depend on the same source of risk, i.e. the asset value of the firm. Based on the tight link between equity options and credit claims implied from structural models, many studies use options data to infer the credit spread of the corresponding firm.[1] However, in practice, this link can be distorted due to market imperfections even if the structural models are correct. It is unclear whether the option and credit market integration assumption is empirically valid.

In contemporaneous work, Collin-Dufresne, Junge, and Trolle (2020) study the integration between option and credit markets using aggregate claims on the SP500 index and a basket of credit derivatives. For these claims, the composition of the underlying asset baskets is not identical, in contrast to single name equity options and credit claims, which share the same underlying firm value.

[1] Hull, Nelken, and White (2005), Carr and Wu (2009), Carr and Wu (2011), Culp, Nozawa, and Veronesi (2018); among others.

I test the integration between option and credit markets at the *firm level* by comparing the credit spreads implied from a firm's options, henceforth IS, and the credit spreads observed from the credit default swap market, henceforth CDS spreads. I adopt two methods in constructing the IS based on Carr and Wu (2011) and Culp, Nozawa, and Veronesi (2018). I provide validation on these methods by conducting the Merton model regression following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009). I show that the IS from both methods are driven by theoretical credit risk determinants, suggesting that it is suitable to use the IS as the credit spread proxy to study the relation between option and CDS markets.

To test the integration between option and CDS markets, I focus on the co-movement between the IS and CDS spreads. The co-movement of two series can be tested through two different angles. First, the co-movement indicates an equilibrium relation between the IS and CDS spreads. Second, it suggests that the two series move in the same direction, henceforth alignment. Therefore, I adopt two separate tests, focusing on these two angles, to examine the integration between option and CDS markets.

To test whether the IS and CDS spreads converge to an equilibrium relation in the long run, I adopt the co-integration test following Engle and Granger (1987). I find that most firms have co-integrated IS and CDS spreads time series for both IS metrics. Given the long-run equilibrium relation, the deviation between the two series at shorter horizons, such as the daily or weekly frequency, should predict future IS and (or) CDS spread changes. In the spirit of the error correction model, I find that the cross-market deviation, defined as the IS minus CDS spreads, significantly predicts both the future IS and CDS spread movements in the direction of convergence. The evidence suggests that the two markets integrate well in the long run, but that they exhibit short-lived price discrepancies.

In the market alignment perspective, I perform the non-parametric integration test from Kapadia and Pu (2012), henceforth KP. I find significant misalignment between the IS and CDS spreads at a daily or weekly frequency, and that the misalignment is associated with economically large IS and CDS spread movements. The frequency of misalignment decreases with the investment horizon, and these patterns hold both for Investment

Grade and High Yield firms. This again suggests the existence of short-lived price discrepancies.

Given the existence of short-lived price discrepancies, I study their determinants by examining frictions from two major sources motivated by the literature. First, I explore asset-specific frictions, such as trading costs (e.g. Gromb and Vayanos, 2010; Kapadia and Pu, 2012; Cao and Han, 2013; Han, Subrahmanyam, and Zhou, 2017). Second, I study a friction associated with market participants, such as the health of financial intermediaries (e.g. Gârleanu and Pedersen, 2011; Bongaerts, De Jong, and Driessen, 2011; He and Krishnamurthy, 2013; Du, Tepper, and Verdelhan, 2018).

For the asset-specific frictions, I test the relation between arbitrage costs and the price discrepancy from the two co-movement perspectives discussed above. First, if the arbitrage costs are associated with price discrepancies, the two series will be more aligned when the arbitrage costs are lower. Second, since the cointegration relation implies that the price discrepancy predicts the future IS and CDS changes, the predictability of the IS and CDS spread changes from the cross-market deviation will be stronger for firms with high arbitrage costs.

From the perspective of market misalignment, I project the Kendall correlation metric from KP onto a number of arbitrage cost variables. I find that the IS and CDS spreads are more misaligned when the assets have higher arbitrage costs, such as high illiquidity, high idiosyncratic risk, low institutional ownership, and low analyst coverage. The economic impacts of CDS illiquidity and firm's transparency proxies are largest among all arbitrage costs. The results are not driven by the misalignment between equity and CDS markets as documented in the literature (e.g. Kapadia and Pu, 2012; Augustin, Jiao, Sarkissian, and Schill, 2019).

In the perspective of the IS and CDS spread changes predictability through the cross-market deviation, I find that the cross-market deviation has stronger predictive powers for the IS or CDS spread changes when the assets have higher illiquidity. This indicates that the price discrepancy is associated with arbitrage costs. Furthermore, the predictability of IS (CDS spread) changes is weaker (stronger) for firms with low institutional ownership and analyst coverage, suggesting that the options contain more timely information than the CDSs for firms that are less transparent.

For the frictions tied to market participants, the health of financial intermediaries is shown to create a divergence for risk premiums and prices of two identical assets. I conduct panel regressions of both the contemporaneous cross-market spread basis, defined as IS minus CDS spreads, and the future cross-market return basis, defined as the IS return minus the CDS return,[2] onto the financial intermediary health proxies, such as the intermediary capital ratio from He, Kelly, and Manela (2017), broker dealer leverage ratio from Adrian, Etula, and Muir (2014), TED spread, LIBOR-OIS spread, and default spread. The financial intermediary health has both economically and statistically significant impact on the contemporaneous spread basis and it significantly positively predicts the future return basis.

To rationalize the relation between the financial intermediary health and the price discrepancy, I provide a stylized intermediary asset pricing framework building on He, Khorrami, and Song (2019). Different from the previous literature, this framework incorporates both asset transaction costs and an intermediary margin type constraint with two zero net supply assets. I analyze the impact of the financial intermediary health on the price discrepancy through both the asset-specific friction and the financial intermediary friction.

Under this framework, I show that an increase in the intermediary's wealth will decrease the asset risk premium through relaxing the intermediary constraint, but will increase the asset risk premium through an increase in compensation for the illiquidity cost. The net effect of these two channels depends on the relative magnitudes of the risk aversion of intermediary and its counterparty. I show that the intermediary constraint channel (illiquidity channel) dominates when the intermediary is much more (less) risk tolerant than its counterparty.

As the liquidity provider, the intermediary is likely to be more risk tolerant than its counterparty. Under that assumption, the intermediary constraint channel dominates.

[2]I adopt 3 return metrics in the literature, the simple spread changes, the log spread changes, and the metric from Augustin, Saleh, and Xu (2020).

When the intermediary has a long (short) position in the asset, the asset risk premium decreases (increases) with the financial intermediary health. Therefore, if the intermediary is a net buyer (seller) of the CDS (option), the financial intermediary health positively predicts the future return basis. In contrast, if the intermediary is a net buyer or seller in both markets, the sign of the return basis predictability by the financial intermediary health is determined by the relative magnitudes of the transaction costs. Since the CDS is traded in the over-the-counter market and the option is traded on an organized exchange, the CDS transaction costs are expected to be higher. In this case, the positive return basis predictability from the health of the financial intermediary can arise when the intermediary is a buyer in both markets.

Some studies provide evidence suggesting that intermediaries are net buyers of the CDS (Carey, Stulz, Allen, and Gale, 2013; Siriwardane, 2019; Cetina, Paddrik, and Rajan, 2018; Augustin and Izhakian, 2020; Czech, 2020) while others argue that they are net sellers (e.g. Junge and Trolle, 2015). In the option literature, some papers suggest that intermediaries are net buyers of short-term equity options, but net sellers of long term equity put options (Gârleanu, Pedersen, and Poteshman, 2009; Cao and Han, 2013; Christoffersen, Goyenko, Jacobs, and Karoui, 2018). According to the theoretical framework, the empirical evidence that the financial intermediary health positively predicts the future IS and CDS return basis is consistent with the view that intermediaries are net buyers of CDSs and sellers of long term equity put options.

In sum, my analysis suggests that market integration may be impeded by market imperfections, such as limits to arbitrage and the financial intermediary constraint. While structural models of credit risk can jointly price all corporate contingent claims on the same underlying perfectly without frictions, empirically, the models might perform poorly because of market imperfections. My work, therefore, sheds light on the conditions under which it is appropriate to extract and use credit spreads implied from option prices under the structural framework.

This paper is organized as follows. Section 5.2 describes the methodologies in constructing the option implied credit spreads. Section 5.3 describes the data and conducts preliminary analysis. Section 5.4 examines the integration between the option and CDS markets at both short and long horizons. In Section 5.5, I study the determinants of the price discrepancy between option implied credit spreads and CDS spreads motivated by the literature. Section 5.6 provides a stylized intermediary based asset pricing framework to rationalize the empirical findings. Section 5.7 concludes.

5.2 Methodology

To study the relation between the option and CDS markets, I obtain the credit spreads implied from the options, and the credit spreads observed from the CDS market for the same firm. I construct option implied credit spreads based on the recent literature.[3] The literature has proposed many ways to extract credit risk information from the option market (Hull, Nelken, and White, 2005; Carr and Wu, 2011; Culp, Nozawa, and Veronesi, 2018; among others). In particularly, I adopt the methodology based on Carr and Wu (2011) and Culp, Nozawa, and Veronesi (2018). In this section, I first outline two methodologies in computing the option implied credit spread. Next, I provide additional discussion on the other methodologies related to constructing the IS at the end of the section.

5.2.1 Carr and Wu (2011) option implied credit spread

Carr and Wu (2011), henceforth CW, provide a simple link between deep out of money put options and CDS spreads. This approach depends on the dynamic of a firm's equity value around the default event based on the classic Merton (1974) framework. In this framework, the firm value is the sum of its equity value and debt value. Merton (1974) assumes that the firm value follows a continuous dynamic and the firm defaults as soon as its value falls below the value of its debt. Since the firm value is continuous, its equity value reaches zero right before the default and stays at zero afterwards. However, the firm value might not follow a continuous dynamic especially around the default event. For example, a firm might default before its value falling below its debt value due to

[3]The literature tends to use return metrics to study the relation between two markets. However, there are a lot of institutional details in computing CDS returns which are absent from the option return computation. Augustin, Saleh, and Xu (2020) show that such institutional details can create large distortion of the CDS returns.

strategic default.[4] Accordingly, the stock value might be positive before the default and jump to zero afterwards. Merton (1976) also build a reduced form model capturing this phenomenon.

Building on this insight, CW assume that the stock price stays above a strictly positive barrier B before default but drops below a lower barrier A after default, thus generating a default corridor [A, B] that the stock price can never enter. Based on this assumption, a put option with strike price $K \in [A, B]$ will only be exercised at default with payoff $K - A$. The stock price is commonly assumed to be zero after default (Merton, 1976). CW also sets $A = 0$ in their analysis. Therefore, the put option with $\frac{1}{K}$ position will earn 1 dollar at default. This closely relates to the payoff structure of a CDS contract. Based on this nice feature of the put option struck within the default corridor, one can estimate the default intensity of the firm in a much simpler way.

Suppose the price of the deep out of the money (DOTM) put option struck within the default corridor is $P_t(K, T)$. Assuming that the risk free rate and hazard rate is constant, CW show that the DOTM put price has the following expression:

$$P_t(K, T) = K \left(\lambda^Q \frac{1 - e^{-(r+\lambda^Q)(T-t)}}{r + \lambda^Q} \right), \tag{5.1}$$

where λ^Q is the option implied risk neutral default intensity.[5] Equation (5.1) offers a direct one to one mapping between the put option price and the default intensity. Using the constant option implied default intensity, I can compute the $T - t$ maturity option implied credit spread, henceforth IS, following Hull, Nelken, and White (2005) (HNW) and Chen, Collin-Dufresne, and Goldstein (2009) (CCG):

$$IS(t, T) = -\frac{1}{T - t} \log(1 - e^{-\lambda^Q(T-t)} L), \tag{5.2}$$

where L is the loss given default, which is assumed to be constant.[6]

[4]See Carr and Wu (2011) for detailed discussion.

[5]The proof of the formula can be found in Carr and Wu (2011), which is also presented in the appendix J in this paper.

[6]As stated in HNW, this formula is based on the assumption that the creditor get a fraction of the price of the equivalent remaining maturity Treasury at default ("Reovery of Treasury").

5.2.2 Culp, Nozawa, and Veronesi (2018) pseudo credit spread

Building on the classic Merton (1974) framework, Culp, Nozawa, and Veronesi (2018), henceforth CNV, construct a pseudo firm whose asset is a firm's equity with value S. This firm issues a zero-coupon debt with face value K and maturity T. At maturity, the payoff to the pseudo bond holders is $\min(K, S_T) = K - \max(K - S_T, 0)$. This is exactly the payoff of the risk-free debt K minus the payoff on the equity put option. The no-arbitrage value of the pseudo bond at $t < T$ is

$$\hat{B}_t(K,T) = Ke^{-rT} - \hat{P}_t^{equity}(K,T), \tag{5.3}$$

where r is the risk free rate, and $\hat{P}_t^{equity}(K,T)$ is the value of the equity put option at t with strike price K and maturity T.

To construct the pseudo bond to be comparable to the real bond, CNV match the firm's default probability with the pseudo firm's default probability. The firm's default probability is implied from the Moody's credit rating. The pseudo firm's default probability is implied from the historical distribution of the stock returns.[7]

In a slight departure from CNV, I estimate the default intensity from the pseudo bond based on the following risk neutral pricing formula following HNW and CCG:

$$\hat{B}_t(K,T) = e^{-rT}(\mathbb{P}^Q RK + (1-\mathbb{P}^Q)K) = e^{-rT}K(1-(1-e^{-\lambda^Q T})L), \tag{5.4}$$

where $\mathbb{P}^Q$ denotes the risk neutral default probability, R denotes the recovery, L denotes the constant loss given default, and λ^Q denotes the risk neutral default intensity. With the risk neutral default intensity, I can obtain the option implied credit spread with any maturity using Equation (5.2).[8]

[7]Details can be found in appendix K.

[8]The results in this paper is not driven by the "Recovery of Treasury" assumption nor the constant default intensity assumption. The results are robust when I directly compute the yield from the 2-year pseudo bond as CNV without recovery or intensity assumption and compare it with the 2-year CDS spread without extrapolating the term structure.

5.2.3 Additional discussion

Besides the two methodologies outlined above, a number of other studies develop different methodologies in extracting credit spreads from option prices. For example, some papers develop structural or reduced form credit risk models with multiple factors in estimating the firm's underlying parameters governing the default risk using both the options and CDSs (Du, Elkamhi, and Ericsson, 2019; Carr and Wu, 2009; Kuehn, Schreindorfer, and Schulz, 2017). While such models provide relatively accurate estimates of the credit spread dynamics, the estimation usually involves using information from equities or CDSs besides the options.[9] Furthermore, the computation of such methods are rather complicated. A simpler approach by Kelly, Manzo, and Palhares (2019) construct the credit implied asset volatility, which can be used to compare with the option implied asset volatility based on a compound option structural model developed in Geske (1979), Toft and Prucyk (1997) and Hull, Nelken, and White (2005). However, these methods also use information from the equity market as model input.

The CW and CNV methods have two important advantages relative to other approaches to extract synthetic credit spreads from option prices. First, it does not rely on the compound option feature to infer the default intensity based on the structural model. This largely simplifies the inference process. Second, the CW IS are completely derived from the DOTM put options struck within the default corridor. While the CNV method uses the historical distribution of stock returns to select the appropriate options in constructing the pseudo firm, the IS are computed purely from the selected option prices. Since this paper tries to examine the integration between the option and CDS markets, using information from other asset markets might bias the inference.

However, one critical caveat of the CW methodology is that we cannot observe the default corridor. If the option I pick is struck outside the default corridor, the IS computed using this method will include a non-default component. On the contrary, the CNV method does not suffer from this problem. One caveat of the CNV method is that there

[9]There is extensive literature discussing the segmentation between equity and credit markets. This paper studies the segmentation between option and credit markets *beyond* the equity credit market discrepancy. Hence I resort to other methodologies to compute the IS.

is no theory that guarantees the equivalence between the CNV IS and the CDS spreads. However, this issue is less severe when the firm has low leverage, since the equity has very little optionality and can be viewed as the firm's asset. In sum, these two methods complement each other.

In addition, the observed CDS spread is likely to include a premium for illiquidity. This might generate additional noise, which leads to inaccurate comparison between IS and CDS spreads. However, I emphasize that the goal of this paper is *not* to use options to perfectly match the CDS spread levels. Similar to Blanco, Brennan, and Marsh (2005) and Kapadia and Pu (2012) in studying the co-movement between other assets, I provide integration evidence using the IS and CDS spreads through the *co-movement* angle. As long as the credit risk is the main driver of the CDS spreads[10], the co-movement analysis is appropriate. Similarly, The IS metric is a non-linear transform between existing option prices and default information. As long as the default risk is the main driver of these metrics, it is also appropriate to study the co-movement between option and CDS markets using such metrics. Furthermore, I focus on the time series dynamics of the cross-market return deviation in studying the time series determinants of the integration. The levels of the IS and CDS spreads are not likely to matter much and additional noise will be controlled for in the empirical analysis.[11]

5.3 Preliminary analysis

In this section, I first describe the data used in this paper and provide summary statistics of different credit spread metrics. Second, to verify that the observed and synthetic credit spreads are similar and indeed related to variables suggested by structural credit risk models, I implement the Merton model regressions for both series, following Collin-Dufresne, Goldstein, and Martin (2001), henceforth CGM, and Ericsson, Jacobs, and Oviedo (2009), henceforth EJO.

[10]Bongaerts, De Jong, and Driessen (2011) show that the illiquidity component embedded in the CDS spread is economically insignificant.

[11]For example, the CW and CNV methodology assumes constant recovery. Following Blanco, Brennan, and Marsh (2005), I introduce the S&P500 index return as a proxy of the debt recovery in the following regressions.

5.3.1 Data

I obtain daily CDS data from MARKIT. The sample period ranges from January 2002 to April 2018. The MARKIT database contains CDS quotes across different countries, tiers, denominations, sectors, and restructuring clauses etc.. I restrict the sample to contain only the senior unsecured USD denominated CDS contracts of the non-government sector with the MR restructuring clause.[12] Since 5-year CDSs are the most liquid contracts, I focus on this tenor for my analysis.[13]

The option data is obtained from OptionMetrics. First, I prepare for the option data to construct the IS based on CW. The CW method requires options struck within the default corridor. I eliminate the following put option series based on CW: (1) options with non-positive open interests; (2) options with strike prices greater than \$5; (3) options with negative bid prices; (4) options with deltas smaller than -0.15. After applying these filters, if there are more than one option for a particular firm date combination, I choose only 1 contract by applying the filters in the following order: highest open interest, smallest strike, and largest delta. After applying the filters and matching with the Markit CDS, I am left with a sample of 325 firms with unbalanced panel data at a daily frequency ranging from January 2002 until April 2018. Figure B.1 documents the histograms of the selected options' moneyness, defined as strike price over spot price, delta, and maturity. Most of the moneyness of the options is around 0.4 – 0.5, and most of the deltas are very close to 0. Furthermore, almost all the moneyness is under 0.7 and the deltas are above -0.15. This suggests that the options I pick are all DOTM put options and very likely to be struck within the default corridor. Similar to CW, I pick the maturity of the options greater than 365 days to mitigate maturity mismatch because the most liquid CDS contract has a maturity of 5 years.

[12] The CDS "Big Bang" in April 2009 changed the standard for CDS contracts. As a result, the standard restructuring clause for US CDS is Modified Restructuring (MR) prior to the "Big Bang" and No Restructuring (XR) after. For robustness, I also restrict the sample to only contain the CDS contracts with the standard restructuring clause. The results are robust.

[13] Since options are usually traded up to 2-year maturity, I also use 2-year CDSs for the following analysis. The results are virtually the same. The key element in my analysis is the co-movement between IS and CDS spreads. Figure B.2 shows that 2-year CDS spreads and 5-year CDS spreads have extremely high correlation with each other. The pair wise correlation is over 96% in the sample, indicating that the dynamics of the 2-year CDS spreads is similar to the 5-year CDS spreads. Thus, I focus on the 5-year CDS spreads for higher liquidity.

Second, I prepare for the option data to construct the CNV IS. I remove the option series with non-positive open interests or negative bid prices. Furthermore, based on Section 5.2.2, the options are chosen such that the pseudo firm's default probability matches with the real firm's default probability. After constructing the CNV IS and matching it with the MARKIT CDS data, I am left with a sample of 458 firms with unbalanced panel data at a daily frequency ranging from January 2002 until April 2018.

Due to data availability, the CW and CNV methods provide different sample compositions. In this paper, I focus on the overlapping sample provided by these two methods. However, all the analysis in this paper exhibits similar results when using the separate full sample based on the CW or CNV method as shown in the appendix. Table 5.1 documents the summary statistics of the overlapping sample. The unbalanced panel data ranges from Jan 2002 to April 2018. It consists of 78,493 firm-day observations with 240 firms in total. Panel A reports the descriptive statistics by rating. The sample averages of CDS spreads, CW IS, and CNV IS are 464.48, 323.55, and 609.26, respectively. The high level of sample averages is likely because firms with DOTM put options available are usually riskier. Most firms are rated around BB rating. All the credit risk metrics show similar magnitudes across different rating categories. The bid-ask spreads of the options selected based on the CW method and the CNV method are similar for the IG firms but the CW bid-ask spreads are higher than the CNV bid-ask spreads for the HY firms.[14] This is because the CNV methods pick options more near the money as the firm's rating decreases. The CNV moneyness is similar to the CW moneyness for the IG firms but becomes significantly higher for the HY firms. Panel B reports the firm fundamentals summary statistics. The sample average leverage ratio is 40%, indicating most firms are low rated firms. The average market capitalization, book-to-market ratio, institutional ownership values are 15.39, 0.1, and 0.71, as opposed to the averages of the Compustat universe 14.87, 0.08, and 0.49. This suggests that my sample consists of a large proportion of value firms.

[14]Due to concerns of the liquidity issue associated with long term DOTM put options, I also perform the main tests in this paper using both the bid price and offer price, or filtering out zero trading volume contracts. All the results remain.

Table B.1 and B.2 in the appendix provides the descriptive statistics of the separate full sample provided by the CW and CNV methods, respectively. For the CW sample, the 5-year CDS spreads and IS have a mean of 464.67 bps and 373.15 bps respectively. A majority of firms in the sample are High Yield firms. The 5-year CDS spreads for the Investment Grade firms are high. The average CDS spread for A rated firms is around 200 bps. Similar to the above discussion, the high level of credit spreads are likely due to the riskier nature of firms with DOTM put. For the CNV sample, the sample mean of the CDS spreads and IS are 165.39 and 274.96 bps respectively. This is similar to the average CDS level documented in the literature (EJO). Most of the firms are rated round BBB. For robustness, I also provide the integration analysis in the following sections using the separate samples.

5.3.2 Are option-implied credit spreads reflecting credit risk?

Before conducting the integration analysis using IS, it is essential to validate whether the IS from the two methods are close proxies for the firm's credit risk.

Figure 5.1 plots the aggregate IS and CDS time series. All three series shoot up during recession and stay low during calm periods. Figure 5.1 shows that visually these three series move almost one to one to each other, indicating that they have similar time series dynamics. Panel D in Table 5.1 reports the pairwise correlations among CDS, CW IS, and CNV IS. Quantitatively, the CDS spreads have a correlation of 0.79 with the CW IS and 0.77 with the CNV IS. Furthermore, the CW IS and CNV IS have a correlation of 0.85 with each other. This suggests that all three metrics have close time series dynamics in aggregate, consistent with the evidence provided in Culp, Nozawa, and Veronesi (2018).

To further justify that the IS are driven by the credit risk information, I examine whether the IS time series dynamics are explained by the Merton model variables. I perform the Merton model regression following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009). The regression specifications are as below:

$$
\begin{aligned}
S_t^i &= \beta_0^i + \beta_1^i lev_t^i + \beta_2^i vol_t^i + \beta_3^i r_t, \\
\Delta S_t^i &= \beta_0^i + \beta_1^i \Delta lev_t^i + \beta_2^i \Delta vol_t^i + \beta_3^i \Delta r_t,
\end{aligned}
\tag{5.5}
$$

where $S \in \{CDS, IS\}$. Similar to the previous literature, for each of the N firms in my sample, I regress both the CDS spreads and IS on the firm's leverage ratio (Leverage), the firm's realized annualized equity volatility computed using daily stock returns within the previous month, and the 10 year constant maturity Treasury rate (10-year yield). Since the leverage data is not available at a daily frequency, I perform the regression at a weekly frequency similar to EJO. In Table 5.2, I report the cross-sectional averages of the coefficient estimates and R^2 values. Columns (3) to (5) report the results of the level regression and columns (6) to (8) report the results of the difference regression. The t-statistics are calculated from the cross-sectional averages of the coefficient estimates divided by the standard deviation of the N estimates and scaled by $\sqrt{N}$. Leverage is defined as the ratio of the sum of book value of debt and the value of preferred equity to the sum of market value of equity, book value of debt, and book value of preferred equity. I interpolate the book value of equity to compute weekly leverage ratios. Volatility is computed as the annualized standard deviation of daily equity returns of the previous month.

Columns (3) and (6) in Table 5.2 provide similar results as the Merton model regressions in EJO. The precise values are slightly different due to a different sample composition and time period. Columns (4), (5), (7), and (8) report the Merton model regressions using CW IS and CNV IS as the dependent variable. If the IS time series dynamic is driven by Merton model variables, the signs of the coefficients should be consistent with what the theory predicts. Table 5.2 shows that the signs of all Merton variable coefficients in the IS regression are consistent with the theory. The results are consistent across both CW and CNV IS . Compared with the coefficients of the CDS regression, even though the IS regression coefficient magnitudes are slightly different from the CDS regression coefficients, the signs of the coefficients are almost all identical across both regressions.

In Table C.1 in the appendix, I report the augmented Merton model regressions including yield curve slope, 10-year yield squared, S&P 500 index returns, and S&P 500 index option implied volatility smirk slope. Except different signs of some Treasury yields variables due to collinearity, most of the other variables show the same signs across the CDS spreads and IS regressions and the signs are consistent with the theory predictions. This provides additional support that IS are closely related to the theoretical credit risk determinants and that the IS and CDS spreads have similar time series dynamics.

5.4 The integration between option and CDS markets

In this section, I provide evidence on the integration between option and CDS markets focusing on the co-movement of the IS and CDS spread time series. The co-movement can be tested through two different angles. First, the co-movement indicates an long-run equilibrium relation between the two series. Second, it suggests that the two series move in the same direction, i.e. aligned.

To provide intuition of these two angles, Figure 5.2 plots the IS and CDS spread weekly time series of the Cox Communication Inc.. Panel (a) shows that these two series clearly establish a close long-run trend visually. This suggests the existence of an equilibrium relation between IS and CDS spreads. However, at shorter horizons, these two series do not move in the same direction at different periods, as indicated by the grey areas in the figure. To document the short-run dynamics more clearly, panel (b) plots these time series during a relatively short horizon in September 2002. The solid lines indicate that the two series move in the same direction and the dotted lines indicate that the two series move in the opposite directions. Visually, although these two series have similar trends, they move in the opposite directions between September 1st to September 7th and September 14th to September 21st.

In the following sections, I formally test the co-movement through both the equilibrium relation and the market alignment angles.

5.4.1 Equilibrium relations

To examine the long-run integration, I perform a cointegration test. If the IS and CDS spreads are cointegrated, there exists a β such that $IS_t - \beta CDS_t$ is stationary. If the IS are the exact proxies of the firm's credit risk, one would expect $\beta = 1$ if the two markets integrate with each other. However, β might deviate from 1 if the model assumption is not perfect in constructing the IS. One possible scenario could be that the two methods assume an exogenous bond recovery. The credit spreads can be approximated as $\lambda(1 - R)$ where λ denotes the default intensity and R denotes the recovery. If the true bond recovery is different from the recovery I exogenously pick, the β could be different from 1. However, at the minimum, there should exist $\beta > 0$ such that $IS_t - \beta CDS_t$ is stationary, if the option and CDS market integrate with each other.

I perform the cointegration test following the Engle-Granger two-step method (Engle and Granger, 1987).[15] The first step of the Engle-Granger procedure is to estimate β by regressing IS onto CDS spreads:

$$IS_{i,t} = \alpha_i + \beta_i CDS_{i,t} + \epsilon_{i,t}. \tag{5.6}$$

The second step is to perform a unit root test on the residual using Augmented Dickey-Fuller (ADF) test. I perform the cointegration test on each firm and count the fraction of firms having cointegrated IS and CDS spreads with $\beta_i > 0$.

Table 5.3 reports the fraction of firms having cointegrated IS and CDS series. Panel A shows that about 81% (80%) of the firms have cointegrated IS and CDS series for the CW (CNV) IS, indicating that the IS and CDS spreads integrate well in the long run. Appendix E provides further discussion and robustness checks using different samples. The results remain the same.

Furthermore, since IS is computed using options data with maturity around 2 years while the CDS spread has maturity of 5 years, I provided the same cointegration analysis using 2-year CDS spread and 2-year IS, the result remains the same.

[15] Before conducting this method, I perform the unit roots test for both the IS and CDS spread time series for each firm to keep only the non-stationary series.

Despite the long-run equilibrium relation between IS and CDS spreads, there could be price discrepancies at shorter time horizons. The cointegration relation predicts that such divergences should have predictive power for the future movement of the cross-market basis. I thus conduct a panel regression in the spirit of the error correction model:

$$\begin{pmatrix} \Delta IS_{i,t} \\ \Delta CDS_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS} \\ \alpha_{i,CDS} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta_{IS,Dev} \\ \beta_{CDS,Dev} \end{pmatrix} Dev_{i,t-1} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}, \quad (5.7)$$

where $Dev_{i,t-1} = IS_{i,t-1} - CDS_{i,t-1}$, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the vector of firm specific control variables. To account for possible model misspecification in constructing IS, I introduce firm specific controls including firm leverage ratio, log market capitalization, annualized stock volatility computed using the previous month daily stock returns, rating, stock daily return, and stock market beta computed using the previous month daily stock returns.[16] For robustness, I also substitute time fixed effects into year-month fixed effects with macroeconomic control variables including S&P 500 index returns, CBOE VIX index, 10 year Treasury yield, the Treasury yield slope defined as 10 year yield minus 2 year yield, and default spread.

If there is a positive shock in the option (CDS) prices, $Dev_{i,t-1}$ increases (decreases) and $\Delta IS_{i,t}$ ($\Delta CDS_{i,t}$) should decrease. Therefore, $\beta_{IS,Dev}$ ($\beta_{CDS,Dev}$) should be significantly negative (positive) if the IS and CDS spreads are cointegrated. Table 5.4 reports the panel regression results for different regression specifications. I find that $\beta_{IS,Dev}$ ($\beta_{CDS,Dev}$) is significantly negative (positive) across all specifications in regressions based on both the CW and CNV IS. In addition, the daily integration result might be mechanically driven by the measurement error when constructing IS. To mitigate this concern, I perform the same regression using weekly data. The results are also robust in the unreported table.

[16] The relationship between put options and CDS is tied to underlying spot and bond positions, as the dealers are likely to hedge using spot positions. A four-variable VAR model consisting of IS, CDS spreads, stock returns and bond returns would be an appropriate model. I introduce stock and bond return determinants, such as leverage, equity volatility, size, etc, as controls to avoid model misspecification. For further research, I will introduce bond return, and employ VAR impulse response and variance decomposition techniques to tease out the relative contribution of each component in affecting the IS and CDS spreads.

In sum, I provide firm level evidence that the option and CDS markets integrate well with each other in the long run, complementing the integration evidence in the literature, but there exists short-run price discrepancies between the IS and CDS spreads.

5.4.2 Market misalignment

I next examine whether the IS and CDS spreads are aligned at shorter time horizons. I test the existence of price discrepancy following Kapadia and Pu (2012). KP provide a non-parametric integration metric in their paper (Equations (2) and (3)) to measure the misalignment between two time series.

Following KP, I define $\Delta IS^{\tau}_{i,t}$ and $\Delta CDS^{\tau}_{i,t}$ as the changes in IS and CDS spreads for firm i over non-overlapping period τ, respectively. Since both the IS and CDS spreads are proxies for a firm's default risk, any shocks of the firm will drive the two spreads moving in the same direction. In other words, the IS and CDS spreads are considered aligned if $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} > 0$, misaligned if $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} < 0$, and neither aligned nor misaligned if $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} = 0$. The KP metric for firm i is defined as

$$\kappa_i = \frac{\sum_{k=1}^{T_i} \mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}}}{T_i}, \tag{5.8}$$

where T_i is the total observations with $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} \neq 0$ of firm i.[17] This metric is closely related to the Kendall correlation. I use the term KP metric and Kendall correlation interchangeably for the rest of the paper.

To gauge the level of price discrepancies across the full panel observations, I aggregate the kendal correlation across each firm following KP. More specifically, the sample price discrepancy for time horizon τ is defined as $\frac{\sum_{i=1}^{N}\sum_{k=1}^{T_i} \mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}}}{\sum_{i=1}^{N} T_i}$, where N denotes the number of firms in the whole sample. Table 5.5 describes the results for both the CW and CNV metric. I find significant price discrepancy between the option and CDS markets. There are 46.09% (45.70%), 40.76% (42.15%), 35.18% (36.30%), and 26.51% (31.73%)

[17] In the original KP metric, T_i is the total observations within a given window including $\Delta IS\Delta CDS = 0$. To avoid counterfactual inference due to stale prices at short horizons, I compute the fraction of $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} > 0$ and $\Delta IS^{\tau}_{i,t}\Delta CDS^{\tau}_{i,t} < 0$ categories among the total observations with $\Delta IS\Delta CDS \neq 0$ for both CW and CNV IS.

of observations establish price discrepancy at daily, weekly, monthly, and quarterly frequency respectively for the CW (CNV) IS. The magnitude of the misaligned fractions is comparable to those in KP.

In addition, the misalignment is associated with economically large movements of both IS and CDS spreads. The discrepancies over daily frequency occur with an average absolute change in IS of 11.13 (11.64) bps and an average absolute change in CDS spreads of 24.04 (37.81) bps in the wrong directions for the analysis based on CW (CNV) methods. These magnitudes are economically significant. This evidence demonstrates that it is important to understand what drives the misalignment between the IS and CDS spreads.

The price discrepancy κ_i decreases as the horizon increases. The patterns hold across both investment grade (IG) and high yield (HY) categories for both the CW and CNV metrics. In sum, the evidence again indicates the existence of short-run price discrepancies between the IS and CDS spreads.[18]

5.5 The determinants of the short-run price discrepancy

In this section, I explore the determinants of the short-run price discrepancy. The seminal work by Shleifer and Vishny (1997) shows that limits to arbitrage create price anomalies. Gromb and Vayanos (2010) provide a comprehensive review on the literature on limits to arbitrage. Most frictions contributing to the impediments to arbitrage can be grouped into two categories: the frictions in trading assets and frictions of market participants. On the asset-specific friction side, there are a number of studies document that high arbitrage costs result in asset prices deviating from their fundamental values (Kapadia and Pu, 2012; Cao and Han, 2013; Han, Subrahmanyam, and Zhou, 2017; among others).

On the market participant friction side, a growing literature shows that the intermediary financial constraint drives the price discrepancy among assets (Gârleanu and Pedersen, 2011; Barras and Malkhozov, 2016; Du, Tepper, and Verdelhan, 2018; Fleckenstein

[18]The long-term (quarterly) misalignment fraction should be interpreted with caution. Appendix F simulates the IS and CDS time series which are cointegrated with cointegration vector [1,-1,0.005] and 7 days of half-life. The simulation shows that even though the two series cointegrated in the long-run, the long-run misalignment fraction might be significantly different from zero when the short-term price discrepancy is volatile.

and Longstaff, 2020; among others). Besides the limits to arbitrage channel, financial intermediary health can also impact the asset prices through demanding higher or lower compensation of bearing illiquidity cost (Bongaerts, De Jong, and Driessen, 2011).

Motivated by the literature, I test whether the asset-specific frictions and financial intermediary health is related to the price discrepancy between the IS and CDS spreads.

5.5.1 Asset-specific frictions

To study the asset-specific frictions, I focus on the two co-movement angles examined in the integration analysis. In particular, I test whether the IS and CDS spreads are more misaligned when the asset-specific frictions are larger. Furthermore, since the cointegration between the IS and CDS spreads implies that the price discrepancy predicts the future changes of the IS and CDS spreads. I test whether the price discrepancy is related to the asset-specific frictions by studying how the predictive power of the price discrepancy is affected by the frictions.

The impact on market misalignment

Both the option and CDS are claims written on the firm value. If there are no frictions, the arbitrageurs will fully take advantage of any arbitrage opportunities between the option and CDS. Since the IS and CDS spreads are driven by the same sources of risk, both the IS and CDS spreads should move in the same direction. However, impediments to arbitrage might cause anomalous movements of the two credit spreads. Hence, I formulate the following hypothesis:

Hypothesis 1. *The directional misalignment between the IS and CDS spreads is stronger when the impediments to arbitrage are more severe.*

As a first step, I sort the full sample into three subsamples based on the average arbitrage cost of each IS and CDS pair. I then obtain the misalignment fraction of each subsample to examine the patterns across different subsamples. Figure 5.3 plots these fractions (y-aixis) on the Low, Median, and High tercile (x-axis). Visually, the misalignment frequency is increasing with the CDS and option illiquidity, as well as the stock idiosyncratic risk. This is consistent with Hypothesis 1.

To test Hypothesis 1 formally, I follow KP to project the Kendall correlation onto a number of proxies for arbitrage costs. To increase the data availability, I construct the Kendall correlation based on a weekly window with daily data and perform the panel regression at the weekly frequency. Since the half-life of the cointegration analysis is approximately a week, according to Table 5.3, the weekly Kendall correlation should capture the short-run price discrepancy and thus be suitable for the analysis in this section. The KP metric is computed as $\kappa_i = \frac{2}{T_i}\sum_{k=1}^{T_i} \mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau} \Delta CDS^{\tau}_{i,k\tau} < 0\}} - 1$ where T_i denotes the number of business days with non-zero daily CDS spread changes within a week.[19]

According to the definition of the KP metric, $\kappa_{i,t} \in [-1, 1]$ and the higher the $\kappa_{i,t}$ is, the more misaligned the two series are. Table D.1 in the appendix reports the summary statistics of the Kendall correlations computed based on the CW IS and CNV IS. The mean and median of the $\kappa_{i,t}$ are both negative. This indicates that a majority of the observations have aligned IS and CDS spreads. Panel B reports the correlations between $\kappa_{i,t}$ and other firm specific and macroeconomic variables. Not surprisingly, the CW and CNV $\kappa_{i,t}$ have high correlation with each other. Interestingly, $\kappa_{i,t}$ is negatively related to leverage, equity volatility, 5y CDS spreads, VIX, and default spreads, suggesting the IS and CDS spreads are more aligned when the firm's credit condition or the macroeconomic condition worsens. While this seems counterintuitive at first glance, I extend the theoretical framework in this paper in Appendix N and show that if the credit risk component is more volatile than the transitory component, i.e. frictions, the IS and CDS spreads can be more aligned since they are driven by the same credit risk component.

I apply Fisher's z transformation on κ_i to obtain a stationary KP metric ($\bar{\kappa} = \frac{1}{2}\log\frac{1+\kappa}{1-\kappa}$) as the dependent variable following KP. The general panel regression specification is:

$$\bar{\kappa}_{i,t} = \alpha_i + \gamma_t + \beta_{var} Var_{i,t} + Y'_{i,t}\beta_Y, \tag{5.9}$$

[19]This formula is slightly different from Equation (5.8) because this formula standardize the Kendall correlation between -1 to 1.

where α_i refers to the firm fixed effect, γ_t refers to the time fixed effect, $\bar{\kappa}$ is the transformed Kendall correlation, Var is the variable of interest, and Y_i is the vector of firm specific control variables.

Following KP, I introduce the option bid-ask spread and volume as the option illiquidity and liquidity proxies and CDS depth and "Spreadzero", computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS spread changes over the week, as CDS liquidity and illiquidity proxies. I introduce the idiosyncratic risk variable as the ratio of the idiosyncratic volatility to the total volatility for each stock. The idiosyncratic volatility is the standard deviation of the residual from the Fama-French three-factor (FF3) model. It can be shown that the idiosyncratic volatility ratio can be expressed as $1 - R^2$ where R^2 is the R-square of the FF3 regression (Ferreira and Laux, 2007). I compute the log transformation of idiosyncratic volatility ratio as $\log \frac{1-R^2}{R^2}$ following KP.

Apart from the arbitrage cost variables introduced in KP, I include proxies for the information transparency of the firms. Similar to Han, Subrahmanyam, and Zhou (2017), the arbitrageurs might face higher arbitrage cost if the firms are less transparent. I obtain analyst coverage ($\#Analyst$) and institutional ownership (IO) variables to proxy the transparency of a firm. IO is computed as the fraction of common shares owned by institutions based on Thomson 13F filings.

I also introduce firm specific control variables including firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. For robustness, I also substitute time fixed effects into year-month fixed effects with macroeconomic control variables including S&P 500 index returns, CBOE VIX index, 10 year Treasury yield, the Treasury yield slope defined as 10 year yield minus 2 year yield, and default spread.

Tables 5.6 reports the panel regression results for both the CW and CNV metrics. All specifications in both tables include firm fixed effects, time fixed effect, and firm specific controls to control for permanent and transitory firm specific factors, as well as the systematic variations. To mitigate the autocorrelation and heteroskedasticity concern, I cluster the standard error by firm and date.

Columns (1) – (8) reports the effects of CDS and option liquidity on the option and CDS market alignment. The signs of all four liquidity proxies of option and CDS in both tables are consistent with Hypothesis 1. In addition, the depth and bid-ask spread coefficients are statistically significant in the regression based on both CW and CNV $\bar{\kappa}$. Columns (9) and (10) report the effects of idiosyncratic risk on IS and CDS spread alignment. The sign of the idiosyncratic risk variable is consistent with Hypothesis 1. It is highly statistically significant in the regression based on CNV IS but not significant in the regression based on CW IS. Columns (11) – (14) report the effect of firm's transparency on the market alignment. The coefficients of both institutional ownership and analyst coverage have the correct signs. The IO coefficient is significant in the regression based on CNV IS and the $\#Analyst$ coefficient is significant in the regression based on CW IS. Columns (15) and (16) perform regressions including all variables. All variables have qualitatively and quantitatively similar coefficients as the ones in specification (1) – (14).

To understand the economic significance of the variables, I focus on columns (15) and (16) of Tables 5.6 since they have the highest R^2 among the CW and CNV regressions, respectively. The standard deviation of the average Kendall correlation $\bar{\kappa}$ across firm is about 0.162 (0.165) for the CW (CNV) metrics. A change of one standard deviation of CDS depth and option bid-ask spread explains 12.9% (8.6%) and 6.3% (11.8%) of the Kendall correlation variation for the CW (CNV) metric, respectively. A change of one standard deviation of idiosyncratic risk, institutional ownership, and analyst coverage explains 3.9% (7.7%), 6.8% (11.3%), and 12.3% (12.3%) of the Kendall correlation variation for the CW (CNV) metric, respectively. All variables are economically significant. In particular, the CDS illiquidity and the analyst coverage have large economic impacts on market integration among all the other variables.

For robustness, Table G.6 in Appendix G documents the regression results controlling for the CDS - equity Kendall correlation to understand whether the misalignment between CDS and option markets is purely driven by the misalignment between the CDS and equity markets. Not surprisingly, the CDS - equity Kendall correlation also explains a large proportion (16%) of variation of the $\bar{\kappa}$, since the option and equity are closely related in theory. However, the IS and CDS spreads misalignment is still significantly related to the asset-specific arbitrage cost variables. The magnitudes of the coefficients of all the arbitrage costs remain similar as the regression results in Table 5.6. The economic impacts of these arbitrage costs on the misalignment between IS and CDS spreads are comparable to the economic impact of the price discrepancy between the CDS and equity markets. This again highlights the importance of these arbitrage costs and the importance of the price discrepancy between IS and CDS beyond the price discrepancy between the equity and CDS markets.

In addition, Appendix G reports the same regressions using the separate full samples based on the two methods. Furthermore, it also reports the regression results using 2-year IS and 2-year CDS spreads as input. Finally, I also compute the IS based on bid and offer quotes of the options and perform the same analysis. While the significance of some arbitrage cost variables reduces in a few specifications, most results are consistent with Hypothesis 1.

In sum, I provide cross-sectional evidence that the misalignment between the option and CDS is stronger for assets with high arbitrage costs such as high illiquidity, high idiosyncratic risk, low institutional ownership, or low analyst coverage.[20]

The impact on cross-sectional predictability

Due to limits to arbitrage, the asset-specific frictions might create price discrepancies between the two credit spreads. Based on the cointegration relation, these price discrepancies should predict the future IS or CDS spread movements. While the cointegration indicates the two credit spreads should converge to each other, it is an empirical question on whether one market leads the other markets. Next, I discuss the impact of the frictions studied in the previous section on the predictability between the option and CDS markets.

The option (CDS) illiquidity mainly impacts the price discovery of its own market. For firms with high option (CDS) illiquidity, if the arbitrageurs are unlikely to engage in arbitrage trades due to high transaction costs, the cross-market deviation, defined as

[20]While it is interesting to analyze whether the basis between IS and CDS spreads across firms presents arbitrage opportunities, the IS are computed based on certain assumptions and thus might not reflect the actual credit spread level, which makes it hard to infer which firm presents higher arbitrage opportunity.

IS minus CDS spreads, should have stronger predictive power on the IS (CDS spread) changes than that of firms with low asset illiquidity.

Hypothesis 2. *Conditional on high option (CDS) transaction costs, the predictive power of the cross-market deviation, defined as $IS - CDS$, is stronger for the future IS (CDS spread) changes.*

The information transparency of a firm could impact both the options and CDSs of the corresponding firm. For less transparent firms, if the option (CDS) market contains more timely information over the other market, and the arbitraging activities are not effective due to the information transparency, the cross-market deviation should have a stronger predictive power on the CDS spread (IS) movements than that of the transparent firms. Similarly, the cross-market deviation should have a weaker predictive power on the IS (CDS spread) movements.

Hypothesis 3. *If either the option or CDS market contains more timely information over the other when the firm is less transparent, conditional on firms with low information transparency proxies, one should observe one of the following two patterns:*

1. *Option market leads CDS market: The predictive power of the cross-market deviation is weaker for IS, but stronger for CDS spread changes, or*

2. *CDS market leads option market: The predictive power of the deviation is weaker for the CDS spread changes, but stronger for the IS change.*

To test these two hypothesis, I perform the error correction regression by interacting the cross-market deviation with the asset-specific arbitrage cost variables. The regression specification is

$$\begin{pmatrix} \Delta IS_{i,t+1} \\ \Delta CDS_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t+1} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta^u_{IS,Dev} + \beta^c_{IS,Dev} D_{c,t} \\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev} D_{c,t} \end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix} \tag{5.10}$$

where $D_{c,t}$ denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation.

Table 5.7 reports the regression results. Panel A (B) reports the regression results of $\Delta IS_{i,t+1}$ ($\Delta CDS_{i,t+1}$). If the predictive power of the cross-market deviation Dev is stronger (weaker) conditional on high arbitrage costs, the conditional beta should have the same (opposite) sign compared to the unconditional beta.

Columns (1) to (4) document the predictive effect of Dev conditional on firms with high CDS or option illiquidity. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile. Columns (3) and (4) in panel A shows that in the regression predicting IS, the beta of $D_{CDSIlliquid} * Dev$ is strongly significant and negative, same as the unconditional beta. Columns (1) and (2) in panel B shows that in the regression predicting CDS, the beta of $D_{OptionIlliquid} * Dev$ is strongly significant and positive, same as the unconditional beta. This indicates that conditional on high CDS illiquidity, the option and CDS with high illiquidity has stronger predictability through the cross-market deviation, consistent with Hypothesis 2. Furthermore, the magnitude of the interaction beta is larger than the unconditional beta. For example, in column (3) of panel A, conditional on high option illiquidity, a one standard deviation increase in the cross-market deviation results in the change of CW IS to decrease almost 2 times more than the unconditional effect, indicating the conditional effect is economically significant.

Columns (7) and (8) report the predictive power of the cross-market deviation conditional on firms with low transparency. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. Panel A shows that in the regression predicting IS, the beta of $D_{Transparency} * Dev$ is strongly significant and positive, opposite to the unconditional beta. Panel B shows that in the regression predicting CDS, the beta of $D_{Transparency} * Dev$ is positive for both CW and CNV metrics, same as the unconditional beta. It is strongly significant for the regression based on CNV metrics as shown in column (8). Interestingly, the conditional effect in column (8) drives out the significance of the unconditional effect, suggesting most of the CDS predictability comes from the firms with less public information. The evidence indicates that conditional on firms that are less transparent, the options contain more timely information over the CDSs. The economic impact of the information transparency is large. For example, column (7) in panel A shows that conditional on low transparency, a one standard deviation increase in the cross-market deviation increases the future changes of the CW IS about 42% compared to the unconditional effect, indicating the conditional effect is economically significant.

When conducting the same analysis using the separate sample, or the 2-year IS and CDS spreads, bid or offer quotes as input, I find similar evidence as Table 5.7.

One concern in interpreting the result is that options and CDSs are derivatives written on stocks and bonds. Since bonds are dealer intermediated OTC market products, the speed of the information diffusion in the bond markets is likely to be slower than the stock market due to the presence of information frictions (Hong and Stein, 1999; Jostova, Nikolova, Philipov, and Stahel, 2013, etc.). The underreaction of the bond market compared to the stock market might contribute to the underreaction of the CDS market compared to the option market. To mitigate such concern, Regression (5.10) includes lagged equity return as a control variable to subsume the information spillover between stock and credit markets. My result hence does not appear to be driven by the information diffusion between the stock and credit markets. The lead lag relationship is driven by the information diffusion between option and CDS markets due to limits to arbitrage frictions.

Overall, the evidence suggests that the IS and CDS spreads predictabilities through the cross-market deviation are stronger when they have high illiquidity. However, the option market contains more timely information than the CDS market for firms that are less transparent.

5.5.2 Market participant related frictions

Starting from Allen (2001) and Duffie (2010), intermediaries have been receiving increasing attention in the literature. They serve as market-makers for equity options to provide liquidity to end-users by taking the other side of the end-user net demand (Gârleanu, Pedersen, and Poteshman, 2009). They are also influential market players in the CDS market (Augustin, Subrahmanyam, Tang, and Wang, 2014). He, Kelly, and Manela (2017) find that banks are the marginal investors for a number of asset markets including option and CDS markets.

The health of the financial intermediary impacts the financial asset risk premiums, as it can amplify the premiums associated with asset-specific frictions such as transaction costs, or premiums associated with the financial constraints of intermediaries. Bongaerts, De Jong, and Driessen (2011) show that the wealth and risk aversion of the intermediary impact the sign of the liquidity premium. Gârleanu and Pedersen (2011) demonstrate theoretically that the financial intermediary margin constraint can generate deviation between the risk premiums of two assets with identical payoff structures. An increasing number of studies document empirically that the financial intermediary health predicts the asset returns (Adrian, Moench, and Shin, 2010; Haddad and Muir, 2018).

Motivated by the literature, the price discrepancies between IS and CDS spreads can be caused by their risk premium (price) deviation impacted by the financial intermediary. As a first step, I plot the weekly time series of the average cross-market deviation between IS and CDS spreads, defined as $\log(IS) - \log(CDS)$, and the proxies of the financial interemdiary health, as shown in Figure 5.4. The proxies include the intermediary capital ratio from He, Kelly, and Manela (2017), TED spread, LIBOR-OIS spread, and default spread. Visually, these financial intermediary health proxies co-move strongly with the aggregate cross-market deviation.

Next, I test empirically whether the financial intermediary health relates to the contemporaneous IS and CDS spread deviation, as well as whether it predicts the return deviation between the IS and CDS spreads. I approximate the IS and CDS returns using simple spread changes, log spread changes, and the return metric based on Augustin, Saleh, and Xu (2020).[21] Since the CNV IS are an empirical construction of the credit risk proxy rather than an equivalent counterpart of the CDS spread, to avoid counterfactual inference, I use the CW IS to study whether the risk premium (price) deviation is related to the financial intermediary.[22]

[21] Let s denote the CDS spread, the return metric in Augustin, Saleh, and Xu (2020) is $\frac{\Delta \widetilde{P}_t}{\phi}$ where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, c denotes the coupon payment which is set to the s_{t-1} prior to the "Big Bang" and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1.

[22] Even though the CNV IS might not be exactly equivalent to the CDS spread, I still find similar evidence by conducting the following analysis and the results are especially stronger when the firms are highly rated as shown in Appendix I, because the firm's equity behaves more similarly to the asset and the CNV IS resemble to the CDS spreads more in this case.

I conduct both the contemporaneous panel regression and the predictive panel regression. For the contemporaneous regression, the dependent variable is $\log(IS)-\log(CDS)$.[23] For the predictive regression, the dependent variable is the lag return deviation between the IS and CDS spreads. The independent variables of both regressions are the financial intermediary health proxies, including the intermediary capital ratio variable from He, Kelly, and Manela (2017) (HKM), the broker-dealer leverage ratio from Adrian, Etula, and Muir (2014) (AEM), TED spread, LIBOR-OIS spread, and default spread to proxy the financial health of the intermediary. The panel regressions are specified as follow:

$$\begin{aligned} S^{Dev}_{i,t} &= \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t} \\ R^{Dev}_{i,t+1} &= \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t} \end{aligned} \tag{5.11}$$

where $S^{Dev}_{i,t} = \log(IS_{i,t}) - \log(CDS_{i,t})$, $R^{Dev}_{i,t+1} = R^{IS}_{i,t+1} - R^{CDS}_{i,t+1}$, $health_t$ denotes the financial intermediary health proxy, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth.

Table 5.8 reports the contemporaneous regression result. Except for the AEM leverage ratio, all variables have signs suggesting that the financial intermediary health negatively related to $S^{Dev}_{i,t+1}$. Since the AEM leverage ratio is at the quarterly frequency and the test here is performed at the daily frequency, the AEM ratio does not have enough variability to account for the variation of the return basis, resulting in counterfactual inference. All other proxies for financial intermediary health variables are significant.

The impact of financial intermediary health on the $S^{Dev}_{i,t}$ is economically significant, especially for the HKM-ICR variable. The average change of HKM-ICR is 6.6 bps per day. This translates to about 35 bps changes of the credit spread deviation $S^{Dev}_{i,t}$. Given the daily log spread deviation changes are about 330 bps on average, the average change of HKM-ICR explains over 10% of the average movement of daily log spread deviation,

[23] Since there is noise associated with the IS construction, I adopt the $\log(IS) - \log(CDS)$ to mitigate the noise in the regression analysis.

suggesting that the financial intermediary is an important factor in understanding the deviation between IS and CDS spreads.

Table 5.9 shows the predictive regression results. Similar to the contemporaneous regression results, all variables have signs suggesting that the financial intermediary health positively predicts $R^{Dev}_{i,t+1}$ except AEM leverage ratio. All variables establish different degrees of significance across the three return metrics. The HKM intermediary capital ratio variable is the most robust and significant. In addition, the significance of the HKM capital ratio survives in the regressions including all financial intermediary health variables. Hence, I focus on the HKM metric, henceforth ICR, in the following robustness analysis.

Table 5.10 reports the results of regressions using different subsamples and regression specifications. All specifications include firm fixed effects to control for unobserved firm specific variations. In addition, specifications (1), (4), and (7) include the year-month fixed effect to control for the unobserved systematic factors. Specifications (2), (5), and (8) further introduce firm specific controls to eliminate the potential bias caused by firm specific factors or model misspecifications. Lastly, specifications (3), (6), and (9) introduce macroeconomic controls including S&P 500 index returns, CBOE VIX index, 10 year Treasury yield, the Treasury yield slope defined as 10 year yield minus 2 year yield, TED spread, and default spread to reduce the bias caused by other macroeconomic variables.

Panel A in Table 5.10 documents the regression results using the full sample. I find that the ICR coefficients are highly significantly positive across all specifications. The magnitudes of the coefficients remain almost the same regardless of whether more controls are added. Different from ICR economic magnitude in the contemporaneous regression, the magnitudes of ICR in these predictive regressions are economically small. According to columns (2), (5), and (8), the average change of ICR explains about 1% to 3% of the movement of the future return deviation. The results are robust across both IG and HY samples as shown in panel B and C. Panel D shows that the result is not driven by the crisis. The results are also not driven by IS or CDS stale price since the regression is performed on the sample excluding stale prices. In an unreported regression, I find that the results are still highly robust with data at the weekly frequency. For other robustness, I perform the same analysis using separate full samples, IS implied from option bid or offer quotes, and

2-year IS and CDS spreads. As shown in appendix I, all results are strongly statistically significant with the positive signs.

5.6 A simple intermediary based asset pricing framework

In this section, I provide an intermediary based asset pricing framework that can rationalize why the financial intermediary health is strongly positively related to the future return basis. In particular, I extend the model by He, Khorrami, and Song (2019) to incorporate both the friction in the asset, such as transaction costs, and friction in the intermediary, such as intermediary constraint. This framework aims at studying how the health of the financial intermediary impacts these two frictions, and how the interaction between these two channels give rise to the positive return basis predictability documented in the previous section.

Suppose there are two periods 1 and 2. I assume that there are 2 risky assets in the economy, namely CDS and put option.[24] Suppose these two assets have identical payoffs. There is a risk-free saving technology with return 1. The price of CDS (put option) at period 2 is $\widetilde{p}_{cds}$ ($\widetilde{p}_{put}$) with mean μ_{cds} (μ_{put}). To simplify notation, I denote the quantity at period 2 with "~". The equilibrium price of CDS (put option) at time 1 is p_{cds} (p_{put}).

There are two agents in the economy, an intermediary and a residual investor.[25] Both the intermediary and the residual investor have exponential utilities[26] with absolute risk aversion $\gamma^I(W^I)$ and $\gamma^R(W^R)$, respectively.[27] I assume that the intermediary and the residual investor are endowed with θ_c^I and θ_c^R units of credit insurance inventories at period 2 (Bongaerts, De Jong, and Driessen, 2011; Kondor and Vayanos, 2019; He, Khorrami,

[24]Since CDS and bond are both OCT contracts with zero net supply, switching CDS with bond in this model will not generate additional predictions. However, switching option with equity will, since equity is in positive net supply. In the latter sections, I show that the option prices are affected by the relative magnitudes of the risk aversion of intermediary and its counterparty. Due to positive net supply, equity prices will be affected by the aggregate risk aversion of the economy instead.

[25]The intermediary corresponds to the holding company of the primary dealer of both markets including all its subsidiaries. The residual investor includes other financial institutions such as insurance companies and retail investors.

[26]The exponential utility assumption is for tractability reasons and the qualitative implications remain if I substitute it with power utility.

[27]I follow He, Khorrami, and Song (2019) to introduce the dependence of wealth of the agent's risk aversion. In particular, wealth is negatively related to risk aversion.

and Song, 2019).[28] The credit inventory has price $\widetilde{p}_c$ and standard deviation σ_c. Since both the CDS and the put option are proxies for the credit risk, I assume the variance of the CDS and the put option to be σ_c^2.

Following Bongaerts, De Jong, and Driessen (2011), I introduce transaction cost c_{cds} (c_{put}) for CDS (put option). For simplicity, I assume that the transaction cost at period 2 is idiosyncratic with mean 0 and variance $\sigma_{c_i}, i \in \{cds, put\}$.[29] Lastly, I assume that the CDS and option have additional idiosyncratic noise. For ease of notation, I denote the total variance of asset i to be $\sigma_c^2 + \sigma_i^2$ where σ_i incorporates both the transaction cost variance and other idiosyncratic noises.

The exponential preference implies that the agents choose a mean-variance portfolio.[30] The agents maximize the following objective function:

$$
\begin{aligned}
\max_{\theta^j_{cds}, \theta^j_{put}} \; & \mathbb{E}(\theta^j_{cds}(\widetilde{p}_{cds} - (p_{cds} + \delta^j_{cds} c_{cds})) + \theta^j_{put}(\widetilde{p}_{put} - (p_{put} + \delta^j_{put} c_{put})) + \theta^j_c \widetilde{p}_c) \\
& - \frac{\gamma^j(W^j)}{2} \mathbb{V}\mathrm{ar}(\theta^j_{cds}\widetilde{p}_{cds} + \theta^j_{put}\widetilde{p}_{put} + \theta^j_c \widetilde{p}_c),
\end{aligned} \tag{5.12}
$$

where δ_i^j is the sign of the holding position of asset i. It captures the idea that the agent always pays c_i transaction cost no matter if he buys or sells the asset.

Following Gârleanu and Pedersen (2011), I assume that the intermediary faces a margin type of constraint. Different from the usual margin constraint, I introduce transaction cost in the constraint:

$$
(m_{cds} + c_{cds}) \left|\theta^I_{cds}\right| + (m_{put} + c_{put}) \left|\theta^I_{put}\right| \leq W^I, \tag{5.13}
$$

[28] A negative position in the credit insurance inventory is identical to a positive exposure to credit risk.

[29] Bongaerts, De Jong, and Driessen (2011) and Choy and Wei (2020) document empirically that the liquidity risks of options and CDSs are economically small. For simplicity, I assume that the transaction cost at period 2 is idiosyncratic and the expected transaction cost to be 0. Changing it to be non-zero value won't impact the following analysis.

[30] As demonstrated in the objective function, the agents maximize the mean and minimize the variance of their portfolio holdings.

where m_{cds} and m_{put} is the dollar value of the margin requirement for the CDS and put option, respectively. For ease of exposition, I set $m_i, i \in \{cds, put\}$ to be 0 for the rest of my analysis.[31]

When the constraint is slack, the FOCs of both agents imply

$$\begin{cases} \mu_{put} - p_{put} = \frac{(\theta_c^I+\theta_c^R)\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{put}^I c_{put} \\ \mu_{cds} - p_{cds} = \frac{(\theta_c^I+\theta_c^R)\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^B(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{cds}^I c_{cds}, \end{cases} \tag{5.14}$$

where $\gamma^j(W^j)^{-1} = \frac{1}{\gamma^j(W^j)}$, $j \in \{B, R\}$. The risk premium of both assets can be decomposed into two components. The first component corresponds to the credit risk premium earned by hedging credit inventory risk. The second component corresponds to the illiquidity compensation. Similar to Bongaerts, De Jong, and Driessen (2011), if the intermediary is less risk averse or has more wealth than the residual investor, the illiquidity component will be positive provided that the intermediary is the net buyer of the asset. In other words, the compensation for illiquidity cost will be earned by whoever has lower risk aversion or higher wealth. Due to this feature, the illiquidity compensation is increasing with the intermediary wealth and decreasing with its risk aversion.

When the constraint is binding, the risk premiums become

$$\begin{cases} \mu_{put} - p_{put} = \frac{(\theta_c^I+\theta_c^R)\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{put}^I c_{put} + \frac{\gamma^I(W^I)^{-1}\phi\delta_{put}^I c_{put}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} \\ \mu_{cds} - p_{cds} = \frac{(\theta_c^I+\theta_c^R)\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^B(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{cds}^I c_{cds} + \frac{\gamma^I(W^I)^{-1}\phi\delta_{cds}^I c_{cds}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}, \end{cases} \tag{5.15}$$

where ϕ is the shadow cost of the constraint. Compared to Equation (5.14), (5.15) has an extra component generated by the binding constraint $\frac{\gamma^I(W^I)^{-1}\phi\delta_i^I c_i}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$. The higher the shadow cost of the constraint is, the larger the magnitude of this component is. The sign of this component is dependent on the sign of the intermediary position. If the intermediary is a buyer of the asset i, he will demand a higher premium if the constraint is more binding, i.e. the shadow cost is larger.

Similar to He, Khorrami, and Song (2019), the intermediary wealth W^I is a proxy for the intermediary health in this model. To understand the relation between the health of fi-

[31] Setting the margin requirement to be zero and symmetric across long and short positions is for simplicity reason. It won't impact the following model implications without such assumptions.

nancial intermediaries and the future return basis in the empirical evidence, it is essential to understand the relation between the intermediary wealth and the risk premium basis, defined as option risk premium minus CDS risk premium. To do so, I need to understand how the shadow cost of the constraint ϕ moves with the intermediary wealth.

Proposition 1. *Suppose the intermediary constraint is binding.*

$$\frac{\partial \phi}{\partial W^I} < 0. \tag{5.16}$$

Proposition 1 demonstrates that the shadow cost of intermediary constraint is decreasing with the intermediary's wealth. This is intuitive since the higher the intermediary wealth is, the less likely the constraint will bind. The cost of the constraint reduces accordingly. Based on proposition 1, I can establish the relation between the intermediary financial wealth and the risk premium basis.

Proposition 2. *The risk premium basis between the option and CDS defined as* $(\mu_{put} - p_{put}) - (\mu_{cds} - p_{cds})$ *is:*

$$\left(\frac{\gamma^I (W^I)^{-1} \phi}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}} + \frac{\gamma^I (W^I)^{-1} - \gamma^R (W^R)^{-1}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}\right) (\delta^I_{put} c_{put} - \delta^I_{cds} c_{cds}). \tag{5.17}$$

Suppose the intermediary constraint is binding, and $\gamma^R(W^R) \gg \gamma^I(W^I)$*. If* $\delta^I_{put} c_{put} < \delta^I_{cds} c_{cds}$*, the cross-market risk premium deviation* $(\mu_{put} - p_{put}) - (\mu_{cds} - p_{cds})$ *is increasing with* W^I*.*

Proposition 2 demonstrates two important implications from the model. First, the model shows that there are two offsetting impacts of the financial intermediary health. On the one hand, $\frac{\gamma^I (W^I)^{-1} - \gamma^R (W^R)^{-1}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}$ is increasing with W^I. This term measures the relative aggressiveness of the intermediary and the residual investor in determining who earns the illiquidity compensation. The higher the intermediary wealth is, the higher compensation it requires from its counterparty to bear the illiquidity cost. This is consistent with the argument in Bongaerts, De Jong, and Driessen (2011). On the other hand, a higher intermediary wealth relaxes the intermediary constraint and reduces its incentive to increase the risk premium. If $\gamma^R(W^R) \gg \gamma^I(W^I)$,[32] $\frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ can be approximated to be 1. This means that the intermediary gets full compensation on the illiquidity cost if its risk aversion is small enough compared to that of the residual investor. Thus, an increase in the intermediary wealth will not increase the illiquidity compensation much further. However, an increase in the intermediary wealth will largely decrease the shadow cost of the intermediary constraint to 0. Therefore the cross-market basis dynamic is driven by ϕ. In other words, the intermediary constraint force dominates the former force in affecting the risk premium basis when $\gamma^R(W^R) \gg \gamma^I(W^I)$. Similarly, if $\gamma^R(W^R) \ll \gamma^I(W^I)$, $\frac{\gamma^I(W^I)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ will be approximated to be 0. This term captures the importance of the intermediary constraint through the relative risk aversions of both agents. In this case, the intermediary constraint is trivial and the illiquidity channel dominantes. Since the intermediary is served as a liquidity provider and is likely to be more risk tolerant than its counterparty, the scenario where the intermediary constraint channel dominates is more likely to happen.

Second, the sign of the risk premium basis depends on the sign of the intermediary position δ_i^I and the relative magnitudes of the asset transaction costs c_i. To generate positive predictability of the return basis from the intermediary health, $\delta_{put}^I c_{put}$ need to be smaller than $\delta_{cds}^I c_{cds}$ under the assumption that $\gamma^R(W^R) \gg \gamma^I(W^I)$. In other words, the following three scenarios can generate the positive predictability: 1) the intermediary is a net buyer of the CDS but a net seller of the DOTM equity put options;[33] 2) the intermediary is a net buyer of both the CDS and the DOTM equity put options, and the option trading cost is smaller than the CDS transaction costs; 3) the intermediary is a net seller of both the CDS and the DOTM equity put options, and the option trading cost is larger than the CDS transaction costs.[34]

A number of studies document that the intermediary is a net buyer of the CDS (Carey, Stulz, Allen, and Gale, 2013; Siriwardane, 2019; Cetina, Paddrik, and Rajan, 2018; Au-

[32] A special case will be that the intermediary is risk neutral. This corresponds to the case in He, Khorrami, and Song (2019).

[33] This scenario happens if there are two residual investors with comparative advantages in trading options and CDSs. The extension of the model is in Appendix P and the key insights remain the same.

[34] Since the options are mostly traded on the organized exchange and the CDSs are traded in the Over-The-Counter (OTC) market, the trading cost of options is likely to be smaller than the trading cost of CDSs. Hence, scenario 3) is not likely to be the case in reality.

gustin and Izhakian, 2020; Czech, 2020). Furthermore, several studies document that the dealers are net buyers of single name equity options for shorter maturity and sellers of DOTM put options for longer maturity (Gârleanu, Pedersen, and Poteshman, 2009; Carr and Wu, 2011; Cao and Han, 2013). Based on the assumption that the intermediary is a net seller of DOTM long term put options but buyer of the CDS, the model is able to generate the positive predictability of the return basis from the financial intermediary health provided that the intermediary is much less risk averse than its counterparty.

5.7 Conclusion

An increasing number of studies extract credit spreads from options data under the assumption of market integration implied from various structural models of credit risk. It is important to empirically validate this assumption for future research along this direction. By constructing option implied credit spreads following the literature, I find that most firms have cointegrated IS and CDS spreads in my sample, suggesting that the IS and CDS spreads converge to a long-run equilibrium relation. However, the IS and CDS spreads time series exhibit a lack of synchronicity at shorter horizons such as the daily or weekly frequency, according to the non-parametric integration test developed in Kapadia and Pu (2012).

To understand the determinants of the short-lived price discrepancy, I explore both the asset-specific frictions and market participants related frictions motivated by the literature. In the asset-specific friction dimension, I find that the IS and CDS spreads co-move less for assets with higher arbitrage costs such as high illiquidity, high idiosyncratic risk, low institutional ownership, or low analyst coverage. The cross-market deviation, defined as the difference between the IS and CDS spreads, predicts both the IS and CDS spreads future changes in the direction of convergence. The predictability diminishes for assets with lower arbitrage costs. Furthermore, the predictability of IS (CDS spreads) changes is weaker (stronger) for firms with low institutional ownership and analyst coverage, suggesting that the options contain more timely information than the CDSs for firms that are less trasparent. In the market participants related friction dimension, this paper finds that the financial intermediary health significantly relates to both the level and return deviation between the IS and CDS spreads.

A simple intermediary asset pricing framework demonstrates that if the intermediary is constrained and is much less risk averse than its counterparty, an increase in the intermediary wealth will relax the constraint more than the increase in the demand for compensation for illiquidity costs. If the intermediary is a net buyer of the CDS but a net seller of the DOTM long term equity put option, the model shows that the financial intermediary health significantly positively predicts the return basis, defined as IS return minus CDS return.

Overall, the evidence suggests that it is appropriate to use equity options to infer a firm's credit spreads. For firms that are less transparent, options might contain more timely information compared to CDSs and have more advantages over the CDSs to gauge the firms' credit risk. However, special care needs to be taken when there are significant impediments to arbitrage or when the financial intermediary is constrained. This paper also sheds light on the tension regarding the accuracy of the structural model of credit risk. While a lot of attempts have been made in reducing the model error to improve the model empirical performance, extending the credit risk models by incorporating frictions such as limits to arbitrage and financial intermediary constraint can be another interesting research avenue. I leave this for future work.

Bibliography

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial Intermediaries and the Cross-Section of Asset Returns, *Journal of Finance* 69, 2557–2596.

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin, 2010, Financial Intermediation, Asset Prices and Macroeconomic Dynamics, *Federal Reserve Bank of New York Staff Reports* 422.

Allen, Franklin, 2001, Do financial institutions matter?, *Journal of Finance* 56, 1165–1175.

Augustin, Patrick, and Yehuda Izhakian, 2020, Ambiguity, Volatility, and Credit Risk, *The Review of Financial Studies* 33, 1618–1672.

Augustin, Patrick, Feng Jiao, Sergei Sarkissian, and Michael J Schill, 2019, Cross-Listings and the Dynamics between Credit and Equity Returns, *Review of Financial Studies* 33, 112–154.

Augustin, Patrick, Fahad Saleh, and Haohua Xu, 2020, CDS Returns, *Journal of Economic Dynamics and Control* 118.

Augustin, Patrick, Marti G Subrahmanyam, Dragon Y Tang, and Sarah Q Wang, 2014, Credit Default Swaps: A Survey, *Foundations and Trends in Finance* 9, 1–196.

Barras, Laurent, and Aytek Malkhozov, 2016, Does variance risk have two prices? Evidence from the equity and option markets, *Journal of Financial Economics* 121, 79–92.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* 60, 2255–2281.

Bongaerts, Dion, Frank De Jong, and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* 66, 203–240.

Cao, Jie, and Bing Han, 2013, Cross section of option returns and idiosyncratic stock volatility, *Journal of Financial Economics* 108, 231–249.

Carey, Mark, René M. Stulz, Franklin Allen, and Douglas Gale, 2013, Systemic Risk and Regulation, (in *The Risks of Financial Institutions*,).

Carr, Peter, and Liuren Wu, 2009, Stock options and credit default swaps: A joint framework for valuation and estimation, *Journal of Financial Econometrics* 8, 409–449.

Carr, Peter, and Liuren Wu, 2011, A simple robust link between american puts and credit protection, *Review of Financial Studies* 24, 473–505.

Cetina, Jill, Mark Paddrik, and Sriram Rajan, 2018, Stressed to the core: Counterparty concentrations and systemic losses in CDS markets, *Journal of Financial Stability* 35, 38–52.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein, 2009, On the relation between the credit spread puzzle and the equity premium puzzle, *Review of Financial Studies* 22, 3367–3409.

Choy, Siu Kai, and Jason Wei, 2020, Liquidity risk and expected option returns, *Journal of Banking & Finance* 111, Forthcoming.

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2018, Illiquidity premia in the equity options market, *Review of Financial Studies* 31, 811–851.

Collin-Dufresne, Pierre, Robert S Goldstein, and J Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Collin-Dufresne, Pierre, Benjamin Junge, and Anders B Trolle, 2020, How integrated are credit and equity markets? Evidence from index options, .

Culp, Christopher L., Yoshio Nozawa, and Pietro Veronesi, 2018, Option-Based Credit Spreads, *American Economic Review* 108, 454–488.

Czech, Robert, 2020, Credit Default Swaps and Corporate Bond Trading, .

Du, Du, Redouane Elkamhi, and Jan Ericsson, 2019, Time-Varying Asset Volatility and the Credit Spread Puzzle, *Journal of Finance* 74, 1841–1885.

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018, Deviations from Covered Interest Rate Parity, *The Journal of Finance* 73, 915–957.

Duffie, Darrell, 2010, Asset Price Dynamics with Slow-Moving Capital, *Journal of Finance* 65, 1237–1267.

Engle, Robert F, and C W J Granger, 1987, Co-Integration and Error Correction : Representation, Estimation, and Testing, *Econometrica* 55, 251–276.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2009, The Determinants of Credit Default Swap Premia, *Journal of Financial and Quantitative Analysis* 44, 109–132.

Ferreira, Miguel A., and Paul A. Laux, 2007, Corporate governance, idiosyncratic risk, and information flow, *Journal of Finance* 62, 951–989.

Fleckenstein, Matthias, and Francis A Longstaff, 2020, Renting Balance Sheet Space: Intermediary Balance Sheet Rental Costs and the Valuation of Derivatives, *The Review of Financial Studies* 9, Forthcoming.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies* 22, 4259–4299.

Geske, Robert, 1979, The valuation of compound options, *Journal of Financial Economics* 7, 63–81.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361–407.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage, *Annual Review of Financial Economics* 2, 251–275.

Haddad, Valentin, and Tyler Muir, 2018, Do Intermediaries Matter for Aggregate Asset Prices?, *Nber Working Paper*.

Hakkio, Craig S., and Mark Rush, 1991, Cointegration: how short is the long run?, *Journal of International Money and Finance* 10, 571–581.

Han, Bing, Avanidhar Subrahmanyam, and Yi Zhou, 2017, The term structure of credit spreads, firm fundamentals, and expected stock returns, *Journal of Financial Economics* 124, 147–171.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

He, Zhiguo, Paymon Khorrami, and Zhaogang Song, 2019, Commonality in Credit Spread Changes: Dealer Inventory and Intermediary Distress, .

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–770.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *The Journal of Finance* 6, 2143–2184.

Hull, John, Izzy Nelken, and Alan White, 2005, Merton's model, credit risk and volatility skews, *The Journal of Credit Risk* 1, 3–27.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel, 2013, Momentum in corporate bond returns, *Review of Financial Studies* 26, 1649–1693.

Junge, Benjamin, and Anders B Trolle, 2015, Liquidity Risk in Credit Default Swap Markets, *Working Paper*.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Kelly, Bryan, Gerardo Manzo, and Diogo Palhares, 2019, Credit-Implied Volatility, *Working Paper*.

Kondor, Péter, and Dimitri Vayanos, 2019, Liquidity Risk and the Dynamics of Arbitrage Capital, *Journal of Finance* 74, 1139–1173.

Kuehn, Lars-Alexander, David Schreindorfer, and Florian Schulz, 2017, Credit and Option Risk Premia, *Working Paper*.

Merton, Robert, 1976, Option Pricing When Underlying Stock Returns are Discontinuous, *Jounral of Financial Economics* 3, 125–144.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *The Journal of Finance* 29, 449–470.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52, 35–55.

Siriwardane, Emil, 2019, Limited Investment Capital and Credit Spreads, *Journal of Finance* 74, 2303–2347.

Toft, Klaus Bjerre, and Brian Prucyk, 1997, Options on Leveraged Equity: Theory and Empirical Tests, *The Journal of Finance* 52, 1151.

Figure 5.1: Aggregate CDS Spreads and Option Implied Credit Spreads Time Series Plot

In this figure, I report the weekly time series of aggregate 5 year CDS spreads (red line, in bps), the option implied credit spreads computed based on Carr and Wu (2011) (CW IS, black line, in bps), and the option implied credit spreads computed based on Culp, Nozawa, and Veronesi (2018) (CNV IS, grey line, in bps). The aggregate time series is computed as cross sectional averages of the CDS and option implied credit spreads. The sample consists of firms with both non-missing 5 year CDS spreads and option implied credit spreads. The data period ranges from January 2002 until April 2018. Sources: Markit, OptionMetrics, author's computation.

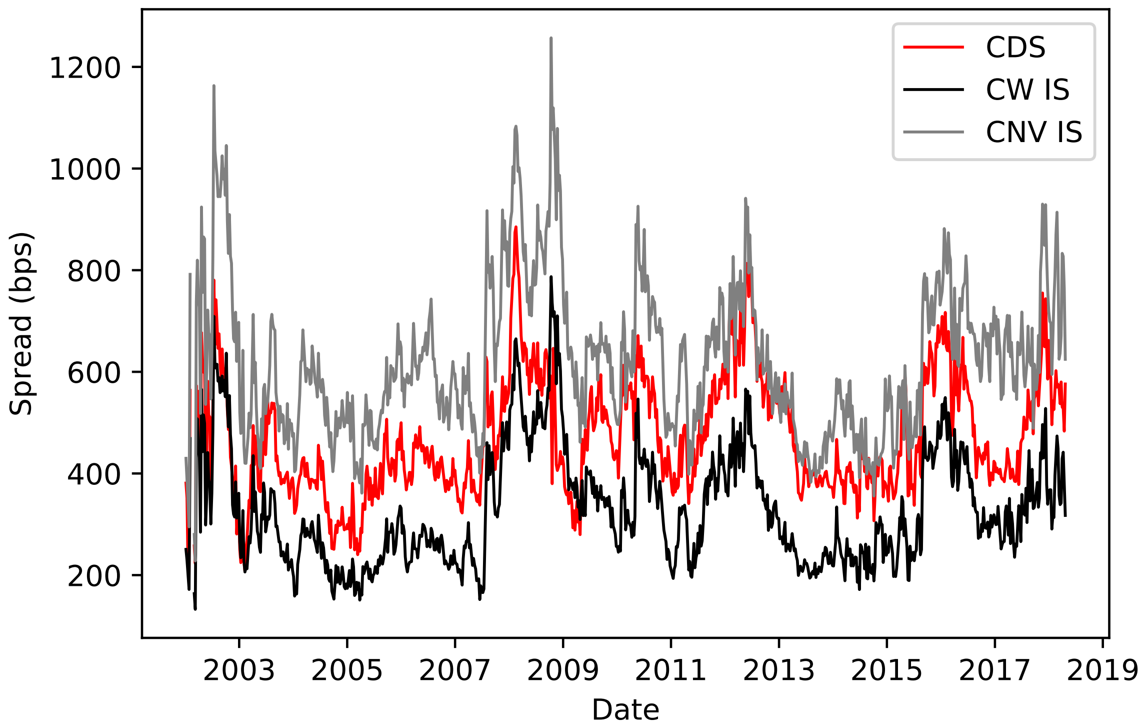
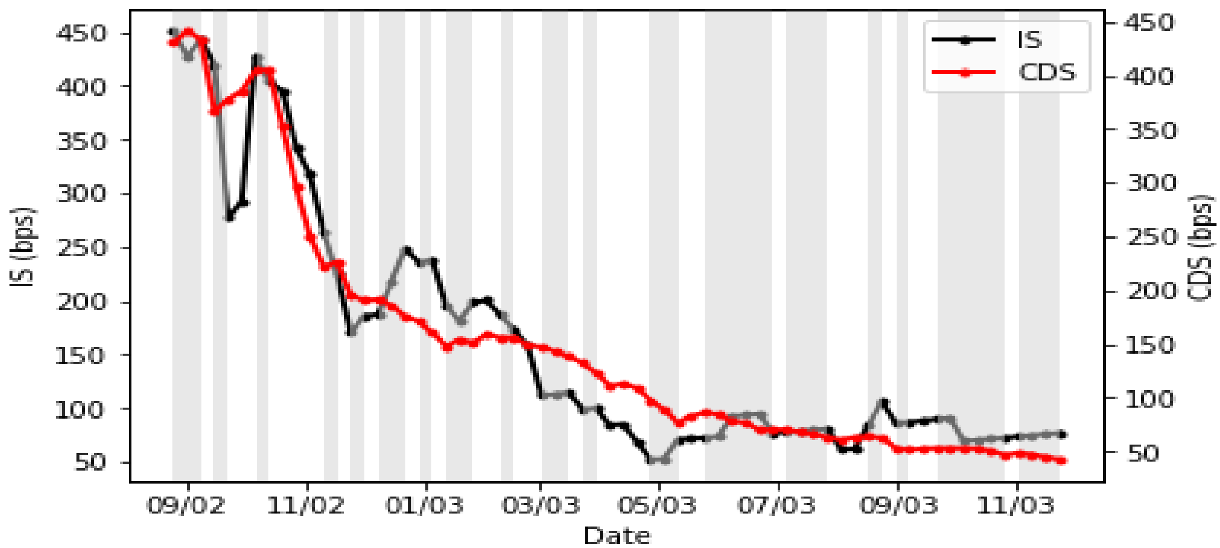


Figure 5.2: Cox Communications IS and CDS Spreads Time Series Plot

In this figure, I report the weekly time series of the IS (black line, in bps), and the CDS spreads (red line, in bps), of the Cox Communications company. The IS are computed based on Carr and Wu (2011). Panel (a) reports the IS and CDS spread time series for a long horizon ranging from August 2002 until November 2003. The grey area corresponds to the periods when the IS and CDS spreads move in the opposite directions. Panel (b) reports the time series for a shorter horizon ranging from September 1st 2002 to September 28th 2002. The solid lines indicate that the two series move in the same direction and the dotted lines indicate that the two series move in the opposite direction. Sources: Markit, OptionMetrics, author's computation.

(a) Long Horizon



(b) Short Horizon

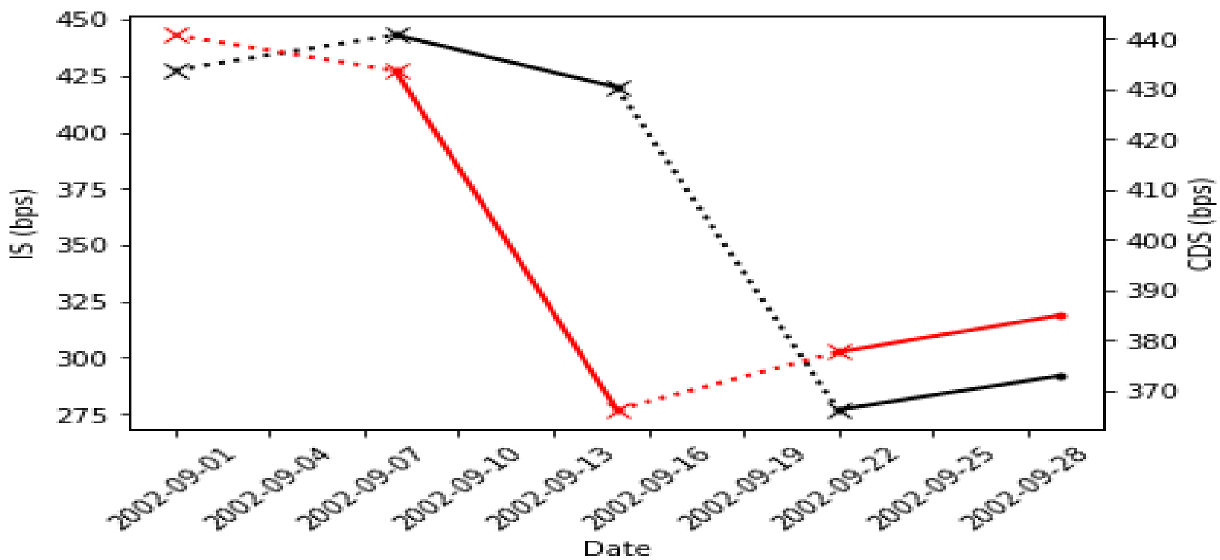
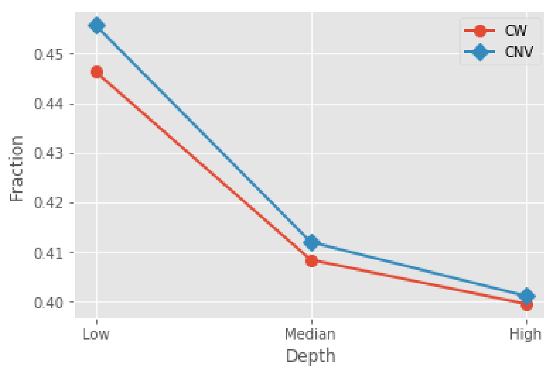


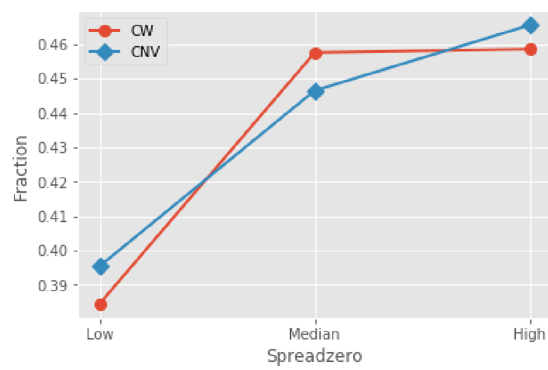
Figure 5.3: Misalignment fraction of samples sorted by arbitrage cost variables

In this figure, I report the fraction of observations with misaligned IS and CDS, i.e. $\Delta IS \Delta CDS < 0$, at a weekly frequency of the samples sorted by different arbitrage cost variables. The sample is sorted into 3 subsamples (Low, Median, and High) based on the average arbitrage cost of each IS and CDS pair. The x-axis corresponds to the subsamples and the y-axis is the misalignment frequency of the corresponding subsample. The arbitrage cost variables include CDS depth, CDS Spreadzero, option volume, option bid-ask spread, and stock idiosyncratic risk. The CDS Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS spread changes over the sample. The stock idiosyncratic risk is computed as the ratio of the idiosyncratic volatility to the total volatility for each stock. Sources: Markit, OptionMetrics, author's computation.

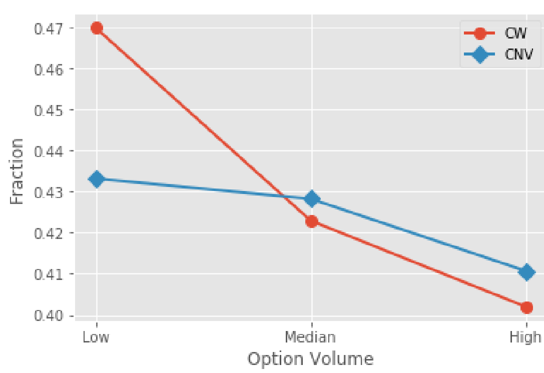
(a) CDS Depth



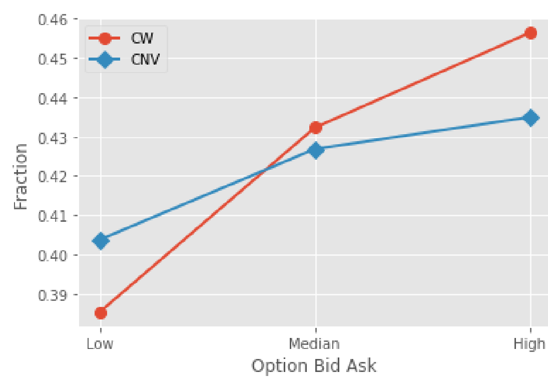
(b) Spreadzero



(c) Option Volume



(d) Option Bid-Ask Spread



(e) Stock Idiosyncratic Risk

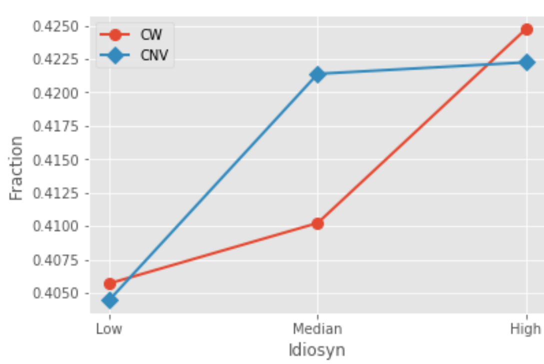
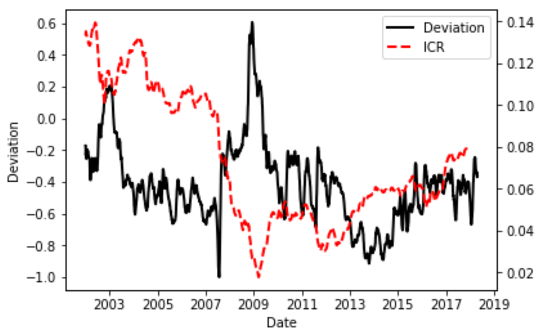


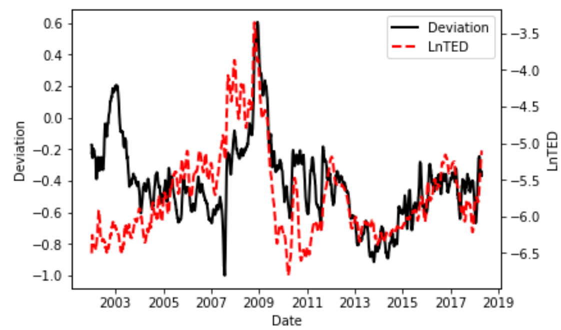
Figure 5.4: Cross-market deviation and financial intermediary health

In this figure, I report the daily time series of the average cross-market deviation, defined as $\log(IS) - \log(CDS)$, and the proxies of the financial intermediary health. The proxies include the intermediary capital ratio from He, Kelly, and Manela (2017) (ICR), log TED spread (LnTed), defined as the difference between 3-month LIBOR and 3-month T-bill rate, log LIBOR-OIS spread (Log LIBOR-OIS), defined as the difference between 3-month LIBOR and 3-month overnight indexed swap rate, and default spread, defined as the difference between BAA and AAA-rated corporate bond yields. All variables are computed as the simple 20-day moving averages. The data period ranges from January 2002 until April 2018. Sources: Markit, OptionMetrics, FRED, Bloomberg, author's computation.

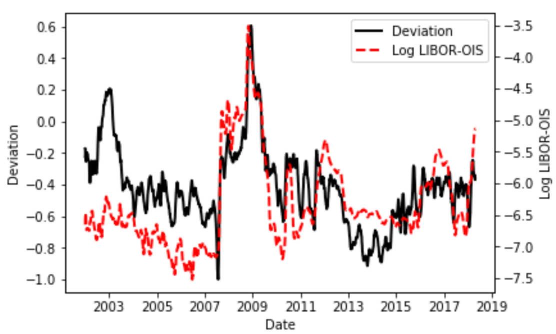
(a) ICR



(b) TED Spread



(c) LIBOR-OIS



(d) Default Spread

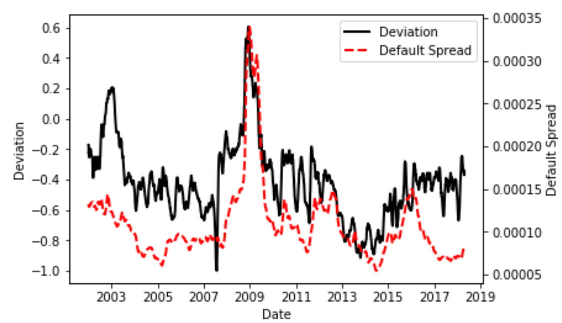


Table 5.1: Descriptive Statistics.

This table presents the descriptive statistics of the overlapping sample. In panel A, I report the averages of the IS, CDS, CDS depth, the bid ask spreads, and the option moneyness, defined as the strike price over the spot price, of selected options from the CW and CNV methodologies respectively by rating. Panel B reports the summary statistics of the firm fundamentals, including log market capitalization (MC), book-to-market (BM), leverage ratio, and institution ownership computed as the fraction of common shares owned by institutions based on Thomson 13F filings. Panel C reports the correlations among the 5 year CDS, CW IS, and CNV IS. The sample consists of firms with both non-missing 5 year CDS spreads and IS. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, and authors' computations.

Panel A: IS and CDS Descriptive Statistics by Rating

Rating	#firms	Obs.	5y CDS	5y IS (CW)	5y IS (CNV)	Depth	Bidask (CW)	Bidask (CNV)	Money (CW)	Money (CNV)
AAA	2	151	66.10	51.94	78.76	3.38	0.86	1.06	0.16	0.12
AA	2	160	80.24	94.56	164.80	7.03	0.81	0.60	0.13	0.15
A	43	7397	130.94	146.23	251.19	6.37	0.64	0.65	0.24	0.24
BBB	49	7404	215.48	189.38	308.45	7.36	0.72	0.75	0.27	0.27
BB	58	20591	386.04	263.11	471.42	6.36	0.63	0.55	0.35	0.40
B	79	38212	568.54	385.82	748.59	6.45	0.60	0.46	0.40	0.52
CCC-	7	4578	917.01	596.16	1164.29	5.26	0.44	0.28	0.41	0.64
Full Sample	240	78493	464.48	323.55	609.26	6.43	0.61	0.52	0.36	0.44

Panel B: Firm Fundamentals Descriptive Statistics

	mean	std	min	25%	50%	75%	max
MC	15.39	1.41	10.51	14.46	15.30	16.31	19.77
BM	0.10	0.11	0.00	0.04	0.07	0.11	1.80
Leverage	0.39	0.24	0.00	0.20	0.37	0.55	0.98
IO	0.71	0.27	0.00	0.60	0.76	0.88	1.50

Panel C: Correlations

	5y CDS	5y IS (CW)	5y IS (CNV)
5y CDS	1.00		
5y IS (CW)	0.79	1.00	
5y IS (CNV)	0.77	0.85	1.00

Table 5.2: Merton Model Regression.

This table provides the Merton model regression following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009). Column 3 to 5 report the results of the level regression and column 6 to 8 report the results of the difference regression. For each of the N firms in my sample, I regress both CDS and IS on the firm's leverage ratio (Leverage), the firm's realized annualized equity volatility computed using daily stock returns within the previous month, and the 10 year constant maturity Treasury rate (10-year yield). I report the cross-sectional averages of the coefficient estimates and R^2 values. The last column reports the difference of the coefficients between CDS and IS regressions. The t-statistics are calculated from the cross-sectional averages of the coefficient estimates divided by the standard deviation of the N estimates and scaled by $\sqrt{N}$. I drop firms with less than 25 observations. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. Leverage is defined as the ratio of the sum of book value of debt and the value of preferred equity to the sum of market value of equity, book value of debt, and book value of preferred equity. I interpolate the book value of equity to compute weekly leverage ratio. Volatility is computed as the annualized standard deviation of daily equity returns of the previous month. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Center for Research in Security Prices, Compustat, FRED, and author's computation.

		Level Regression			Difference Regression		
	Expected Sign	CDS	CW IS	CNV IS	CDS	CW IS	CNV IS
Constant		-0.042***	-0.025***	-0.014	-0.000	-0.000***	-0.000***
		(-3.63)	(-3.78)	(-1.47)	(-0.93)	(-3.41)	(-3.74)
Leverage	+	0.179***	0.153***	0.199***	0.132***	0.213***	0.182***
		(10.76)	(11.86)	(9.11)	(8.54)	(12.9)	(4.19)
Equity volatility	+	0.020***	0.025***	0.030***	0.003***	0.002*	0.003*
		(7.79)	(11.95)	(10.81)	(2.96)	(1.89)	(1.77)
10-year yield	-	0.076	-0.376***	-0.425***	-0.198***	-0.317***	-0.234**
		(0.49)	(-3.92)	(-3.26)	(-2.86)	(-5.95)	(-2.33)
R^2		68.7%	67.2%	61.5%	22.4%	23.8%	16.1%
No. of companies		147	147	147	137	137	137
Avg. no. of obs.		116	116	116	113	113	113

Table 5.3: The long-run integration between CDS and IS.

In this table, I report the results of the Engle and Granger cointegration test on each firm's CDS spreads and the corresponding option implied credit spreads (IS). $\overline{HalfLife}$ denotes the median half life for the cointegrated series. N_{total} denotes the number of firms in the sample. T_{avg} denotes the average number of days across all series. $\frac{N_{cointegrated}}{N_{total}}$ denotes the percentage of firms with cointegrated IS and CDS among the total number of firms. For each firm, I search for the longest string of more than 250 daily non-missing IS and CDS that were no more than 5 business days apart. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Overlapping Sample				
	$\overline{HalfLife}$	T_{avg}	N_{total}	$\frac{N_{cointegrated}}{N_{total}}$
CW IS	6.49	450	32	81.25%
CNV IS	7.01	444	35	80.00%
Panel B: Separate Sample				
	$\overline{HalfLife}$	T_{avg}	N_{total}	$\frac{N_{cointegrated}}{N_{total}}$
CW IS	9.43	493	72	75.00%
CNV IS	9.69	554	137	70.80%

Table 5.4: Predicting future market movements based on current cross-market deviations.

In this table, I report the results of the panel regression below:

$$\begin{pmatrix} \Delta IS_{i,t} \\ \Delta CDS_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta_{IS,Dev} \\ \beta_{CDS,Dev} \end{pmatrix} Dev_{i,t-1} + X_t'\beta_X + Y_{i,t}'\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}$$

where α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. Panel A reports the regression results based on the CW IS and panel B reports the results based on the CNV IS. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. The macro controls include SP 500 index return, CBOE VIX index (VIX) changes, 10 year Treasury yield changes, Treasury slope changes, defined as 10 year yield minus 2 year yield, and default spread changes. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

Panel A: CW IS								
	ΔIS (t)				ΔCDS (t)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dev	-0.015***	-0.019***	-0.016***	-0.021***	0.005***	0.005***	0.005***	0.005***
	(-6.523)	(-7.990)	(-6.357)	(-8.161)	(4.689)	(5.438)	(5.179)	(5.608)
Observations	65555	58656	64410	57630	65555	58656	64410	57630
R^2	0.204	0.223	0.104	0.122	0.223	0.233	0.044	0.058
Adjusted R^2	0.153	0.167	0.098	0.115	0.173	0.178	0.038	0.051

Panel B: CNV IS								
	ΔIS (t)				ΔCDS (t)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dev	-0.020***	-0.025***	-0.022***	-0.027***	0.002***	0.003***	0.002***	0.003***
	(-7.307)	(-8.926)	(-7.105)	(-8.789)	(2.603)	(3.762)	(2.853)	(3.897)
Observations	65555	58656	64410	57630	65555	58656	64410	57630
R^2	0.203	0.218	0.116	0.129	0.221	0.232	0.042	0.057
Adjusted R^2	0.152	0.161	0.110	0.122	0.171	0.176	0.035	0.050
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓			✓	✓		
Year-Month FE			✓	✓			✓	✓
Firm Control		✓		✓		✓		✓
Macro Control			✓	✓			✓	✓

Table 5.5: Kapadia and Pu (2012) price discrepancy.

In this table, I report the misalignment between individual IS and CDS, $\Delta IS \Delta CDS < 0$, as a proportion (Fraction) of total observations with $\Delta IS \Delta CDS \neq 0$ measured over non-overlapping daily, weekly, monthly, and quarterly time intervals following Kapadia and Pu (2012). Column 3 to 5 reports the misalignment statistics based on the CW metric and column 6 to 8 reports the misalignment statistics based on the CNV metric. Obs. denotes the number of dates with non missing observations in the full sample. $\Delta|IS|$ and $\Delta|CDS|$ represents the mean absolute changes of IS and CDS. The data period ranges from Jan 2002 until April 2018. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Full Sample								
	CW IS				CNV IS			
Freq.	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)
daily	73722	46.43	11.13	24.04	73722	45.96	11.64	37.81
weekly	13972	40.95	21.17	36.09	13972	42.26	21.85	61.33
monthly	2747	35.68	44.21	59.38	2747	36.48	58.32	91.57
quarterly	531	25.80	114.06	73.40	531	30.51	98.43	142.68
Panel B: Investment Grade								
	CW IS				CNV IS			
Freq.	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)
daily	14354	46.64	5.13	18.50	14354	46.75	5.31	28.70
weekly	2615	40.73	11.32	32.71	2615	40.65	10.91	54.40
monthly	481	33.89	19.37	45.01	481	35.55	20.76	75.25
quarterly	93	29.03	34.65	70.39	93	32.26	33.90	118.95
Panel C: High Yield								
	CW IS				CNV IS			
Freq.	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)	Obs.	Fraction(%)	$\Delta\|IS\|$ (bps)	$\Delta\|CDS\|$ (bps)
daily	59368	46.38	15.18	27.78	59368	45.77	15.93	43.99
weekly	11357	41.00	27.40	38.23	11357	42.63	28.81	65.74
monthly	2266	36.05	54.37	65.26	2266	36.67	74.17	98.46
quarterly	438	25.11	139.06	74.35	438	30.14	117.68	149.76

Table 5.6: The relation between arbitrage costs and the integration between the option and CDS markets.

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1) $\kappa^{CW}_{i,t}$	(2) $\kappa^{CNV}_{i,t}$	(3) $\kappa^{CW}_{i,t}$	(4) $\kappa^{CNV}_{i,t}$	(5) $\kappa^{CW}_{i,t}$	(6) $\kappa^{CNV}_{i,t}$	(7) $\kappa^{CW}_{i,t}$	(8) $\kappa^{CNV}_{i,t}$	(9) $\kappa^{CW}_{i,t}$	(10) $\kappa^{CNV}_{i,t}$	(11) $\kappa^{CW}_{i,t}$	(12) $\kappa^{CNV}_{i,t}$	(13) $\kappa^{CW}_{i,t}$	(14) $\kappa^{CNV}_{i,t}$	(15) $\kappa^{CW}_{i,t}$	(16) $\kappa^{CNV}_{i,t}$
Lndepth	-0.039**	-0.027*													-0.037**	-0.025
	(-2.570)	(-1.660)													(-2.473)	(-1.504)
Spreadzero			0.123	0.299**											0.100	0.286**
			(1.047)	(2.415)											(0.850)	(2.288)
Bidask					0.043***	0.066***									0.040**	0.064***
					(2.736)	(4.384)									(2.553)	(4.285)
Volume							-0.000	-0.000							-0.000	-0.000
							(-0.581)	(-1.030)							(-0.460)	(-0.765)
Idiosyn									0.009	0.016***					0.008	0.016***
									(1.507)	(3.038)					(1.470)	(3.105)
IO											-0.039	-0.083**			-0.048	-0.080**
											(-1.258)	(-2.358)			(-1.615)	(-2.343)
$\#Analyst$													-0.032**	-0.030	-0.034**	-0.034*
													(-1.991)	(-1.585)	(-2.071)	(-1.883)
Observations	8888	9008	8888	9008	8888	9008	8888	9008	8888	9008	8888	9008	8888	9008	8888	9008
R^2	0.169	0.128	0.169	0.129	0.170	0.130	0.169	0.128	0.169	0.129	0.169	0.129	0.169	0.128	0.171	0.132
Adjusted R^2	0.076	0.031	0.075	0.032	0.076	0.033	0.075	0.031	0.075	0.032	0.075	0.032	0.075	0.031	0.077	0.035
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 5.7: Predicting future market movements based on current cross-market deviations for different conditions.

In this table, I report the results of the panel regression below:

$$\begin{pmatrix}\Delta IS_{i,t+1}\\ \Delta CDS_{i,t+1}\end{pmatrix} = \begin{pmatrix}\alpha_{i,IS,t}\\ \alpha_{i,CDS,t}\end{pmatrix} + \begin{pmatrix}\gamma_{IS,t}\\ \gamma_{CDS,t}\end{pmatrix} + \begin{pmatrix}\beta^u_{IS,Dev} + \beta^c_{IS,Dev}D_{c,t}\\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev}D_{c,t}\end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix}\epsilon_{i,IS,t}\\ \epsilon_{i,CDS,t}\end{pmatrix}$$

where D_c denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the firm specific control variables. Panel A (B) reports the regression results of $\Delta IS_{i,t+1}$ ($\Delta CDS_{i,t+1}$). Columns (1), (3), (5), and (7) correspond to the regressions based on CW IS and the rest columns correspond to the regressions based on CNV IS. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise. $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. The data period ranges from 2002/01 until 2018/04. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) CW	(2) CNV	(3) CW	(4) CNV	(5) CW	(6) CNV	(7) CW	(8) CNV
Panel A: IS predictability								
	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$
Dev	-0.017***	-0.025***	-0.013***	-0.022***	-0.019***	-0.026***	-0.019***	-0.028***
	(-7.109)	(-8.800)	(-6.198)	(-8.241)	(-7.572)	(-8.344)	(-6.998)	(-8.475)
$D_{CDSIlliquid} * Dev$	0.002	-0.005						
	(0.621)	(-1.499)						
$D_{OptionIlliquid} * Dev$			-0.025***	-0.029***				
			(-5.831)	(-5.968)				
$D_{Idiosyn} * Dev$					0.005***	0.000		
					(2.868)	(0.013)		
$D_{Transparency} * Dev$							0.008***	0.009**
							(2.647)	(2.324)
Observations	58833	58610	58833	58610	58833	58610	58833	58610
R^2	0.221	0.217	0.224	0.220	0.222	0.217	0.222	0.218
Adjusted R^2	0.165	0.161	0.168	0.163	0.165	0.161	0.166	0.161
Panel B: CDS spreads predictability								
	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$
Dev	0.004***	0.002***	0.004***	0.002**	0.004***	0.003***	0.004***	0.002
	(3.643)	(2.746)	(3.566)	(2.597)	(3.349)	(3.280)	(3.391)	(1.535)
$D_{CDSIlliquid} * Dev$	0.006***	0.004***						
	(3.017)	(2.772)						
$D_{OptionIlliquid} * Dev$			-0.001	0.002**				
			(-0.824)	(2.206)				
$D_{Idiosyn} * Dev$					-0.000	-0.001		
					(-0.241)	(-0.829)		
$D_{Transparency} * Dev$							0.001	0.003**
							(0.297)	(2.001)
Observations	58833	58662	58833	58662	58833	58662	58833	58662
R^2	0.224	0.228	0.224	0.228	0.224	0.227	0.224	0.228
Adjusted R^2	0.168	0.172	0.168	0.172	0.168	0.172	0.168	0.172
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓

Table 5.8: The relation between financial intermediary health and the level deviation between IS and CDS spreads.

In this table, I report the results of the following panel regression using 5 different proxies for financial intermediary health:

$$S_{i,t}^{Dev} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y_{i,t}'\beta_Y + \epsilon_{i,t}$$

where $S_{i,t}^{Dev} = \log(IS_{i,t}) - \log(CDS_{i,t})$. $health_t$ denotes the financial intermediary health variable, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The 5 financial intermediary health variables include the dealer leverage ratio from Adrian, Etula, and Muir (2014) (AEM-LV), the intermediary capital ratio from He and Krishnamurthy (2013) (HKM-ICR), the ted spread (TED), the LIBOR-OIS spread (LIBOR-OIS), and default spread (DEF). The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. IS are computed using the CW method. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)
AEM-LV	-0.000					
	(-0.857)					
HKM-ICR		-5.819***				-5.370***
		(-4.154)				(-3.826)
TED			16.717***			4.787**
			(6.983)			(2.229)
LIBOR-OIS				27.555***		21.232***
				(7.242)		(5.201)
DEF					1669.753***	421.520
					(4.371)	(1.023)
Observations	70593	69682	68693	69268	70044	61965
R^2	0.545	0.620	0.617	0.617	0.617	0.630
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓

Table 5.9: The relation between financial intermediary health and lag return deviation between IS and CDS spreads.

In this table, I report the results of the following panel regression using 5 different proxies for financial intermediary health:

$$R_{i,t+1}^{Dev} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y_{i,t}' \beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Dev} = R_{i,t+1}^{IS} - R_{i,t+1}^{CDS}$, where $R_{i,t+1}^{IS}$ and $R_{i,t+1}^{CDS}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the financial intermediary health variable, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The 5 financial intermediary health variables include the dealer leverage ratio from Adrian, Etula, and Muir (2014) (AEM-LV), the intermediary capital ratio from He and Krishnamurthy (2013) (HKM-ICR), the ted spread (TED), the LIBOR-OIS spread (LIBOR-OIS), and default spread (DEF). The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. IS are computed using CW method. The data period ranges from Jan 2002 until April 2018 excluding financial crisis. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) Δs	(2) $\Delta \log s$	(3) $\frac{\Delta \widetilde{P}}{\phi}$	(4) Δs	(5) $\Delta \log s$	(6) $\frac{\Delta \widetilde{P}}{\phi}$	(7) Δs	(8) $\Delta \log s$	(9) $\frac{\Delta \widetilde{P}}{\phi}$	(10) Δs	(11) $\Delta \log s$	(12) $\frac{\Delta \widetilde{P}}{\phi}$	(13) Δs	(14) $\Delta \log s$	(15) $\frac{\Delta \widetilde{P}}{\phi}$	(16) Δs	(17) $\Delta \log s$	(18) $\frac{\Delta \widetilde{P}}{\phi}$
AEM-LV	0.000	0.000	0.000															
	(0.550)	(0.767)	(0.276)															
HKM-ICR				0.034**	2.251***	0.204***										0.036*	2.157***	0.199***
				(2.139)	(5.098)	(3.979)										(1.944)	(4.405)	(3.362)
TED							-0.064*	-1.571	-0.265**							-0.004	0.333	-0.045
							(-1.688)	(-1.565)	(-2.009)							(-0.063)	(0.168)	(-0.208)
LIBOR-OIS										-0.151*	-4.128**	-0.602**				-0.121	-2.025	-0.315
										(-1.935)	(-2.004)	(-2.141)				(-1.000)	(-0.537)	(-0.714)
DEF													8.064	-322.444*	3.612	14.809**	-95.493	29.164
													(1.438)	(-1.840)	(0.188)	(2.502)	(-0.534)	(1.469)
Observations	52444	52444	51996	51653	51653	51205	50938	50938	50490	51432	51432	50984	51974	51974	51526	46633	46633	46200
R^2	0.003	0.004	0.003	0.006	0.007	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.008	0.008	0.007
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 5.10: The relation between intermediary capital ratio and lag return deviation between IS and CDS spreads.

In this table, I report the results of the panel regression below:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Full Sample									
	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICR	0.072***	0.063***	0.053***	2.478***	2.575***	2.240***	0.306***	0.292***	0.254***
	(3.805)	(3.744)	(2.609)	(5.993)	(6.039)	(4.117)	(4.844)	(5.269)	(3.533)
Observations	66279	59075	53293	66279	59075	53293	65769	58622	52856
R^2	0.005	0.007	0.008	0.005	0.007	0.009	0.005	0.008	0.009
Panel B: IG Sample									
ICR	0.072***	0.073***	0.052***	4.264***	4.499***	3.623***	0.306***	0.315***	0.222***
	(3.559)	(4.457)	(2.726)	(5.608)	(5.885)	(4.236)	(3.923)	(4.779)	(2.853)
Observations	14395	13673	12236	14395	13673	12236	14287	13574	12140
R^2	0.018	0.023	0.025	0.011	0.014	0.017	0.018	0.024	0.026
Panel C: HY Sample									
ICR	0.073***	0.060***	0.053**	1.854***	1.842***	1.731***	0.308***	0.285***	0.262***
	(3.069)	(2.907)	(2.080)	(4.417)	(4.352)	(2.961)	(4.035)	(4.272)	(3.012)
Observations	51883	45401	41055	51883	45401	41055	51481	45047	40714
R^2	0.005	0.008	0.009	0.004	0.007	0.009	0.004	0.008	0.009
Panel D: Excluding Financial Crisis									
ICR	0.038**	0.034**	0.040*	2.086***	2.251***	2.061***	0.201***	0.204***	0.206***
	(2.386)	(2.139)	(1.915)	(4.982)	(5.098)	(3.529)	(3.731)	(3.979)	(2.867)
Observations	57952	51653	46633	57952	51653	46633	57452	51205	46200
R^2	0.004	0.006	0.008	0.004	0.007	0.008	0.003	0.006	0.007
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Appendix

A Definitions of key variables

- IS: Option implied credit spread.
- CW and CNV IS: IS computed by Carr and Wu (2011) and Culp, Nozawa, and Veronesi (2018) method.
- Leverage ratio: ratio of the sum of book value of debt and the value of preferred equity to the sum of market value of equity, book value of debt, and book value of preferred equity
- Volatility: the annualized standard deviation of daily equity returns of the previous month.
- Log market capitalization (MC): log of the product of equity price and outstanding shares of the equity.
- Book-to-market (BM): Following Fama-French procedure.
- Rating: S&P rating of a firm.
- Stock market beta: beta coefficient of the Fama-French 3 factor regression using the previous month daily stock return.
- institution ownership: fraction of common shares owned by institutions based on Thomson 13F filings.
- #Analyst: analyst coverage computed as the number of analyst.

- Kapadia and Pu (2012) (KP) metric: computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}}$ 1 and N denotes the number of business days with non zero daily CDS spread changes within a week.

- Spreadzero: computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week.

- Idiosyn: computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns.

- $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise.

- $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile.

- $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile.

- AEM-LV: dealer leverage ratio from Adrian, Etula, and Muir (2014)

- HKM-ICR: intermediary capital ratio from He and Krishnamurthy (2013)

- TED: ted spread

- LIBOR-OIS: LIBOR-OIS spread

- DEF: default spread computed as the difference between BAA and AAA-rated corporate bond yields.

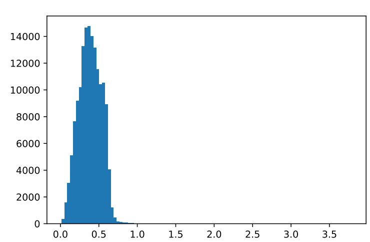
- Treasury slope: 10 year Treasury yield minus 2 year Treasury yield.

B Summary statistics

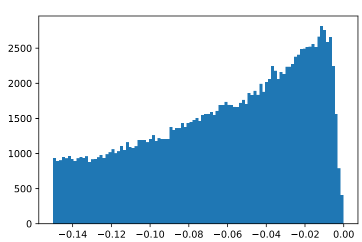
Figure B.1: The Histogram of Selected Option Features

In these figures, I report the histograms of moneyness, defined as the strike price over the spot price, delta, and maturity of options used to construct the option implied credit spread. Following Carr and Wu (2011), I select put options based on the following criteria: 1) positive open interest; 2) strike price smaller than $5; 3) positive bid price; 4) delta greater than -0.15. After applying the filters, if there are more than one option for a particular firm date combination, I choose only 1 contract by applying the filters in the following order: highest open interest, smallest strike, and largest delta. The sample consists of firms with both non-missing 5 year CDS spreads and option implied credit spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics.

(a) Moneyness



(b) Delta



(c) Maturity

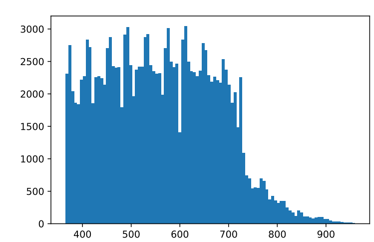


Figure B.2: 2 year CDS Spreads and 5 year CDS Spread Time Series Plot

In this figure, I report the scatter plot of log 2 year CDS spreads and log 5 year CDS spreads across the full overlapping sample. The x axis corresponds to log 2 year CDS spreads and the y axis corresponds to the 5 year CDS spreads. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, author's computation.

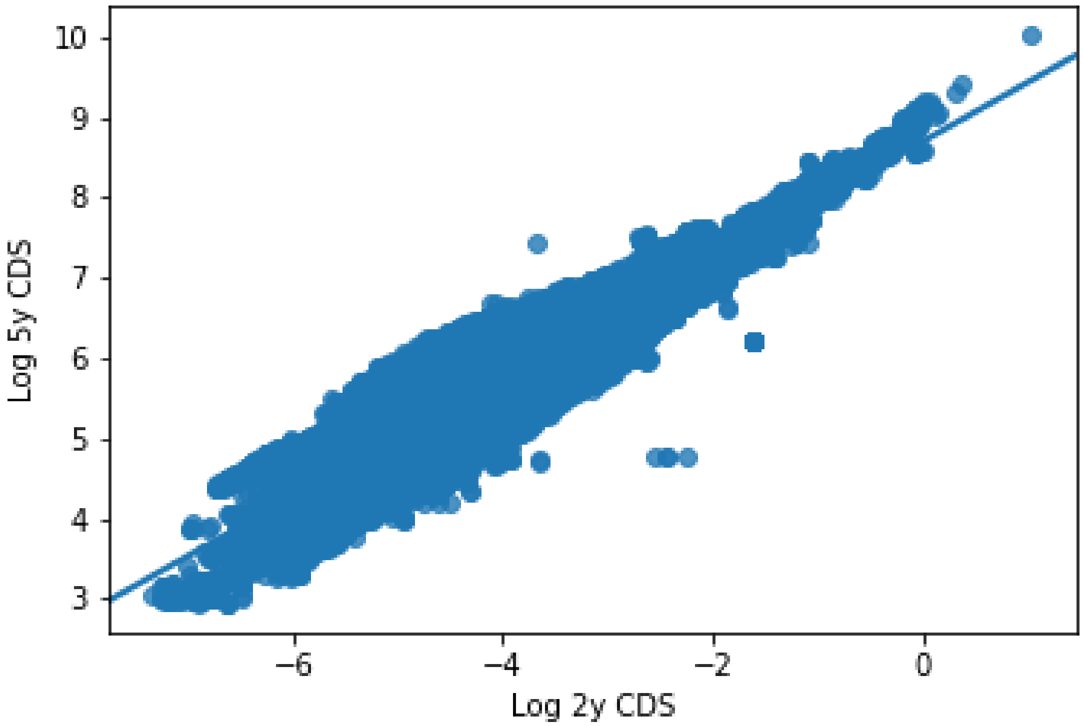


Table B.1: Descriptive Statistics of CW Full Sample.

This table presents the descriptive statistics of the CW separate full sample. In panel A, I report the averages of the IS, CDS, CDS depth, the bid ask spreads, and the option moneyness, defined as the strike price over the spot price, of selected options from the CW methodologies by rating. Panel B reports the summary statistics of the firm fundamentals, including log market capitalization (MC), book-to-market (BM), leverage ratio, and institution ownership computed as the fraction of common shares owned by institutions based on Thomson 13F filings. Panel C reports the correlations between the 5 year CDS and CW IS. The sample consists of firms with both non-missing 5 year CDS spreads and IS. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, and authors' computations.

Panel A: IS and CDS Descriptive Statistics by Rating

Rating	#firms	Obs.	5y CDS	5y IS	Depth	Bidask	Money
AAA	2	278	38.68	232.78	3.45	0.57	0.24
AA	5	2616	145.70	171.38	5.15	0.63	0.24
A	51	15476	200.97	261.28	6.92	0.53	0.29
BBB	84	30664	324.94	318.20	7.55	0.60	0.38
BB	72	42940	447.41	346.75	6.52	0.57	0.40
B	71	46874	653.21	468.17	6.07	0.57	0.43
CCC-	2	846	602.25	381.48	4.43	0.43	0.50
Full Sample	325	153097	464.67	373.15	6.44	0.58	0.39

Panel B: Firm Fundamentals Descriptive Statistics

	mean	std	min	25%	50%	75%	max
MC	15.41	1.41	9.59	14.44	15.31	16.34	19.77
BM	0.10	0.10	0.00	0.04	0.07	0.12	1.80
Leverage	0.40	0.25	0.00	0.20	0.37	0.57	1.00
IO	0.71	0.26	0.00	0.61	0.76	0.88	1.94

Panel C: Correlations

	5y CDS	5y IS
5y CDS	1.00	
5y IS	0.76	1.00

Table B.2: Descriptive Statistics of CNV Full Sample.

This table presents the descriptive statistics of the CNV separate full sample. In panel A, I report the averages of the IS, CDS, CDS depth, the bid ask spreads, and the option moneyness, defined as the strike price over the spot price, of selected options from the CNV methodologies by rating. Panel B reports the summary statistics of the firm fundamentals, including log market capitalization (MC), book-to-market (BM), leverage ratio, and institution ownership computed as the fraction of common shares owned by institutions based on Thomson 13F filings. Panel C reports the correlations between the 5 year CDS and CNV IS. The sample consists of firms with both non-missing 5 year CDS spreads and IS. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, and authors' computations.

Panel A: IS and CDS Descriptive Statistics by Rating

Rating	#firms	Obs.	5y CDS	5y IS	Depth	Bidask	Money
AAA	5	675	32.20	59.56	3.84	0.64	0.38
AA	4	747	47.02	86.81	8.54	0.78	0.29
A	129	146418	50.26	137.49	7.66	0.52	0.50
BBB	133	98430	92.89	167.24	7.78	0.67	0.51
BB	111	96316	249.21	365.76	6.63	0.51	0.53
B	71	60652	407.49	599.44	5.95	0.45	0.57
CCC-	5	4737	464.39	821.90	3.61	0.19	0.72
Full Sample	458	407975	165.39	274.96	7.14	0.54	0.52

Panel B: Firm Fundamentals Descriptive Statistics

	mean	std	min	25%	50%	75%	max
MC	16.51	1.36	10.37	15.59	16.62	17.48	20.42
BM	0.06	0.07	0.00	0.03	0.04	0.07	1.80
Leverage	0.22	0.20	0.00	0.08	0.15	0.30	0.98
IO	0.75	0.20	0.00	0.67	0.78	0.86	1.56

Panel C: Correlations

	5y CDS	5y IS
5y CDS	1.00	
5y IS	0.80	1.00

C Augmented Merton model regression

Table C.1: Augmented Merton model regression.

This table provides the augmented Merton model regression following Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009). Column (3) - (5) report the results for the level regression, and column (6) - (8) report the results for the difference regression. For each of the N firms in my sample, I regress both CDS and IS on the firm's leverage ratio (Leverage), the firm's realized annualized equity volatility (Equity volatility), the 10 year constant maturity Treasury rate (10-year yield), the Treasury yield curve slope (Yield curve slope), the square of 10 yield yield (Sq. 10-year yield), S&P 500 index returns (S&P 500), and the slope of the smirk on S&P 500 index options (Smirk slope). I report the cross-sectional averages of the coefficient estimates and R^2 values. The last column reports the difference of the coefficients between CDS and IS regressions. The t-statistics are calculated from the cross-sectional averages of the coefficient estimates divided by the standard deviation of the N estimates and scaled by $\sqrt{N}$. I drop firms with less than 25 observations. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. Leverage is defined as the ratio of the sum of book value of debt and the value of preferred equity to the sum of market value of equity, book value of debt, and book value of preferred equity. I interpolate the book value of equity to compute weekly leverage ratio. Volatility is computed as the annualized standard deviation of daily equity returns of the previous month. The yield curve slope is defined as the 10 year yield minus 1 year yield. The smirk slope is defined as the -20 delta implied volatility of the S&P 500 index option with 30 days maturity minus the -50 delta implied volatility. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Center for Research in Security Prices, Compustat, FRED, and author's computation.

		Level Regression			Difference Regression		
	Expected Sign	CDS	CW IS	CNV IS	CDS	CW IS	CNV IS
Constant		-0.048	-0.014	-0.019	-0.000	-0.000	-0.000*
		(-1.39)	(-0.78)	(-0.6)	(-0.66)	(-1.63)	(-1.85)
Leverage	+	0.180***	0.156***	0.185***	0.116***	0.175***	0.115**
		(10.58)	(12.5)	(10.18)	(6.75)	(11.69)	(2.15)
Equity volatility	+	0.013***	0.018***	0.021***	0.003***	0.002*	0.003
		(6.02)	(10.34)	(8.49)	(3.07)	(1.9)	(1.61)
10-year yield	-	2.801	-0.295	0.816	-1.361	0.728	2.973
		(1.09)	(-0.31)	(0.53)	(-1.47)	(0.46)	(1.4)
Yield curve slope	-	-2.158**	-0.754***	-0.953**	0.110	-0.009	0.041
		(-2.29)	(-3.5)	(-2.41)	(0.6)	(-0.05)	(0.16)
Sq. 10-year yield	-	-28.239	2.475	-12.739	18.770*	-8.074	-32.716
		(-0.79)	(0.2)	(-0.65)	(1.66)	(-0.45)	(-1.37)
S&P 500	-	0.031*	0.014***	0.023***	-0.011*	-0.023***	-0.032***
		(1.66)	(2.72)	(3.12)	(-1.75)	(-3.56)	(-3.64)
Smirk slope	+	0.101**	0.126***	0.189***	-0.001	0.031**	0.058***
		(2.42)	(7.18)	(5.96)	(-0.11)	(2.5)	(3.46)
R^2		79.5%	75.7%	71.4%	30.2%	32.5%	24.5%
No. of companies		143	143	143	132	132	132
Avg. no. of obs.		114	114	114	112	112	112

D Kendall correlation summary statistics

Table D.1: Descriptive Statistics of Kendall correlations.

This table presents the descriptive statistics of Kendall correlations computed based on CW and CNV IS. In panel A, I report the summary statistics of Kendall correlations. In panel B, I report correlations between the IS and macroeconomic and firm fundamental variables. The macroeconomic variables include S&P 500 index returns (SP500), CBOE VIX index (VIX), 10-year Treasury yield (r_{10y}), Treasury yield curve slope (Slope) defined as 10-year yield minus 2-year yield, and default spreads (DEF). The firm fundamental variables include leverage (Lev), equity volatility (Eqty Vol), log market capitalization (MC), and 5-year CDS spreads (5y CDS). The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. Sources: Markit, OptionMetrics, FRED, Compustat, and authors' computations.

Panel A: IS and CDS Descriptive Statistics

	obs.	mean	std	min	10%	50%	90%	max
CW $\kappa_{i,t}$	11079	-0.07	0.48	-1.00	-0.60	-0.20	0.60	1.00
CNV $\kappa_{i,t}$	11079	-0.08	0.46	-1.00	-0.60	-0.20	0.60	1.00

Panel B: Correlations

	CW $\kappa_{i,t}$	CNV $\kappa_{i,t}$	Lev	Eqty Vol	MC	5y CDS	SP500	VIX	r_{10y}	Slope	DEF
CW $\kappa_{i,t}$	1.00										
CNV $\kappa_{i,t}$	0.51	1.00									
Lev	-0.06	-0.02	1.00								
Eqty Vol	-0.08	-0.05	0.25	1.00							
MC	0.04	0.02	-0.28	-0.35	1.00						
5y CDS	-0.06	-0.03	0.43	0.45	-0.47	1.00					
SP500	0.10	0.06	-0.00	-0.00	0.02	-0.03	1.00				
VIX	-0.09	-0.06	-0.08	0.46	0.11	0.04	-0.20	1.00			
r_{10y}	0.07	0.03	-0.12	-0.05	0.02	-0.10	-0.01	-0.05	1.00		
Slope	-0.02	0.02	0.00	0.05	0.10	-0.00	0.04	0.28	-0.14	1.00	
DEF	-0.04	-0.02	-0.08	0.43	0.11	0.04	-0.00	0.82	-0.13	0.12	1.00

E Further discussion on the cointegration analysis

Since the cointegration test requires sufficient long continuous time series data for both the IS and the CDS, this test is only applicable to a subset of the firms. To increase the size of the testing sample, I also perform the same analysis using the separate full sample produced by the CW and CNV methods, respectively. Panel B reports the cointegration results for the separate samples. Both the CW and CNV test sample increase significantly compared with the overlapping test sample.[35] Nevertheless, about 75% (71%) of the firms in each sample have cointegrated IS and CDS series for the CW (CNV) IS. This again indicates strong integration between the option and CDS markets in the long run.

The average number of days across all firms is 450 (444) in the overlapping sample and 493 (554) in the separate sample with the CW (CNV) metric. One legitimate concern about the cointegration analysis is that the sample period might not be long enough to study the long-term integration. However, Hakkio and Rush (1991) provide evidence that the power of the cointegration test is related to the ratio of the length of the sample to the half-life of the cointegrating vector rather than the sample length itself. A higher ratio indicates a higher power of the cointegration test. Among all the samples, the smallest ratio is about 52.[36] This suggests that the cointegration tests in this paper have stronger power than many purchasing power parity cointegration tests in the literature, with half-life around 3 years and less than 100 years of data.

[35] The reason why the two metrics produce different samples for the cointegration analysis is because some firms have integrated CW IS but not CNV IS or vice versa. The cointegration analysis requires both IS and CDS to be I(1) series.

[36] Blanco, Brennan, and Marsh (2005) documents that the half-life of bond yield and CDS spreads in their cointegration analysis is 6 days and their sample period is about 360 daily data. The ratio is about 60, which is similar to the ratios in most of the samples in this paper. Even though the smallest ratio is 52, it requires over 156 years of data for the purchasing power parity cointegration analysis to reach the same test power. This suggests that my analysis on the shorter sample has stronger testing power than many cointegration analysis in the literature with longer samples.

Table E.1: The long-run integration between 2-year CDS and 2-year IS.

In this table, I report the results of the Engle and Granger cointegration test on each firm's *2-year* CDS spreads and the corresponding *2-year* option implied credit spreads (IS). $\overline{HalfLife}$ denotes the median half life for the cointegrated series. N_{total} denotes the number of firms in the sample. T_{avg} denotes the average number of days across all series. $\frac{N_{cointegrated}}{N_{total}}$ denotes the percentage of firms with cointegrated IS and CDS among the total number of firms. For each firm, I search for the longest string of more than 250 daily non-missing IS and CDS that were no more than 5 business days apart. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Overlapping Sample				
	$\overline{HalfLife}$	T_{avg}	N_{total}	$\frac{N_{cointegrated}}{N_{total}}$
CW IS	6.14	451	31	83.87%
CNV IS	6.63	461	31	83.87%
Panel B: Separate Sample				
	$\overline{HalfLife}$	T_{avg}	N_{total}	$\frac{N_{cointegrated}}{N_{total}}$
CW IS	7.67	476	71	81.69%
CNV IS	8.88	510	124	70.97%

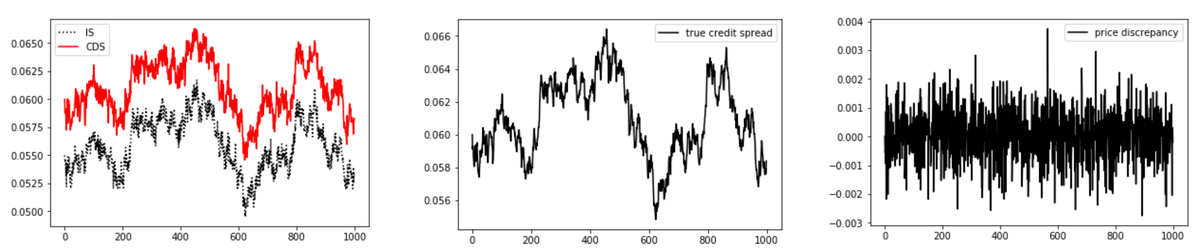
F Further discussion on KP test on misalignment

This section simulates the IS and CDS time series which are cointegrated with cointegrating vector $[1, -1, 0.005]$, i.e. $IS - CDS - 0.005$ is stationary,[37] and half-life of 7 days. The data generating process for the true credit spread resembles the square root process: $\Delta s_{t+1} = \theta(\mu - s_t) + \sigma\sqrt{s_t}\epsilon_{t+1}$. The data generating process for the short-lived price discrepancy due to the frictions is $\eta_{t+1} = \rho\eta_t + \sigma_\eta \nu_{t+1}$, where ρ is -0.099, which can be deduced from the half-life. θ and μ are taken from Augustin, Saleh, and Xu (2020) (henceforth, ASX), which are 0.013 and 0.06, respectively. Based on the volatility value of the CDS spreads data generating process (0.004) in ASX, I divide this volatility into σ and σ_η in my exercise. In particular, I set $\sigma = 0.015$ and $\sigma_\eta = 0.001$. Finally, I set $IS_t = s_t - 0.5\eta_t - 0.005$ and $CDS_t = s_t + 0.5\eta_t$. I simulate 1,000 days of observations. Figure F.1 reports the time series of simulated IS and CDS spreads (panel (a)), true credit spreads (panel (b)), and the price discrepancy between IS and CDS spreads (panel (c)).

Figure F.1: Simulated IS and CDS spreads time series

In this figure, I report the time series of simulated IS and CDS spreads (panel (a)), true credit spreads (panel (b)), and the price discrepancy between IS and CDS spreads (panel (c)). The IS and CDS are cointegrated with cointegrating vector [1,-1,0.005] and half-life of 7 days. The data generating process for the true credit spread resembles the square root process: $\Delta s_{t+1} = \theta(\mu - s_t) + \sigma\sqrt{s_t}\epsilon_{t+1}$. The data generating process for the short-lived price discrepancy due to the frictions is $\eta_{t+1} = \rho\eta_t + \sigma_\eta\nu_{t+1}$, where ρ is -0.099, which can be deduced from the half-life. θ and μ are taken from Augustin, Saleh, and Xu (2020), which are 0.013 and 0.06, respectively. $\sigma = 0.015$ and $\sigma_\eta = 0.001$. In addition, I set $IS_t = s_t - 0.5\eta_t - 0.005$ and $CDS_t = s_t + 0.5\eta_t$. I simulate 1,000 days of observations. Sources: Author's computation.

(a) IS CDS Time Series **(b)** True Credit Spreads **(c)** Price Discrepancy



Visually, these two credit spreads co-move strongly with each other, consistent with the data generating process. Following the same methodology in KP and the main text

[37]The stationary basis 0.005 is for the visual purpose when plotting the simulated time series. It also corresponds to the potential data error or model misspecification in practice.

of this paper, I compute the fraction of misalignment of these two credit spreads at daily, weekly, monthly, and quarterly frequency. Table F.1 reports the misalignment fractions between the simulated IS and CDS. The fractions are decreasing with the data frequency but the fraction is significantly different from 0 at the long horizon, i.e. quarterly. This is mainly driven by the volatile short-lived price discrepancy between the IS and CDS spreads, which can be seen from panel (b) and (c) from Figure F.1. Therefore, the positive value of the long-run misalignment fraction should not be simply interpreted as the existence of long run segmentation between the two markets without further evidence.

Table F.1: Kapadia and Pu (2012) price discrepancy (Simulation)

In this table, I report the misalignment between the simulated IS and CDS, $\Delta IS \Delta CDS < 0$, as a proportion (Fraction) of total observations with $\Delta IS \Delta CDS \neq 0$ measured over non-overlapping daily, weekly, monthly, and quarterly time intervals following Kapadia and Pu (2012). Sources: Author's computations.

	Daily	Weekly	Monthly	Quarterly
Fraction	68.77%	43.50%	37.78%	20.00%

G Additional regressions of IS and CDS spreads misalignment on arbitrage costs

Table G.1: The relation between arbitrage costs and the integration between the option and CDS markets (CW IS separate full sample).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. Macroeconomic control variables include S&P 500 index returns, CBOE VIX index (VIX), 10 year Treasury yield, and the Treasury yield slope defined as 10 year yield minus 2 year yield. The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lndepth	-0.035***							-0.033**	-0.041***
	(-2.708)							(-2.593)	(-3.496)
Spreadzero		0.108						0.090	0.030
		(1.205)						(1.017)	(0.351)
Bidask			0.058***					0.057***	0.068***
			(5.489)					(5.380)	(6.338)
Volume				-0.000				0.000	0.000
				(-0.061)				(0.169)	(0.109)
Idiosyn					0.008**			0.008**	0.013***
					(1.973)			(2.022)	(3.367)
IO						-0.023		-0.025	-0.025
						(-1.171)		(-1.257)	(-1.182)
$\#Analyst$							-0.019	-0.018	-0.022*
							(-1.613)	(-1.441)	(-1.797)
Observations	16746	16746	16746	16746	16746	16746	16746	16746	16630
R^2	0.124	0.123	0.125	0.123	0.123	0.123	0.123	0.126	0.053
Adjusted R^2	0.069	0.069	0.071	0.069	0.069	0.069	0.069	0.071	0.037
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	
Year FE									✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Macro Control									✓

Table G.2: The relation between arbitrage costs and the integration between the option and CDS markets (CNV IS separate full sample).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. Macroeconomic control variables include S&P 500 index returns, CBOE VIX index (VIX), 10 year Treasury yield, and the Treasury yield slope defined as 10 year yield minus 2 year yield. The KP metric is computed as $\bar{\kappa}_i = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lndepth	-0.022***							-0.023***	-0.018***
	(-3.211)							(-3.324)	(-2.605)
Spreadzero		0.051						0.036	0.052
		(1.103)						(0.772)	(1.093)
Bidask			0.033***					0.032***	0.030***
			(4.995)					(5.007)	(4.608)
Volume				-0.000				-0.000	-0.000
				(-1.467)				(-1.173)	(-1.632)
Idiosyn					0.006***			0.006***	0.008***
					(2.826)			(2.751)	(3.680)
IO						-0.036**		-0.033*	-0.034*
						(-2.083)		(-1.931)	(-1.940)
$\#Analyst$							0.002	0.003	0.005
							(0.281)	(0.387)	(0.575)
Observations	51376	51376	51376	51376	51376	51376	51376	51376	50920
R^2	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.051	0.024
Adjusted R^2	0.028	0.028	0.029	0.028	0.028	0.028	0.028	0.029	0.015
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	
Year FE									✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Macro Control									✓

Table G.3: The relation between arbitrage costs and the integration between the option and CDS markets (IS computed based on option bid prices).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS_{i,k\tau}^{\tau}\Delta CDS_{i,k\tau}^{\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$	$\kappa_{i,t}^{CW}$	$\kappa_{i,t}^{CNV}$
Lndepth	-0.039**	-0.026*													-0.035*	-0.024*
	(-2.033)	(-1.769)													(-1.776)	(-1.655)
Spreadzero			0.103	0.234*											0.079	0.224*
			(0.867)	(1.892)											(0.662)	(1.806)
Bidask					0.036**	0.060***									0.035**	0.057***
					(2.451)	(3.658)									(2.408)	(3.453)
Volume							-0.000	-0.000							-0.000	-0.000
							(-0.333)	(-0.985)							(-0.262)	(-0.683)
Idiosyn									0.005	0.006					0.005	0.006
									(0.898)	(1.295)					(0.906)	(1.288)
IO											-0.019	-0.107***			-0.015	-0.099**
											(-0.468)	(-2.798)			(-0.360)	(-2.559)
$\#Analyst$													0.026	-0.000	0.025	-0.006
													(1.307)	(-0.004)	(1.294)	(-0.316)
Observations	8818	8986	8818	8986	8818	8986	8818	8986	8818	8986	8818	8986	8818	8986	8818	8986
R^2	0.185	0.143	0.185	0.143	0.185	0.144	0.185	0.143	0.185	0.143	0.185	0.143	0.185	0.143	0.186	0.145
Adjusted R^2	0.092	0.047	0.092	0.047	0.093	0.048	0.092	0.047	0.092	0.047	0.092	0.048	0.092	0.047	0.093	0.049
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table G.4: The relation between arbitrage costs and the integration between the option and CDS markets (IS computed based on option offer prices).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1) $\kappa^{CW}_{i,t}$	(2) $\kappa^{CNV}_{i,t}$	(3) $\kappa^{CW}_{i,t}$	(4) $\kappa^{CNV}_{i,t}$	(5) $\kappa^{CW}_{i,t}$	(6) $\kappa^{CNV}_{i,t}$	(7) $\kappa^{CW}_{i,t}$	(8) $\kappa^{CNV}_{i,t}$	(9) $\kappa^{CW}_{i,t}$	(10) $\kappa^{CNV}_{i,t}$	(11) $\kappa^{CW}_{i,t}$	(12) $\kappa^{CNV}_{i,t}$	(13) $\kappa^{CW}_{i,t}$	(14) $\kappa^{CNV}_{i,t}$	(15) $\kappa^{CW}_{i,t}$	(16) $\kappa^{CNV}_{i,t}$
Lndepth	-0.027	-0.034*													-0.024	-0.032*
	(-1.644)	(-1.742)													(-1.420)	(-1.655)
Spreadzero			0.137	0.200											0.123	0.179
			(1.214)	(1.536)											(1.062)	(1.356)
Bidask					0.050***	0.066***									0.048***	0.066***
					(3.019)	(4.137)									(2.894)	(4.130)
Volume							-0.000	0.000							-0.000	0.000
							(-1.489)	(0.115)							(-1.291)	(0.434)
Idiosyn									0.004	0.011*					0.004	0.011*
									(0.670)	(1.889)					(0.692)	(1.924)
IO											-0.011	-0.018			-0.018	-0.012
											(-0.309)	(-0.432)			(-0.512)	(-0.296)
$\#Analyst$													-0.021	-0.002	-0.020	-0.004
													(-1.238)	(-0.098)	(-1.208)	(-0.234)
Observations	8861	8963	8861	8963	8861	8963	8861	8963	8861	8963	8861	8963	8861	8963	8861	8963
R^2	0.192	0.145	0.192	0.145	0.193	0.147	0.192	0.145	0.192	0.145	0.192	0.145	0.192	0.145	0.194	0.148
Adjusted R^2	0.100	0.050	0.100	0.049	0.102	0.051	0.100	0.049	0.100	0.050	0.100	0.049	0.100	0.049	0.102	0.052
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table G.5: The relation between arbitrage costs and the integration between the option and CDS markets (2-year IS and 2-year CDS spreads).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, and annualized stock volatility computed using the previous month daily stock returns. The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1) $\kappa^{CW}_{i,t}$	(2) $\kappa^{CNV}_{i,t}$	(3) $\kappa^{CW}_{i,t}$	(4) $\kappa^{CNV}_{i,t}$	(5) $\kappa^{CW}_{i,t}$	(6) $\kappa^{CNV}_{i,t}$	(7) $\kappa^{CW}_{i,t}$	(8) $\kappa^{CNV}_{i,t}$	(9) $\kappa^{CW}_{i,t}$	(10) $\kappa^{CNV}_{i,t}$	(11) $\kappa^{CW}_{i,t}$	(12) $\kappa^{CNV}_{i,t}$	(13) $\kappa^{CW}_{i,t}$	(14) $\kappa^{CNV}_{i,t}$	(15) $\kappa^{CW}_{i,t}$	(16) $\kappa^{CNV}_{i,t}$
Lndepth	-0.009	-0.007													-0.008	-0.010
	(-0.600)	(-0.412)													(-0.486)	(-0.585)
Spreadzero			-0.100	-0.200*											-0.103	-0.208*
			(-0.780)	(-1.731)											(-0.787)	(-1.807)
Bidask					0.047***	0.038**									0.047***	0.037**
					(2.755)	(2.189)									(2.662)	(2.124)
Volume							0.000	-0.000							0.000	0.000
							(0.461)	(-0.103)							(0.614)	(0.092)
Idiosyn									0.010*	0.007					0.010*	0.007
									(1.815)	(1.378)					(1.799)	(1.410)
IO											-0.001	-0.069*			-0.006	-0.067*
											(-0.023)	(-1.922)			(-0.162)	(-1.871)
$\#Analyst$													-0.026	-0.012	-0.023	-0.014
													(-1.339)	(-0.630)	(-1.193)	(-0.736)
Observations	8425	8542	8425	8542	8425	8542	8425	8542	8425	8542	8425	8542	8425	8542	8425	8542
R^2	0.155	0.129	0.155	0.129	0.157	0.129	0.155	0.129	0.156	0.129	0.155	0.129	0.156	0.129	0.157	0.130
Adjusted R^2	0.056	0.028	0.056	0.028	0.058	0.028	0.056	0.028	0.057	0.028	0.056	0.028	0.056	0.028	0.058	0.029
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table G.6: The relation between arbitrage costs and the integration between the option and CDS markets (Controlling for equity and CDS misalignment).

In this table, I report the results of the panel regression of Kendall correlation on different arbitrage cost proxies. The arbitrage cost proxies include log depth (Lndepth) and Spreadzero for CDS liquidity and illiquidity, option bid ask spread (Bidask) and volume for option illiquidity and liquidity, idiosyncratic volatility ratio (Idiosyn) for potential arbitrage cost in holding the positions, institutional ownership (IO) and analyst coverage (#Analyst) for the transparency of the firm. The firm specific control variables include firm leverage ratio, log market capitalization, annualized stock volatility computed using the previous month daily stock returns, and the Kendall correlation between the equity and CDS ($\kappa_{eqty,CDS}$). The KP metric is computed as $\bar{\kappa_i} = \frac{1}{2}\log\frac{1+\kappa_i}{1-\kappa_i}$ where $\kappa_i = \frac{2}{N}\sum_{k=1}^{N}\mathbb{I}_{\{\Delta IS^{\tau}_{i,k\tau}\Delta CDS^{\tau}_{i,k\tau}<0\}} - 1$ and N denotes the number of business days with non zero daily CDS spread changes within a week. Spreadzero is computed as the ratio of zero daily spread changes to the total number of non-missing daily CDS changes over the week. Idiosyn is computed as $\log\frac{1-R^2}{R^2}$, where R^2 is the R-square of the Fama-French three-factor regression of stock returns. The data period ranges from Jan 2002 until April 2018. The data frequency is weekly. All independent variables are winsorized at 0.1% and 99.9% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, Fred, Kenneth R. French data library, and author's computation.

	(1) $\kappa^{CW}_{i,t}$	(2) $\kappa^{CNV}_{i,t}$	(3) $\kappa^{CW}_{i,t}$	(4) $\kappa^{CNV}_{i,t}$	(5) $\kappa^{CW}_{i,t}$	(6) $\kappa^{CNV}_{i,t}$	(7) $\kappa^{CW}_{i,t}$	(8) $\kappa^{CNV}_{i,t}$	(9) $\kappa^{CW}_{i,t}$	(10) $\kappa^{CNV}_{i,t}$	(11) $\kappa^{CW}_{i,t}$	(12) $\kappa^{CNV}_{i,t}$	(13) $\kappa^{CW}_{i,t}$	(14) $\kappa^{CNV}_{i,t}$	(15) $\kappa^{CW}_{i,t}$	(16) $\kappa^{CNV}_{i,t}$
Lndepth	-0.031*	-0.015													-0.029*	-0.013
	(-1.905)	(-0.934)													(-1.794)	(-0.778)
Spreadzero			0.068	0.281**											0.050	0.273**
			(0.579)	(2.151)											(0.424)	(2.119)
Bidask					0.048***	0.059***									0.045***	0.057***
					(3.028)	(3.672)									(2.797)	(3.576)
Volume							-0.000	-0.000							-0.000	-0.000
							(-0.806)	(-1.495)							(-0.686)	(-1.339)
Idiosyn									0.009	0.019***					0.009	0.019***
									(1.497)	(3.133)					(1.455)	(3.175)
IO											-0.039	-0.066*			-0.049	-0.061
											(-1.126)	(-1.674)			(-1.428)	(-1.588)
$\#Analyst$													-0.037**	-0.030	-0.038**	-0.033
													(-2.197)	(-1.421)	(-2.212)	(-1.609)
Observations	7943	8028	7943	8028	7943	8028	7943	8028	7943	8028	7943	8028	7943	8028	7943	8028
R^2	0.196	0.153	0.196	0.153	0.197	0.154	0.196	0.153	0.196	0.154	0.196	0.153	0.196	0.153	0.198	0.157
Adjusted R^2	0.094	0.046	0.094	0.047	0.095	0.048	0.094	0.046	0.094	0.048	0.094	0.046	0.094	0.046	0.096	0.050
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

H Predictability

Table H.1: Predicting future market movements based on current cross-market deviations for different conditions (IS computed based on option bid prices).

In this table, I report the results of the panel regression below:

$$\begin{pmatrix} \Delta IS_{i,t+1} \\ \Delta CDS_{i,t+1} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta^u_{IS,Dev} + \beta^c_{IS,Dev} D_{c,t} \\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev} D_{c,t} \end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}$$

where D_c denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the firm specific control variables. Panel A (B) reports the regression results of $\Delta IS_{i,t+1}$ ($\Delta CDS_{i,t+1}$). Columns (1), (3), (5), and (7) correspond to the regressions based on CW IS and the rest columns correspond to the regressions based on CNV IS. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise. $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) CW	(2) CNV	(3) CW	(4) CNV	(5) CW	(6) CNV	(7) CW	(8) CNV
Panel A: IS predictability								
	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$
Dev	-0.019***	-0.033***	-0.012***	-0.024***	-0.022***	-0.034***	-0.023***	-0.037***
	(-6.893)	(-9.809)	(-5.000)	(-7.744)	(-7.140)	(-8.575)	(-6.805)	(-9.915)
$D_{CDSIlliquid} * Dev$	-0.001	-0.007						
	(-0.271)	(-1.360)						
$D_{OptionIlliquid} * Dev$			-0.026***	-0.025***				
			(-6.909)	(-4.835)				
$D_{Idiosyn} * Dev$					0.006***	0.002		
					(2.966)	(0.804)		
$D_{Transparency} * Dev$							0.010***	0.012**
							(3.042)	(2.348)
Observations	58833	58702	58833	58702	58833	58702	58833	58702
R^2	0.216	0.221	0.225	0.226	0.216	0.221	0.216	0.222
Adjusted R^2	0.159	0.165	0.169	0.171	0.159	0.165	0.160	0.165
Panel B: CDS spreads predictability								
	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$
Dev	0.003***	0.001**	0.004***	0.002**	0.004***	0.002**	0.003***	0.001
	(3.739)	(2.023)	(3.685)	(1.991)	(3.137)	(2.401)	(3.614)	(1.178)
$D_{CDSIlliquid} * Dev$	0.006***	0.004***						
	(3.063)	(3.025)						
$D_{OptionIlliquid} * Dev$			-0.002	0.001				
			(-1.426)	(0.744)				
$D_{Idiosyn} * Dev$					-0.000	-0.001		
					(-0.111)	(-0.824)		
$D_{Transparency} * Dev$							0.001	0.002
							(0.318)	(1.307)
Observations	58833	58746	58833	58746	58833	58746	58833	58746
R^2	0.224	0.226	0.224	0.226	0.224	0.226	0.224	0.226
Adjusted R^2	0.168	0.170	0.168	0.170	0.168	0.170	0.168	0.170
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓

Table H.2: Predicting future market movements based on current cross-market deviations for different conditions (IS computed based on option offer prices).

In this table, I report the results of the panel regression below:

$$\begin{pmatrix} \Delta IS_{i,t+1} \\ \Delta CDS_{i,t+1} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta^u_{IS,Dev} + \beta^c_{IS,Dev} D_{c,t} \\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev} D_{c,t} \end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}$$

where D_c denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the firm specific control variables. Panel A (B) reports the regression results of $\Delta IS_{i,t+1}$ ($\Delta CDS_{i,t+1}$). Columns (1), (3), (5), and (7) correspond to the regressions based on CW IS and the rest columns correspond to the regressions based on CNV IS. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise. $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) CW	(2) CNV	(3) CW	(4) CNV	(5) CW	(6) CNV	(7) CW	(8) CNV
Panel A: IS predictability								
	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$
Dev	-0.027***	-0.038***	-0.021***	-0.031***	-0.030***	-0.040***	-0.032***	-0.042***
	(-7.864)	(-9.850)	(-7.186)	(-9.078)	(-8.271)	(-10.048)	(-7.702)	(-10.198)
$D_{CDSIlliquid} * Dev$	-0.000	-0.006						
	(-0.037)	(-1.416)						
$D_{OptionIlliquid} * Dev$			-0.040***	-0.040***				
			(-6.486)	(-9.198)				
$D_{Idiosyn} * Dev$					0.007***	0.004		
					(2.822)	(1.397)		
$D_{Transparency} * Dev$							0.014***	0.015**
							(3.175)	(2.594)
Observations	58833	58448	58833	58448	58833	58448	58833	58448
R^2	0.235	0.240	0.241	0.246	0.236	0.240	0.236	0.241
Adjusted R^2	0.180	0.185	0.186	0.191	0.181	0.185	0.181	0.186
Panel B: CDS spreads predictability								
	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$
Dev	0.004***	0.003***	0.004***	0.003***	0.004***	0.003***	0.004***	0.002***
	(3.459)	(4.191)	(3.379)	(4.070)	(3.411)	(4.774)	(3.091)	(2.910)
$D\_CDSIlliquid * Dev$	0.006***	0.004**						
	(2.903)	(2.473)						
$D\_OptionIlliquid * Dev$			-0.001	0.000				
			(-0.797)	(0.786)				
$D\_Idiosyn * Dev$					-0.001	-0.001		
					(-0.317)	(-0.787)		
$D\_Transparency * Dev$							0.001	0.003*
							(0.357)	(1.911)
Observations	58833	58518	58833	58518	58833	58518	58833	58518
R^2	0.224	0.231	0.224	0.231	0.224	0.231	0.224	0.231
Adjusted R^2	0.168	0.175	0.168	0.175	0.168	0.175	0.168	0.175
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓

Table H.3: Predicting future market movements based on current cross-market deviations for different conditions (2-year IS and 2-year CDS spreads).

In this table, I report the results of the panel regression below:

$$\begin{pmatrix} \Delta IS_{i,t+1} \\ \Delta CDS_{i,t+1} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta^u_{IS,Dev} + \beta^c_{IS,Dev} D_{c,t} \\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev} D_{c,t} \end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}$$

where D_c denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the firm specific control variables. Panel A (B) reports the regression results of $\Delta IS_{i,t+1}$ ($\Delta CDS_{i,t+1}$). Columns (1), (3), (5), and (7) correspond to the regressions based on CW IS and the rest columns correspond to the regressions based on CNV IS. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise. $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) CW	(2) CNV	(3) CW	(4) CNV	(5) CW	(6) CNV	(7) CW	(8) CNV
Panel A: IS predictability								
	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$	$\Delta IS^{CW}_{i,t+1}$	$\Delta IS^{CNV}_{i,t+1}$
Dev	-0.018***	-0.038***	-0.014***	-0.035***	-0.022***	-0.039***	-0.021***	-0.041***
	(-6.722)	(-10.456)	(-5.708)	(-9.937)	(-7.381)	(-10.549)	(-6.371)	(-10.959)
$D_{CDSIlliquid} * Dev$	0.006	-0.005						
	(1.261)	(-0.882)						
$D_{OptionIlliquid} * Dev$			-0.040***	-0.029***				
			(-6.141)	(-5.023)				
$D_{Idiosyn} * Dev$					0.009***	0.002		
					(2.891)	(0.597)		
$D_{Transparency} * Dev$							0.009**	0.009*
							(2.359)	(1.704)
Observations	56820	56597	56820	56597	56820	56597	56820	56597
R^2	0.217	0.219	0.221	0.221	0.218	0.219	0.217	0.219
Adjusted R^2	0.159	0.161	0.163	0.162	0.159	0.161	0.159	0.161
Panel B: CDS spreads predictability								
	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$	$\Delta CDS_{i,t+1}$
Dev	0.004***	0.003***	0.004***	0.003***	0.004***	0.003***	0.004***	0.002***
	(3.459)	(4.191)	(3.379)	(4.070)	(3.411)	(4.774)	(3.091)	(2.910)
Dev	0.004**	0.001	0.004**	0.001	0.004***	0.002***	0.004***	0.001
	(2.428)	(0.838)	(2.368)	(0.724)	(2.745)	(3.161)	(2.623)	(0.511)
$D_{CDSIlliquid} * Dev$	0.008***	0.003						
	(2.910)	(1.598)						
$D_{OptionIlliquid} * Dev$			0.002	0.003*				
			(0.887)	(1.719)				
$D_{Idiosyn} * Dev$					-0.001	-0.002**		
					(-0.341)	(-2.303)		
$D_{Transparency} * Dev$							-0.000	0.001
							(-0.118)	(0.716)
Observations	56539	56369	56539	56369	56539	56369	56539	56369
R^2	0.163	0.163	0.163	0.164	0.163	0.164	0.163	0.163
Adjusted R^2	0.101	0.100	0.100	0.101	0.100	0.101	0.100	0.100
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓

Table H.4: Predicting future market movements based on current cross-market deviations for different conditions (Separate sample).

In this table, I report the results of the panel regression below:

$$\begin{pmatrix} \Delta IS_{i,t+1} \\ \Delta CDS_{i,t+1} \end{pmatrix} = \begin{pmatrix} \alpha_{i,IS,t} \\ \alpha_{i,CDS,t} \end{pmatrix} + \begin{pmatrix} \gamma_{IS,t} \\ \gamma_{CDS,t} \end{pmatrix} + \begin{pmatrix} \beta^u_{IS,Dev} + \beta^c_{IS,Dev} D_{c,t} \\ \beta^u_{CDS,Dev} + \beta^c_{CDS,Dev} D_{c,t} \end{pmatrix} Dev_{i,t} + Y'_{i,t}\beta_Y + \begin{pmatrix} \epsilon_{i,IS,t} \\ \epsilon_{i,CDS,t} \end{pmatrix}$$

where D_c denotes the condition indicator variable, β^u and β^c denotes the unconditional and conditional effect of cross-market deviation, α_i denotes the firm fixed effect, γ_t denotes the time fixed effect, and Y_i denotes the firm specific control variables. Panel A (B) reports the regression results based on CW IS (CNV IS). Columns (1), (3), (5), and (7) correspond to the regressions of $\Delta IS_{i,t+1}$ and the rest columns correspond to the regressions of $\Delta CDS_{i,t+1}$. The firm specific controls include firm leverage ratio, log market capitalization lag changes, annualized stock volatility lag changes, computed using the previous month daily stock returns, rating, stock lag daily return, and stock market beta, computed using the previous month daily stock returns. $D_{CDSIlliquid}$ ($D_{OptionIlliquid}$) equals 1 if both the CDS depth (option volume) belonging to the bottom tercile and the Spreadzero (option bid-ask spreads) belonging to the top tercile, and 0 otherwise. $D_{Idiosyn}$ equals 1 if the idiosyncratic risk variable belongs to the top tercile. $D_{Transparency}$ equals 1 if both the IO and #Analyst belong to the bottom tercile. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1) ΔIS_{t+1}	(2) ΔCDS_{t+1}	(3) ΔIS_{t+1}	(4) ΔCDS_{t+1}	(5) ΔIS_{t+1}	(6) ΔCDS_{t+1}	(7) ΔIS_{t+1}	(8) ΔCDS_{t+1}
Panel A: CW IS								
Dev	-0.012***	0.003***	-0.010***	0.003***	-0.015***	0.003***	-0.014***	0.004***
	(-7.026)	(3.016)	(-6.571)	(3.238)	(-8.279)	(3.153)	(-6.932)	(5.543)
$D_{CDSIlliquid} * Dev$	0.002	0.007***						
	(0.677)	(4.985)						
$D_{OptionIlliquid} * Dev$			-0.015***	-0.000				
			(-5.177)	(-0.262)				
$D_{Idiosyn} * Dev$					0.005***	-0.000		
					(3.979)	(-0.275)		
$D_{Transparency} * Dev$							0.007***	-0.003**
							(3.226)	(-2.172)
Observations	110459	110459	110459	110459	110459	110459	110459	110459
R^2	0.215	0.191	0.217	0.190	0.216	0.190	0.216	0.190
Adjusted R^2	0.186	0.160	0.187	0.159	0.186	0.159	0.186	0.160
Panel B: CNV IS								
Dev	-0.025***	0.001***	-0.022***	0.001***	-0.025***	0.001***	-0.025***	0.001***
	(-17.489)	(4.208)	(-16.921)	(4.747)	(-17.158)	(5.826)	(-17.549)	(4.400)
$D_{CDSIlliquid} * Dev$	-0.001	0.001**						
	(-0.365)	(2.426)						
$D_{OptionIlliquid} * Dev$			-0.021***	0.000				
			(-8.148)	(0.695)				
$D_{Idiosyn} * Dev$					0.000	-0.000**		
					(0.119)	(-2.031)		
$D_{Transparency} * Dev$							0.002	0.001*
							(0.795)	(1.695)
Observations	328383	328383	328383	328383	328383	328383	328383	328383
R^2	0.170	0.153	0.171	0.153	0.170	0.153	0.170	0.153
Adjusted R^2	0.159	0.142	0.160	0.142	0.159	0.142	0.159	0.142
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓

I Financial intermediary health and cross-market basis

Table I.1: The relation between intermediary capital ratio and lag return deviation between IS and CDS (CW IS separate full sample).

In this table, I report the results of the panel regression below:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}}\left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Full Sample									
	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICR	0.099***	0.091***	0.062***	2.586***	2.638***	2.103***	0.372***	0.367***	0.262***
	(4.857)	(4.482)	(2.671)	(7.224)	(7.157)	(4.703)	(5.582)	(5.569)	(3.343)
Observations	129294	107750	98769	129294	107750	98769	128347	106955	98001
R^2	0.005	0.008	0.009	0.005	0.008	0.010	0.005	0.009	0.011
Panel B: IG Sample									
ICR	0.106***	0.110***	0.080***	3.268***	3.352***	2.821***	0.395***	0.408***	0.305***
	(4.287)	(4.731)	(2.883)	(6.782)	(6.847)	(4.677)	(4.792)	(5.126)	(3.137)
Observations	46590	41038	37633	46590	41038	37633	46257	40743	37347
R^2	0.011	0.015	0.019	0.008	0.011	0.014	0.012	0.016	0.019
Panel C: HY Sample									
ICR	0.095***	0.079***	0.053*	2.056***	1.991***	1.530***	0.358***	0.337***	0.243***
	(3.971)	(3.184)	(1.916)	(5.675)	(5.169)	(3.334)	(4.812)	(4.438)	(2.738)
Observations	82704	66712	61136	82704	66712	61136	82090	66212	60654
R^2	0.004	0.007	0.009	0.004	0.008	0.009	0.004	0.008	0.010
Panel D: Excluding Financial Crisis									
ICR	0.054***	0.048***	0.046**	2.115***	2.210***	2.013***	0.231***	0.233***	0.211***
	(3.878)	(3.270)	(2.347)	(6.135)	(6.130)	(4.732)	(4.815)	(4.787)	(3.261)
Observations	104788	87216	79867	104788	87216	79867	103902	86471	79143
R^2	0.003	0.005	0.007	0.004	0.007	0.008	0.003	0.006	0.007
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Table I.2: The relation between intermediary capital ratio and lag return deviation between IS and CDS (IS computed based on option bid prices).

In this table, I report the results of the panel regression below:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}}\left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. IS are computed using CW method. The option data is taken from the OptionMetrics bid quotes. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
ICR	0.062***	0.035*	0.043*	3.187***	2.233***	2.772***	0.285***	0.199***	0.236***
	(2.828)	(1.948)	(1.931)	(5.192)	(3.702)	(3.457)	(3.807)	(3.237)	(2.905)
Observations	66279	59075	53293	66279	59075	53293	65769	58622	52856
R^2	0.004	0.045	0.046	0.003	0.078	0.079	0.003	0.056	0.057
Panel B: IG Sample									
ICR	0.080***	0.051***	0.035*	6.387***	3.622***	3.608***	0.356***	0.224***	0.157*
	(3.995)	(3.002)	(1.741)	(5.543)	(3.097)	(2.660)	(4.420)	(3.245)	(1.879)
Observations	14395	13673	12236	14395	13673	12236	14287	13574	12140
R^2	0.014	0.067	0.070	0.009	0.100	0.103	0.014	0.072	0.075
Panel C: HY Sample									
ICR	0.056**	0.031	0.046	2.043***	1.434**	2.345**	0.262***	0.191**	0.262**
	(2.010)	(1.396)	(1.608)	(3.217)	(2.228)	(2.574)	(2.815)	(2.570)	(2.602)
Observations	51883	45401	41055	51883	45401	41055	51481	45047	40714
R^2	0.004	0.049	0.050	0.003	0.080	0.081	0.003	0.061	0.063
Panel D: Excluding Financial Crisis									
ICR	0.022	0.009	0.034	2.486***	1.987***	2.916***	0.150**	0.113*	0.199**
	(1.269)	(0.488)	(1.310)	(3.851)	(3.039)	(3.159)	(2.396)	(1.846)	(2.167)
Observations	57952	51653	46633	57952	51653	46633	57452	51205	46200
R^2	0.003	0.045	0.047	0.002	0.078	0.079	0.002	0.056	0.058
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Table I.3: The relation between intermediary capital ratio and lag return deviation between IS and CDS (IS computed based on option offer prices).

In this table, I report the results of the panel regression below:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}}\left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. IS are computed using CW method. The option data is taken from the OptionMetrics offer quotes. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Full Sample									
	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICR	0.076***	0.082***	0.060**	2.178***	2.680***	2.060***	0.299***	0.349***	0.265***
	(3.843)	(4.172)	(2.457)	(5.292)	(6.015)	(3.795)	(4.556)	(5.366)	(3.185)
Observations	66276	59072	53291	66276	59072	53291	65766	58619	52854
R^2	0.004	0.016	0.016	0.004	0.021	0.021	0.004	0.018	0.018
Panel B: IG Sample									
ICR	0.064***	0.091***	0.066***	3.600***	4.833***	3.709***	0.271***	0.386***	0.273***
	(2.777)	(4.450)	(2.712)	(4.813)	(6.085)	(4.005)	(3.086)	(4.709)	(2.784)
Observations	14395	13673	12236	14395	13673	12236	14287	13574	12140
R^2	0.013	0.040	0.038	0.009	0.039	0.037	0.013	0.041	0.038
Panel C: HY Sample									
ICR	0.083***	0.081***	0.056*	1.690***	1.958***	1.511***	0.313***	0.336***	0.255**
	(3.408)	(3.323)	(1.899)	(4.152)	(4.594)	(2.756)	(4.069)	(4.365)	(2.609)
Observations	51880	45398	41053	51880	45398	41053	51478	45044	40712
R^2	0.004	0.016	0.016	0.004	0.020	0.020	0.004	0.018	0.018
Panel D: Excluding Financial Crisis									
ICR	0.053***	0.058***	0.049**	1.924***	2.363***	1.830***	0.227***	0.273***	0.225***
	(2.903)	(3.147)	(2.163)	(4.574)	(5.175)	(3.240)	(3.822)	(4.648)	(2.917)
Observations	57949	51650	46631	57949	51650	46631	57449	51202	46198
R^2	0.004	0.015	0.015	0.004	0.021	0.021	0.003	0.018	0.017
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Table I.4: The relation between intermediary capital ratio and lag return deviation between 2-year IS and 2-year CDS spreads.

In this table, I report the results of the panel regression below:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}}\left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
ICR	0.102***	0.088***	0.076***	2.292***	2.335***	2.225***	0.385***	0.360***	0.318***
	(4.068)	(4.088)	(2.706)	(4.853)	(4.882)	(3.672)	(4.639)	(4.999)	(3.316)
Observations	63252	56121	50653	63252	56121	50653	62769	55690	50239
R^2	0.005	0.007	0.008	0.005	0.007	0.008	0.005	0.008	0.009
Panel B: IG Sample									
ICR	0.090***	0.091***	0.066***	4.101***	4.353***	3.736***	0.381***	0.396***	0.285***
	(3.921)	(4.869)	(3.020)	(4.829)	(5.024)	(4.142)	(4.262)	(5.127)	(3.198)
Observations	13698	12993	11651	13698	12993	11651	13598	12899	11560
R^2	0.022	0.027	0.028	0.012	0.014	0.017	0.022	0.027	0.028
Panel C: HY Sample									
ICR	0.107***	0.089***	0.076**	1.649***	1.577***	1.675**	0.386***	0.345***	0.319***
	(3.421)	(3.298)	(2.182)	(3.310)	(3.233)	(2.556)	(3.818)	(3.936)	(2.724)
Observations	49553	43127	39000	49553	43127	39000	49170	42790	38677
R^2	0.005	0.007	0.009	0.004	0.007	0.008	0.005	0.008	0.010
Panel D: Excluding Financial Crisis									
ICR	0.059***	0.054**	0.055*	1.651***	1.782***	1.816***	0.244***	0.243***	0.244**
	(2.726)	(2.493)	(1.874)	(3.462)	(3.577)	(2.854)	(3.378)	(3.495)	(2.501)
Observations	55204	48961	44212	55204	48961	44212	54730	48535	43802
R^2	0.004	0.006	0.007	0.004	0.006	0.007	0.003	0.006	0.007
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Table I.5: The relation between intermediary capital ratio and lag return deviation between IS and CDS (CNV IS).

In this table, I report the results of the panel regression below:

$$R_{i,t+1}^{Dev} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y_{i,t}' \beta_Y + \epsilon_{i,t}$$

where $R_{i,t+1}^{Dev} = R_{IS,t+1} - R_{CDS,t+1}$, where $R_{IS,t+1}$ and $R_{CDS,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the intermediary capital ratio, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, X denotes the macroeconomic control variables, and Y_i denotes the firm specific control variables. The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. The macro controls include SP 500 index return, CBOE VIX index (VIX), 10 year Treasury yield, Treasury slope, defined as 10 year yield minus 2 year yield, default spread, and TED spread. IS are computed using CW method. The option data is taken from the OptionMetrics offer quotes. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

Panel A: Full Sample									
	Δs			$\Delta \log s$			$\frac{\Delta \widetilde{P}}{\phi}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICR	0.070***	0.071***	0.052**	1.285***	1.443***	1.235***	0.240***	0.255***	0.205**
	(3.291)	(3.570)	(2.006)	(3.786)	(3.970)	(2.695)	(3.664)	(3.923)	(2.456)
Observations	66056	58874	53115	66056	58874	53115	65547	58422	52679
R^2	0.004	0.006	0.006	0.004	0.005	0.006	0.005	0.006	0.007
Panel B: IG Sample									
ICR	0.091***	0.100***	0.069**	2.875***	3.108***	2.964***	0.358***	0.394***	0.301**
	(3.297)	(4.092)	(2.128)	(4.398)	(4.582)	(3.984)	(3.637)	(4.360)	(2.496)
Observations	14394	13672	12235	14394	13672	12235	14286	13573	12139
R^2	0.016	0.021	0.021	0.010	0.012	0.013	0.016	0.021	0.020
Panel C: HY Sample									
ICR	0.063**	0.061**	0.043	0.718**	0.806**	0.591	0.201***	0.201***	0.162*
	(2.485)	(2.582)	(1.416)	(2.156)	(2.267)	(1.283)	(2.685)	(2.735)	(1.771)
Observations	51661	45201	40878	51661	45201	40878	51260	44848	40538
R^2	0.004	0.005	0.006	0.004	0.004	0.005	0.004	0.005	0.006
Panel D: Excluding Financial Crisis									
ICR	0.027	0.031*	0.037	0.729**	0.905**	0.972**	0.105*	0.125**	0.154*
	(1.464)	(1.740)	(1.481)	(2.129)	(2.440)	(2.030)	(1.842)	(2.147)	(1.971)
Observations	57746	51469	46469	57746	51469	46469	57247	51022	46037
R^2	0.003	0.003	0.004	0.004	0.004	0.005	0.003	0.004	0.005
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control		✓	✓		✓	✓		✓	✓
Macro Control			✓			✓			✓

Table I.6: The relation between financial intermediary health and the level deviation between IS and CDS spreads.

In this table, I report the results of the following panel regression using 5 different proxies for financial intermediary health:

$$S_{i,t}^{Dev} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y_{i,t}' \beta_Y + \epsilon_{i,t}$$

where $S_{i,t}^{Dev} = \log(IS_{i,t}) - \log(CDS_{i,t})$. $health_t$ denotes the financial intermediary health variable, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The 5 financial intermediary health variables include the dealer leverage ratio from Adrian, Etula, and Muir (2014) (AEM-LV), the intermediary capital ratio from He and Krishnamurthy (2013) (HKM-ICR), the ted spread (TED), the LIBOR-OIS spread (LIBOR-OIS), and default spread (DEF). The IS are computed based on CNV. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. IS are computed using the CNV method. The data period ranges from Jan 2002 until April 2018. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)
AEM-LV	-0.000					
	(-0.617)					
HKM-ICR		-4.572***				-4.204***
		(-2.846)				(-2.678)
TED			13.510***			3.459*
			(5.331)			(1.790)
LIBOR-OIS				22.598***		16.952***
				(5.616)		(4.235)
DEF					1708.933***	671.190
					(4.274)	(1.583)
Observations	70378	69489	68482	69056	69831	61797
R^2	0.583	0.647	0.644	0.644	0.644	0.654
Firm FE	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓

Table I.7: The relation between financial intermediary health and lag return deviation between IS and CDS spreads (CNV IS).

In this table, I report the results of the following panel regression using 5 different proxies for financial intermediary health:

$$R^{Dev}_{i,t+1} = \alpha_i + \gamma_{t_{ym}} + \beta_{health} health_t + Y'_{i,t}\beta_Y + \epsilon_{i,t}$$

where $R^{Dev}_{i,t+1} = R^{IS}_{i,t+1} - R^{CDS}_{i,t+1}$, where $R^{IS}_{i,t+1}$ and $R^{CDS}_{i,t+1}$ is computed based on the following 3 metrics: Δs_t, $\Delta \log s_t$, and $\frac{\Delta \widetilde{P}_t}{\phi}$ based on Augustin, Saleh, and Xu (2020) where $\widetilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left(1 - e^{-(r_t + \frac{s_t}{1-R})(T-t)}\right)$, s is the IS or CDS, c denotes the coupon payment which is set to the s_{t-1} prior to the Big Bang and 100 (500) bps for IG (HY) firms after the Big Bang, and ϕ denotes the collateral which is set to 1. ICR_t denotes the financial intermediary health variable, α_i denotes the firm fixed effect, $\gamma_{t_{ym}}$ denotes the year-month fixed effect, and Y_i denotes the firm specific control variables. The 5 financial intermediary health variables include the dealer leverage ratio from Adrian, Etula, and Muir (2014) (AEM-LV), the intermediary capital ratio from He and Krishnamurthy (2013) (HKM-ICR), the ted spread (TED), the LIBOR-OIS spread (LIBOR-OIS), and default spread (DEF). The IS are computed based on CW. The firm specific controls include firm leverage ratio, log market capitalization, annualized stock volatility, computed using the previous month daily stock returns, rating, stock daily return, option bid ask spreads, and CDS depth. IS are computed using CW method. The data period ranges from Jan 2002 until April 2018 excluding financial crisis. The data frequency is daily. All variables are winsorized at 1% and 99% level. The standard errors are clustered at both firm and date level. t statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Sources: Markit, OptionMetrics, and author's computation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$	Δs	$\Delta \log s$	$\frac{\Delta \widetilde{P}}{\phi}$
AEM-LV	0.000*	0.000	0.000															
	(1.662)	(1.570)	(1.314)															
HKM-ICR				0.031*	0.905**	0.125**										0.035	0.986**	0.142**
				(1.740)	(2.440)	(2.147)										(1.636)	(2.478)	(2.141)
TED							-0.084	-0.921	-0.265							-0.094	-0.494	-0.251
							(-1.467)	(-0.960)	(-1.348)							(-1.302)	(-0.343)	(-1.001)
LIBOR-OIS										-0.063	-1.451	-0.265				0.090	0.379	0.202
										(-0.592)	(-0.759)	(-0.735)				(0.642)	(0.139)	(0.431)
DEF													3.870	-42.515	12.233	9.673	74.438	33.029
													(0.591)	(-0.294)	(0.586)	(1.417)	(0.487)	(1.496)
Observations	52229	52229	51782	51469	51469	51022	50728	50728	50281	51221	51221	50774	51761	51761	51314	46469	46469	46037
R^2	0.001	0.002	0.002	0.003	0.004	0.004	0.003	0.004	0.004	0.003	0.004	0.004	0.003	0.004	0.004	0.004	0.005	0.005
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

J Proof of (5.1)

If the interest rate r and the default intensity λ is constant,

$$\begin{aligned} P_t(K,T) =& \mathbb{E}_t^Q(e^{-r\tau}(K-R_\tau)\mathbb{I}_{\tau\leq T}) \\ =& \int_t^T \lambda^Q e^{-\lambda^Q s} e^{-rs}(K - Ae^{-r(T-s)})ds \\ =& K\left(\lambda^Q \frac{1-e^{-(r+\lambda^Q)(T-t)}}{r+\lambda^Q}\right) - Ae^{-rT}(1-e^{-\lambda^Q(T-t)}). \end{aligned} \tag{I.1}$$

K Pseudo firm default probability estimation

To compute the pseudo firm's default probability, CNV construct the historical distribution of equity shocks: $\epsilon_{t,\tau} = (\ln(S_{t+\tau}/S_t) - \mu_{t,\tau})/\sigma_{t,\tau}$. $\mu_{t,\tau}$ is the τ year ahead stock return estimates computed as the unconditional average stock return $\ln(S_{u+\tau}/S_t)$ with $u+\tau < t$. $\sigma_{t,\tau}$ is the stock volatility estimate computed using the EGarch model. Therefore, the default probability of the pseudo firm is $\hat{p}_{i,t} = \mathbb{P}[S_{t+\tau} < K_i|\mathcal{F}_t] = \mathbb{P}[\epsilon_{t,\tau} < X_{i,t}|\mathcal{F}_t]$ where $X_{i,t} = (\ln(K_i/S_t) - \mu_{t,\tau})/\sigma_{t,\tau}$. Assuming that the shocks are i.i.d. across the panel, one can use the full panel up to time t to back out the corresponding K_i such that the pseudo firm's default probability matches the firm's default probability.[38]

L Optimal number of contracts when the constraint is slack

The optimal number of contracts are:

$$\begin{cases} \theta^I_{put} = \frac{\gamma^I(W^I)^{-1}(\mu_{put}-p_{put})-(\theta^I_{cds}+\theta^I_c)\sigma_c^2-\delta^I_{put}c_{put}\gamma^I(W^I)^{-1}}{\sigma_c^2+\sigma_{put}^2} \\ \theta^I_{cds} = \frac{\gamma^I(W^I)^{-1}(\mu_{cds}-p_{cds})-(\theta^I_{put}+\theta^I_c)\sigma_c^2-\delta^I_{cds}c_{cds}\gamma^I(W^I)^{-1}}{\sigma_c^2+\sigma_{cds}^2}, \end{cases} \tag{K.1}$$

with $\theta^R_i = -\theta^I_i$, $i \in \{cds, put\}$.

The optimal number of contracts consists of 3 components. The first component $\frac{\gamma^I(W^I)(\widehat{\mu}_i-p_i)}{\sigma_c^2+\sigma_i^2}$ represents the standard CAPM component. The second term $-(\theta^I_{cds}+\theta^I_c)$ for put option or

[38] For detail procedure in matching the default probability between the pseudo firm and real firm, please refer to CNV p461 and their online appendix C.1.

$-(\theta^I_{put}+\theta^I_c)$ for CDS demonstrates the hedging component. For example, if the intermediary has large credit net exposure including the inventory and the CDS, i.e. $-(\theta^I_{cds}+\theta^I_c)$, the more option the intermediary demands to hedge the credit risk. The third component $-\frac{\delta^I_i c_i \gamma^I(W^I)^{-1}}{\sigma^2_c+\sigma^2_i}$ is the liquidity component. If the intermediary is a buyer of the asset i, i.e. $\delta^I_i = 1$, the larger the transaction cost is, the less the intermediary will demand for the asset i.

M Proof of proposition 1

Proof. The FOCs of both agents are:

$$\begin{cases} (\mu_{put}-p_{put})\left(\frac{1}{\gamma^I(W^I)}\right) = \theta^I_{cds}\sigma^2_c + \theta^I_{put}(\sigma^2_c+\sigma^2_{\epsilon_{put}}) + \theta^I_c\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta^I_{put}c_{put} + \frac{\delta^I_{put}c_{put}}{\gamma^I(W^I)} \\ (\mu_{cds}-p_{cds})\left(\frac{1}{\gamma^I(W^I)}\right) = \theta^I_{cds}(\sigma^2_c+\sigma^2_{\epsilon_{cds}}) + \theta^I_{put}\sigma^2_c + \theta^I_c\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta^I_{cds}c_{cds} + \frac{\delta^I_{cds}c_{cds}}{\gamma^I(W^I)} \\ (\mu_{put}-p_{put})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^R_{cds}\sigma^2_c + \theta^R_{put}(\sigma^2_c+\sigma^2_{\epsilon_{put}}) + \theta^R_c\sigma^2_c + \frac{\delta^R_{put}c_{put}}{\gamma^R(W^R)} \\ (\mu_{cds}-p_{cds})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^R_{cds}(\sigma^2_c+\sigma^2_{\epsilon_{cds}}) + \theta^R_{put}\sigma^2_c + \theta^R_c\sigma^2_c + \frac{\delta^R_{cds}c_{cds}}{\gamma^R(W^R)}. \end{cases} \tag{L.1}$$

Market clearing implies:

$$\begin{cases} \mu_{put}-p_{put} = \frac{(\theta^I_c+\theta^R_c)\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta_{put}c_{put} + \left(\frac{1}{\gamma^I(W^I)} - \frac{1}{\gamma^R(W^R)}\right)\delta_{put}c_{put}}{\gamma^B(W^B)^{-1}+\gamma^R(W^R)^{-1}} \\ \mu_{cds}-p_{cds} = \frac{(\theta^I_c+\theta^R_c)\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta_{cds}c_{cds} + \left(\frac{1}{\gamma^I(W^I)} - \frac{1}{\gamma^R(W^R)}\right)\delta_{cds}c_{cds}}{\gamma^B(W^B)^{-1}+\gamma^R(W^R)^{-1}}, \end{cases} \tag{L.2}$$

Based on (L.1) into (L.2), I have

$$\frac{\theta^I_{cds}(\sigma^2_c+\sigma^2_{\epsilon_{cds}}) + \theta^I_{put}\sigma^2_c + \theta^I_c\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta^I_{cds}c_{cds} + \frac{\delta^I_{cds}c_{cds}}{\gamma^I(W^I)}}{(\theta^I_c+\theta^R_c)\sigma^2_c + \frac{\phi}{\gamma^I(W^I)}\delta_{cds}c_{cds} + \left(\frac{1}{\gamma^I(W^I)} - \frac{1}{\gamma^R(W^R)}\right)\delta_{cds}c_{cds}} = \Gamma(W^I), \tag{L.3}$$

where $\Gamma(W^I) = \frac{\gamma^I(W^I)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ Therefore,

$$
\begin{aligned}
\phi =& \frac{\frac{\Gamma(W^I)\left((\theta_c^I+\theta_c^R)\sigma_c^2+\left(\frac{1}{\gamma^I(W^I)}-\frac{1}{\gamma^R(W^R)}\right)\delta_{cds}c_{cds}\right)-\theta_{put}^I\sigma_c^2-\theta_c^I\sigma_c^2-\frac{\delta_{cds}^I c_{cds}}{\gamma^I(W^I)}}{\sigma_c^2+\sigma_{\epsilon_{cds}}^2}-\theta_{cds}^I}{\Gamma(W^R)\delta_{cds}^I c_{cds}}\gamma^I(W^I)(\sigma_c^2+\sigma_{cds}^2) \\
=& \frac{(\theta_{cds,slack}^I-\theta_{cds}^I)+\frac{\theta_{put,slack}^I-\theta_{put}^I}{\sigma_c^2+\sigma_{\epsilon_{cds}}^2}}{\Gamma(W^R)\delta_{cds}^I c_{cds}}\gamma^I(W^I)(\sigma_c^2+\sigma_{cds}^2)
\end{aligned}
$$

.

(L.4)

The last equality is due to $\theta_{cds,slack}^I = \frac{\Gamma(W^I)\left((\theta_c^I+\theta_c^R)\sigma_c^2+\left(\frac{1}{\gamma^I(W^I)}-\frac{1}{\gamma^R(W^R)}\right)\delta_{cds}^I c_{cds}\right)-(\theta_{put,slack}^I+\theta_c^I)\sigma_c^2-\frac{\delta_{cds}^I c_{cds}}{\gamma^I(W^I)}}{\sigma_c^2+\sigma_{cds}^2}$ from (K.1). If the constraint is binding, $(\theta_{cds,slack}^I-\theta_{cds}^I)+\frac{\theta_{put,slack}^I-\theta_{put}^I}{\sigma_c^2+\sigma_{\epsilon_{cds}}^2}$ has the same sign as δ_{cds}^I. In terms of the magnitude, the nominator $(\theta_{cds,slack}^I-\theta_{cds}^I)+\frac{\theta_{put,slack}^I-\theta_{put}^I}{\sigma_c^2+\sigma_{\epsilon_{cds}}^2}$ is decreasing with W^I, since $\theta_{cds}^I \to \theta_{cds,slack}$ and $\theta_{put}^I \to \theta_{put,slack}$ when W^I increases. Furthermore, $\frac{\gamma^I(W^I)}{\Gamma(W^R)} = \gamma^I(W^I)\gamma^R(W^R)(\frac{1}{\gamma^I(W^I)}+\frac{1}{\gamma^R(W^R)})$, which is decreasing with W^I. Therefore, $\frac{\partial\phi}{\partial W^I} < 0$. □

N Relation between arbitrage costs and market misalignment

Without loss of generality, suppose there is a supply shock ϵ_{cds} of the CDS in the economy. The baseline model outlined above can be seen as the unconditional case where the economy is stationary. In particular, the two agents' asset holdings add up to 0. With a supply shock, the market clearing condition becomes $\theta_{cds}^I+\theta_{cds}^R=\epsilon_{cds}$. Furthermore, ϵ_{cds} is assumed to slowly converge to 0, the stationary level. This could be justified as investor inattention (Duffie (2010)).

Under this scenario, the asset risk premiums become

$$
\begin{cases}
\mu_{put}-p_{put} = & \frac{(\theta_c^I+\theta_c^R+\epsilon_{cds})\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}+\frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{put}^I c_{put}+\frac{\gamma^I(W^I)^{-1}\phi\delta_{put}^I c_{put}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} \\
\mu_{cds}-p_{cds} = & \frac{(\theta_c^I+\theta_c^R+\epsilon_{cds})\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}+\frac{\gamma^I(W^I)^{-1}-\gamma^R(W^R)^{-1}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}\delta_{cds}^I c_{cds}+\frac{\gamma^I(W^I)^{-1}\phi\delta_{cds}^I c_{cds}}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}} \\
& +\frac{\epsilon_{cds}\sigma_{cds}^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}},
\end{cases}
\tag{M.1}
$$

Compared with (5.15), both the put option and CDS risk premium in (M.1) contains an extra term $\frac{\epsilon_{cds}\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$. This term represents the additional credit risk the agents need to take apart from their own background inventory risk. The CDS risk premium contains an additional term $\frac{\epsilon_{cds}\sigma_{cds}^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$. This component represents the additional CDS idiosyncratic risk the agents need to take. The idiosyncratic risk can be seen as the arbitrage cost. The sign of these two terms depends on the sign of the supply shock. If the supply shock is positive, the agents will demand a positive premium to absorb the supply. If the supply shock $|\epsilon_{cds}| \leq \left|\theta_c^I + \theta_c^R\right|$, the sign of the supply shock will not impact $\frac{(\theta_c^I+\theta_c^R+\epsilon_{cds})\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ in both the option and CDS risk premium. In other words, the sign of the ϵ_{cds} will not impact the dynamics of the option price. However, the sign of ϵ_{cds} will impact $\frac{\epsilon_{cds}\sigma_{cds}^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ in the CDS risk premium. When the idiosyncratic variance large, $\frac{\epsilon_{cds}\sigma_{cds}^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ will dominate the other terms in driving the dynamics of the CDS prices. Since ϵ_{cds} is random, p_{cds} and p_{put} are likely to be more misaligned when the idiosyncratic variance is high. This justifies the KP regression test in table **??** and **??**.

On the other hand, when the credit variance is large, the $\frac{\epsilon_{cds}\sigma_{cds}^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$ in the CDS premium will not impact the CDS price since it it dominated by $\frac{(\theta_c^I+\theta_c^R+\epsilon_{cds})\sigma_c^2}{\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1}}$. This implies that the two assets will be more aligned when the credit risk variance is larger than the idiosyncratic variance. This justifies why the Kendall correlations are high when the firm has worse credit conditions or when the macroeconomic conditions worsen, as shown in table D.1.

O Relation between arbitrage costs and asset predictability

Suppose the expected price of option and CDS is constant, based on (M.1), the cross-market deviation between the option and CDS prices is

$$p_{put} - p_{cds} = \left(\frac{\gamma^I (W^I)^{-1} - \gamma^R (W^R)^{-1}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}} + \frac{\gamma^I (W^I)^{-1} \phi}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}} \right) (\delta^I_{cds} c_{cds} - \delta^I_{put} c_{put}) + (\mu_{put} - \mu_{cds}) + \frac{\epsilon_{cds} \sigma^2_{cds}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}, \tag{N.1}$$

When the arbitrage cost, i.e. the idiosyncratic variance, is large, the dynamics of $p_{put} - p_{cds}$ is driven by $\frac{\epsilon_{cds}\sigma^2_{cds}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}$. Based on (M.1), the CDS price is also driven by $\frac{\epsilon_{cds}\sigma^2_{cds}}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}$. All else equal, the change of the CDS prices between two consecutive time is $-\frac{\Delta\widetilde{\epsilon}_{cds}(\sigma^2_c + \sigma^2_{cds})}{\gamma^I (W^I)^{-1} + \gamma^R (W^R)^{-1}}$. If ϵ_{cds} is mean reverting to 0 as discussed in appendix N, $\Delta\widetilde{\epsilon}_{cds} = -\kappa\epsilon_{cds} + \widetilde{\eta}$ where $\kappa > 0$. Therefore, $p_{put} - p_{cds}$ is positively related to $\Delta\widetilde{p}_{cds}$. Similarly, if there is a supply shock in the option market and the option arbitrage cost is large, $p_{cds} - p_{put}$ is positively related to $\Delta\widetilde{p}_{put}$, i.e. $p_{put} - p_{cds}$ is negatively related to $\Delta\widetilde{p}_{put}$.

P A general framework

This section provides a general framework which nests the framework in the main text. This general framework can generate different combinations of the signs of the intermediary derivative positions. In this framework, there are two identical residual investors A and B with risk aversion $\gamma^R(W^R)$. In the spirit of Gromb and Vayanos (2002), I assume that investor A specializes in trading the CDS while investor B specializes in trading the option. In other words, I assume an extra cost of trading option (CDS) for investor A (B) to be M.[39] If $M = 0$, this framework boils down to the scenario in the main text. Investors A and B are endowed with credit insurance inventory θ^A_c and θ^B_c, respectively. The FOCs

[39]Setting the costs the same between investor A and B is for simplicity reason.

of these two agents are:

$$\begin{cases} (\mu_{put} - p_{put})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^A_{cds}\sigma^2_c + \theta^A_{put}(\sigma^2_c + \sigma^2_{\epsilon_{put}}) + \theta^A_c\sigma^2_c + \frac{\delta^A_{put}(c_{put}+M)}{\gamma^R(W^R)} \\ (\mu_{cds} - p_{cds})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^A_{cds}(\sigma^2_c + \sigma^2_{\epsilon_{cds}}) + \theta^A_{put}\sigma^2_c + \theta^R_c\sigma^2_c + \frac{\delta^A_{cds}c_{cds}}{\gamma^R(W^R)} \\ (\mu_{put} - p_{put})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^B_{cds}\sigma^2_c + \theta^B_{put}(\sigma^2_c + \sigma^2_{\epsilon_{put}}) + \theta^B_c\sigma^2_c + \frac{\delta^B_{put}c_{put}}{\gamma^R(W^R)} \\ (\mu_{cds} - p_{cds})\left(\frac{1}{\gamma^R(W^R)}\right) = \theta^B_{cds}(\sigma^2_c + \sigma^2_{\epsilon_{cds}}) + \theta^B_{put}\sigma^2_c + \theta^R_c\sigma^2_c + \frac{\delta^B_{cds}(c_{cds}+M)}{\gamma^R(W^R)}. \end{cases} \tag{O.1}$$

The optimal portfolio holdings for A and B are:

$$\begin{cases} \theta^A_{cds} = \frac{1}{\gamma^R(W^R)}\frac{(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+\mu^{ex}_{cds}\sigma^2_{put}+\delta^A_{put}(M+c_{put})\sigma^2_c-\delta^A_{cds}c_{cds}(\sigma^2_c+\sigma^2_{put})-\gamma^R(W^R)\theta^A_c\sigma^2_{put}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}} \\ \theta^B_{cds} = \frac{1}{\gamma^R(W^R)}\frac{(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+\mu^{ex}_{cds}\sigma^2_{put}-\delta^B_{cds}(M+c_{cds})(\sigma^2_c+\sigma^2_{put})+\delta^B_{put}c_{put}\sigma^2_c-\gamma^R(W^R)\theta^B_c\sigma^2_{put}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}} \\ \theta^A_{put} = \frac{1}{\gamma^R(W^R)}\frac{-(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+\mu^{ex}_{put}\sigma^2_{cds}-\delta^A_{put}(M+c_{put})(\sigma^2_c+\sigma^2_{cds})+\delta^A_{cds}c_{cds}\sigma^2_c-\gamma^R(W^R)\theta^A_c\sigma^2_{cds}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}} \\ \theta^B_{put} = \frac{1}{\gamma^R(W^R)}\frac{-(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+\mu^{ex}_{cds}\sigma^2_{cds}+\delta^B_{cds}(M+c_{cds})\sigma^2_c-\delta^B_{put}c_{put}(\sigma^2_c+\sigma^2_{cds})-\gamma^R(W^R)\theta^B_c\sigma^2_{cds}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}}. \end{cases} \tag{O.2}$$

where $\mu^{ex}_i = \mu_i - p_i, i \in \{cds, put\}$. Next, I discuss a case where investor A has positive credit insurance inventory and investor B has negative credit insurance inventory. This case can give rise to different signs of the CDS and option positions of the intermediary. To see this, from Equation (O.2), if the residual investor inventory position is large enough, the sign of the CDS or option position is determined by the sign of the inventory position. Under this assumption, $\theta^A_{cds} < 0$, $\theta^B_{put} < 0$, $\theta^B_{cds} > 0$, and $\theta^B_{put} > 0$. To infer the position of the intermediary, I aggregate the positions of the two residual investors:

$$\begin{cases} \theta^A_{cds} + \theta^B_{cds} = \frac{1}{\gamma^R(W^R)}\frac{2(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+2\mu^{ex}_{cds}\sigma^2_{put}-M\sigma^2_c-M(\sigma^2_c+\sigma^2_{put})-\gamma^R(W^R)(\theta^A_c+\theta^B_c)\sigma^2_{put}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}} \\ \theta^A_{put} + \theta^B_{put} = \frac{1}{\gamma^R(W^R)}\frac{-2(\mu^{ex}_{cds}-\mu^{ex}_{put})\sigma^2_c+2\mu^{ex}_{put}\sigma^2_{cds}+M\sigma^2_c+M(\sigma^2_c+\sigma^2_{cds})-\gamma^R(W^R)(\theta^A_c+\theta^B_c)\sigma^2_{cds}}{(\sigma^2_c+\sigma^2_{put})\sigma^2_{cds}+\sigma^2_c\sigma^2_{put}}. \end{cases} \tag{O.3}$$

Note that the risk premiums for both assets are:

$$\begin{cases} \mu_{put} - p_{put} = \frac{(\theta^I_c+\theta^A_c+\theta^B_c)\sigma^2_c+\frac{\delta^I_{put}c_{put}}{\gamma^I(W^I)}+\frac{\delta^I_{put}\phi c_{put}}{\gamma^I(W^I)}-\frac{M}{\gamma^R(W^R)}}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} \\ \mu_{cds} - p_{cds} = \frac{(\theta^I_c+\theta^A_c+\theta^B_c)\sigma^2_c+\frac{\delta^I_{cds}c_{cds}}{\gamma^I(W^I)}+\frac{\delta^I_{cds}\phi c_{cds}}{\gamma^I(W^I)}+\frac{M}{\gamma^R(W^R)}}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}. \end{cases} \tag{O.4}$$

If θ_c^A and θ_c^B have similar magnitudes and θ_c^I is small, say $\theta_c^A = -\theta_c^B$ and $\theta_c^I = 0$ for simplicity,[40] then

$$\theta_{cds}^A + \theta_{cds}^B = \frac{1}{\gamma^R(W^R)} \frac{\frac{2\gamma^R(W^R)^{-1}M\sigma_c^2}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} - 2M\sigma_c^2 + \frac{2\gamma^R(W^R)^{-1}M\sigma_{put}^2}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} - M\sigma_{put}^2 + \frac{2\gamma^I(W^I)^{-1}\delta_{cds}^I c_{cds}(1+\phi)}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}\sigma_{put}^2}{(\sigma_c^2+\sigma_{put}^2)\sigma_{cds}^2 + \sigma_c^2\sigma_{put}^2}$$
$$= -\frac{1}{\gamma^R(W^R)} \frac{\frac{2(\gamma^I(W^I)^{-1}+\gamma^R(W^R)^{-1})M\sigma_c^2}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}M\sigma_{put}^2}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} - \frac{2\gamma^I(W^I)^{-1}\delta_{cds}^I c_{cds}(1+\phi)}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}\sigma_{put}^2}{(\sigma_c^2+\sigma_{put}^2)\sigma_{cds}^2 + \sigma_c^2\sigma_{put}^2} \tag{O.5}$$

When M is big enough, the first two terms in the numerator dominate the last term, resulting in a negative $\theta_{cds}^A + \theta_{cds}^B$. This implies that $\theta_{cds}^I > 0$. By the same logic, $\theta_{put}^I < 0$.

Based on the position signs of all the agents, the risk premium basis becomes

$$\mu_{put}^{ex} - \mu_{cds}^{ex} = \left(\frac{\gamma^I(W^I)^{-1}}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} + \frac{\gamma^I(W^I)^{-1}\phi}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}\right)(-c_{put} - c_{cds}) - \frac{\gamma^R(W^R)^{-1}2M}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}} \tag{O.6}$$

Similar to the proof in Appendix M, one can show $\frac{\partial \phi}{\partial W^I} < 0$ and $\frac{\gamma^I(W^I)^{-1}\phi}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}$ is decreasing with W^I. Proposition 2 still applies in this framework. Interestingly, the Equation (O.6) contains an addtional term $\frac{\gamma^R(W^R)^{-1}2M}{\gamma^I(W^I)^{-1}+2\gamma^R(W^R)^{-1}}$ compared to Equation (5.17). This term demonstrates the premium caused by the segmentation between the option and CDS markets. The higher the cost (M) of trading CDS (option) by investor B (A) is, the more segmented the markets are. In the extreme when the cost $M = \infty$, agent A (B) only trades in the CDS (option) market. An increase in the wealth of the intermediary reduces the segmentation premium, resulting in a smaller risk premium basis. This also offsets the illiquidity channel where an increase in the wealth of the intermediary increases the risk premium basis. It's easy to see that when $2M > c_{put} + c_{cds}$, the segmentation channel dominates and when $2M < c_{put} + c_{cds}$, the illiquidity channel dominates.

[40] This coincides with the scenario in Gromb and Vayanos (2002).

Chapter 6

Conclusion and Direction for Future Research

6.1 Conclusion

This thesis explores the relation between the credit and equity (derivatives) markets, in order to facilitate the understanding of corporate credit risk using various corporate contingent claims.

Since return is a common metric to be compared across different markets, the first essay provides a novel cash flow based CDS return metric to address the difficulty in the return computation in the CDS market. This metric is directly linked to the stochastic discount factor of the marginal investor, who also trades the other asset classes, provided market integration. Thus, our metric is useful for studying the relation between the CDS and equity (derivatives) markets.

The second essay provides innovative insights on the efficiency between the equity and credit markets. We show that the CDS market predicts the equity market when incorporating the CDS term structure. A frictionless structural framework replicates the empirical results. This finding raises the importance of credit markets compared to the equity market in understanding the corporate credit risk.

The third essay studies the integration between the CDS and option markets. We show that the credit spreads extracted from these two markets co-integrate in the long-run but exhibit short-lived price discrepancy. These price discrepancies are related to limits-to-arbitrage frictions. Thus, this essay sheds light on the condition under which one might have bias inference using the option implied credit spread in evaluating a firm's credit risk.

6.2 Directions for future research

The first essay proposes a novel yet simple-to-compute CDS return metric, which has no less than 99% of correlation with the *real* CDS return metric proposed by ISDA. However, the *real* CDS return metric is based on several assumptions, such as constant default intensity. There are some disagreements in practice about such assumptions. In principle, if the goal of the exercise is to obtain a return metric that has a very high correlation with the true CDS return instead of matching the level, our return metric is likely to provide useful application. Along the same line, there are other practical issues in applying the CDS return metric, such as regulatory capital requirement. In the present essay, we examine how full collateralization affects different metrics.[1] It will still be interesting to apply our metric in some trading strategies by accounting all practical issues. One exciting application would be applying our metric to the state-of-the-art high frequency trading strategy and studying its return dynamics.

The second essay shows that the CDS slope helps disentangle the underlying firm dynamics, leading to equity return predictability. Similarly, option skew is likely to identify different firm's dynamics. It is then interesting to explore how option skew predicts equity return. Relatedly, one can use the option to study how the presence of CDS contracts have a first impact on the level of risk for the underlying stocks, which is a more fundamental economic question to answer related to this essay. One can divide the sample

[1] We do not introduce collateral for metric 1 to 3 since the computation does not make sense with collateral.

based on firms with and without CDS contracts, and study whether the predictability between the option skew and equity returns changes. We leave this for future research.

In addition, the model in the second essay so far is a static trade-off model. However, firms infrequently adjust their leverage to the optimal level over time. A natural next step is to extend the Leland (1994) model into a more realistic Goldstein, Nengjiu, and Leland (2001) model to account for the leverage dynamics and study how such dynamics impact the credit spread level and slope, which might provide predictive power to equity return.

The third essay tests the integration between the option and CDS markets, and explores the drivers of such integration. Several channels deserve further attention. To begin with, it is important to identify the institutional traders in both markets. The short-term deviation between the two markets can be caused by the non-institution noise trading. By identifying the main traders, we can further justify whether the short-term deviation is caused by informed traders' preference on certain markets.

Furthermore, the present essay mainly explores how asset and market participant related frictions impact the price discrepancy. It is also interesting to study which market responds to the credit shock faster. Option market has lower trading cost but the CDS market mainly consists of institutional traders. It is equally plausible that either market responds to credit shock before the other and this question deserves further attention.

Finally, options are mainly traded in the short horizon and CDS is traded mostly at 5-year maturity. It is interesting to construct the basis between short term IS and long term CDS spread to explore the cross market term structure effect.

Bibliography

Goldstein, Robert, Ju Nengjiu, and Hayne Leland, 2001, An EBIT-based model of dynamic capital structure, *Journal of Business* 74, 483.

Leland, Hayne E, 1994, Corporate Debt Value, Bond Covenants, and Optimal Capital Structure, *The Journal of Finance* 49, 1213–1252.

Bibliography

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial Intermediaries and the Cross-Section of Asset Returns, *Journal of Finance* 69, 2557–2596.

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin, 2010, Financial Intermediation, Asset Prices and Macroeconomic Dynamics, *Federal Reserve Bank of New York Staff Reports* 422.

Allen, Franklin, 2001, Do financial institutions matter?, *Journal of Finance* 56, 1165–1175.

Andersen, Leif, Darrell Duffie, and Yang Song, 2019, Funding Value Adjustments, *Journal of Finance* 74, 145–192.

Armstrong, Christopher S., and Rahul Vashishtha, 2012, Executive stock options, differential risk-taking incentives, and firm value, *Journal of Financial Economics* 104, 70–88.

Asquith, Paul, Andrea S Au, Thomas Covert, and Parag A Pathak, 2013, The market for borrowing corporate bonds, *Journal of Financial Economics* 107, 155–182.

Augustin, Patrick, 2018, The term structure of CDS spreads and sovereign credit risk, *Journal of Monetary Economics* 96, 53–76.

Augustin, Patrick, and Yehuda Izhakian, 2020, Ambiguity, Volatility, and Credit Risk, *The Review of Financial Studies* 33, 1618–1672.

Augustin, Patrick, Feng Jiao, Sergei Sarkissian, and Michael J Schill, 2019, Cross-Listings and the Dynamics between Credit and Equity Returns, *Review of Financial Studies* 33, 112–154.

Augustin, Patrick, Fahad Saleh, and Haohua Xu, 2020, CDS Returns, *Journal of Economic Dynamics and Control* 118.

Augustin, Patrick, Marti G Subrahmanyam, Dragon Y Tang, and Sarah Q Wang, 2014, Credit Default Swaps: A Survey, *Foundations and Trends in Finance* 9, 1–196.

Barras, Laurent, and Aytek Malkhozov, 2016, Does variance risk have two prices? Evidence from the equity and option markets, *Journal of Financial Economics* 121, 79–92.

Berndt, Antje, and Iulian Obreja, 2010, Decomposing European CDS returns, *Review of Finance* 14, 189–233.

Binsbergen, Jules_Van, Michael Brandt, and Ralph Koijen, 2012, On the Timing and Pricing of Dividends, *American Economic Review* 102, 1596–1618.

Black, Fischer, and John C. Cox, 1976, Valuing Corporate Securities: Some Effects of Bond Indenture Provisions, *The Journal of Finance* 31, 351–367.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* 60, 2255–2281.

Bongaerts, Dion, Frank De Jong, and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* 66, 203–240.

Cao, Jie, and Bing Han, 2013, Cross section of option returns and idiosyncratic stock volatility, *Journal of Financial Economics* 108, 231–249.

Capponi, Agostino, W Allen Cheng, Stefano Giglio, and Richard Haynes, 2019, The Collateral Rule: An Empirical Analysis of the CDS Market, *Working Paper CFTC*.

Carey, Mark, René M. Stulz, Franklin Allen, and Douglas Gale, 2013, Systemic Risk and Regulation, (in *The Risks of Financial Institutions*,).

Carr, Peter, and Liuren Wu, 2009, Stock options and credit default swaps: A joint framework for valuation and estimation, *Journal of Financial Econometrics* 8, 409–449.

Carr, Peter, and Liuren Wu, 2011, A simple robust link between american puts and credit protection, *Review of Financial Studies* 24, 473–505.

Cetina, Jill, Mark Paddrik, and Sriram Rajan, 2018, Stressed to the core: Counterparty concentrations and systemic losses in CDS markets, *Journal of Financial Stability* 35, 38–52.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein, 2009, On the relation between the credit spread puzzle and the equity premium puzzle, *Review of Financial Studies* 22, 3367–3409.

Chernov, Mikhail, Alexander S. Gorbenko, and Igor Makarov, 2013, CDS Auctions, *Review of Financial Studies* 26, 768–805.

Choi, Jaewon, and Yongjun Kim, 2018, Anomalies and market (dis)integration, *Journal of Monetary Economics* 100, 16–34.

Choy, Siu Kai, and Jason Wei, 2020, Liquidity risk and expected option returns, *Journal of Banking & Finance* 111, Forthcoming.

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2018, Illiquidity premia in the equity options market, *Review of Financial Studies* 31, 811–851.

Cochrane, John H., 2009, Asset pricing, *Princeton University Press.*

Cochrane, John H., and Monika Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160.

Collin-Dufresne, Pierre, Robert S Goldstein, and J Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177–2207.

Collin-Dufresne, Pierre, Benjamin Junge, and Anders B Trolle, 2020, How integrated are credit and equity markets? Evidence from index options, .

Cremers, K. J.Martijn, Joost Driessen, and Pascal Maenhout, 2008, Explaining the level of credit spreads: Option-implied jump risk premia in a firm value model, *Review of Financial Studies* 21, 2209–2242.

Culp, Christopher L., Yoshio Nozawa, and Pietro Veronesi, 2018, Option-Based Credit Spreads, *American Economic Review* 108, 454–488.

Czech, Robert, 2020, Credit Default Swaps and Corporate Bond Trading, .

Das, Sanjiv R., and Rangarajan K. Sundaram, 2007, An integrated model for hybrid securities, *Management Science* 53, 1439–1451.

Du, Du, Redouane Elkamhi, and Jan Ericsson, 2019, Time-Varying Asset Volatility and the Credit Spread Puzzle, *Journal of Finance* 74, 1841–1885.

Du, Songzi, and Haoxiang Zhu, 2017, Are CDS Auctions Biased and Inefficient?, *Journal of Finance* 72, 2589–2628.

Du, Wenxin, Michael B Gordy, S Gadgil, and Clara Vega, 2016, Counterparty Risk and Counterparty Choice in the Credit Default Swap Market, *Working Paper Federal Reserve Board*.

Du, Wenxin, Benjamin Hebert, and Amy Wang, 2020, Are Intermediary Constraints Priced?, .

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018, Deviations from Covered Interest Rate Parity, *The Journal of Finance* 73, 915–957.

Duarte, Jefferson, Francis A Longstaff, and Fan Yu, 2007, Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller?, *Review of Financial Studies* 20, 769–811.

Duffie, Darrell, 2010, Asset Price Dynamics with Slow-Moving Capital, *Journal of Finance* 65, 1237–1267.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, Explaining the rate spread on corporate bonds, *Journal of Finance* 56, 247–277.

Engle, Robert F., Turan G. Bali, and Scott Murray, 2016, (*Empirical Asset Pricing - The Cross Section of Stock Returns*).

Engle, Robert F, and C W J Granger, 1987, Co-Integration and Error Correction : Representation, Estimation, and Testing, *Econometrica* 55, 251–276.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2009, The Determinants of Credit Default Swap Premia, *Journal of Financial and Quantitative Analysis* 44, 109–132.

Ericsson, Jan, and Joel Reneby, 2005, Estimating structural bond pricing models, *Journal of Business* 78, 707–735.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *The Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Feldhütter, Peter, and Stephen M. Schaefer, 2018, The myth of the credit spread puzzle, *Review of Financial Studies* 31, 2897–2942.

Ferreira, Miguel A., and Paul A. Laux, 2007, Corporate governance, idiosyncratic risk, and information flow, *Journal of Finance* 62, 951–989.

Finger, Christopher C., 2002, CreditGrades - Technical Document, *RiskMetrics Group, Inc.* pp. 1–52.

Fleckenstein, Matthias, and Francis A Longstaff, 2020, Renting Balance Sheet Space: Intermediary Balance Sheet Rental Costs and the Valuation of Derivatives, *The Review of Financial Studies* 9, Forthcoming.

Fleckenstein, Matthias, Francis A. Longstaff, and Hanno Lustig, 2017, Deflation risk, *Review of Financial Studies* 30, 2719–2760.

Forte, Santiago, and Lidija Lovreta, 2015, Time-Varying Credit Risk Discovery in the Stock and CDS Markets: Evidence from Quiet and Crisis Times, *European Financial Management* 21, 430–461.

Forte, Santiago, and Lidija Lovreta, 2019, Volatility discovery: Can the CDS market beat the equity options market?, *Finance Research Letters* 28, 107–111.

Friewald, Nils, Christian Wagner, and Josef Zechner, 2014, The Cross-Section of Credit Risk Premia and Equity Returns, *The Journal of Finance* 69, 2419–2469.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies* 22, 4259–4299.

Geske, Robert, 1979, The valuation of compound options, *Journal of Financial Economics* 7, 63–81.

Goldstein, Robert, Ju Nengjiu, and Hayne Leland, 2001, An EBIT-based model of dynamic capital structure, *Journal of Business* 74, 483.

Gourieroux, Christian, and Joann Jasiak, 2006, Autoregressive gamma processes, *Journal of Forecasting* 25, 129–152.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361–407.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage, *Annual Review of Financial Economics* 2, 251–275.

Gruber, Peter H., Claudio Tebaldi, and Fabio Trojani, 2020, The Price of the Smile and Variance Risk Premia, *Management Science*.

Gupta, Sudip, and Rangarajan K. Sundaram, 2015, Inventory effects, the winner's curse, and bid shading in credit default swap auction outcomes, *Journal of Derivatives* 23, 36–52.

Haddad, Valentin, and Tyler Muir, 2018, Do Intermediaries Matter for Aggregate Asset Prices?, *Nber Working Paper*.

Hakkio, Craig S., and Mark Rush, 1991, Cointegration: how short is the long run?, *Journal of International Money and Finance* 10, 571–581.

Han, Bing, Avanidhar Subrahmanyam, and Yi Zhou, 2017, The term structure of credit spreads, firm fundamentals, and expected stock returns, *Journal of Financial Economics* 124, 147–171.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

He, Zhiguo, Paymon Khorrami, and Zhaogang Song, 2019, Commonality in Credit Spread Changes: Dealer Inventory and Intermediary Distress, .

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–770.

Hilscher, Jens, Joshua M Pollet, and Mungo Wilson, 2015, Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets, *Journal of Financial and Quantitative Analysis* 50, 543–567.

Hitzemann, Steffen, Michael Hofmann, Marliese Uhrig-Homburg, and Christian Wagner, 2018, Margin Requirements and Equity Option Returns, .

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *The Journal of Finance* 6, 2143–2184.

Huang, Jing-Zhi, and Ming Huang, 2012, How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?, *Review of Asset Pricing Studies* 2, 153–202.

Hull, John, Izzy Nelken, and Alan White, 2005, Merton's model, credit risk and volatility skews, *The Journal of Credit Risk* 1, 3–27.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3–53.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65–91.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel, 2013, Momentum in corporate bond returns, *Review of Financial Studies* 26, 1649–1693.

Junge, Benjamin, and Anders B Trolle, 2015, Liquidity Risk in Credit Default Swap Markets, *Working Paper*.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Kelly, Bryan, Gerardo Manzo, and Diogo Palhares, 2019, Credit-Implied Volatility, *Working Paper*.

Kondor, Péter, and Dimitri Vayanos, 2019, Liquidity Risk and the Dynamics of Arbitrage Capital, *Journal of Finance* 74, 1139–1173.

Kuehn, Lars-Alexander, David Schreindorfer, and Florian Schulz, 2017, Credit and Option Risk Premia, *Working Paper*.

Kyle, Albert S., and Wei Xiong, 2001, Contagion as a wealth effect, *Journal of Finance* 56, 1401–1440.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *The Journal of Finance* 49, 1541–1578.

Lando, David, 2004, *Credit Risk Modeling*. (Princeton University Press).

Lee, Jongsub, Andy Naranjo, and Guner Velioglu, 2018, When do CDS spreads lead? Rating events, private entities, and firm-specific information flows, *Journal of Financial Economics* 130, 556–578.

Leland, Hayne E, 1994, Corporate Debt Value, Bond Covenants, and Optimal Capital Structure, *The Journal of Finance* 49, 1213–1252.

Leland, Hayne E., 1998, Agency costs, risk management, and capital structure, *Journal of Finance* 53, 1213–1243.

Lewis, Ryan, 2019, Same Firm , Different Betas, .

Loon, Yee Cheng, and Zhaodong Ken Zhong, 2014, The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market, *Journal of Financial Economics* 112, 91–115.

Merton, Robert, 1976, Option Pricing When Underlying Stock Returns are Discontinuous, *Jounral of Financial Economics* 3, 125–144.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *The Journal of Finance* 29, 449–470.

Mitchell, Mark, and Todd Pulvino, 2012, Arbitrage crashes and the speed of capital, *Journal of Financial Economics* 104, 469–490.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Nashikkar, Amrut, Marti G Subrahmanyam, and Sriketan Mahanti, 2011, Liquidity and Arbitrage in the Market for Credit Risk, *Journal of Financial and Quantitative Analysis* 46, 627–656.

Ni, Sophie X., and Jun Pan, 2020, Trading Puts and CDS on Stocks with Short Sale Ban, *Workig Paper*.

Norden, Lars, and Martin Weber, 2009, The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis, *European Financial Management* 15, 529–562.

Palhares, D, 2014, Cash-flow maturity and risk premia in cds markets, *Working Paper*.

Sandulescu, Mirela, 2020, How Integrated Are Corporate Bond and Stock Markets?, .

Schaefer, Stephen M, and Ilya A Strebulaev, 2008, Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* 90, 1–19.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52, 35–55.

Siriwardane, Emil, 2019, Limited Investment Capital and Credit Spreads, *Journal of Finance* 74, 2303–2347.

Toft, Klaus Bjerre, and Brian Prucyk, 1997, Options on Leveraged Equity: Theory and Empirical Tests, *The Journal of Finance* 52, 1151.

Vassalou, Maria, and Yuhang Xing, 2004, Default Risk in Equity Returns, *Journal of Finance* 59, 831–868.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Zviadadze, Irina, 2017, Term-Structure of Consumption Risk Premia in the Cross-Section of Currency Returns, *The Journal of Finance* 72, 1529–1566.