THREE ESSAYS ON THE EFFECTS OF CREDIT DEFAULT SWAPS

by

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Abstract

This thesis investigates the effect of credit default swaps on firm behaviour. A credit default swap (CDS) is an insurance contract under which buyers make periodic payments over the contract's life to insure against credit events related to the underlying entities.[1] As an efficient tool for lenders or bond investors to hedge the credit exposures associated with their investments in a firm while maintaining their control rights, the market for CDSs has developed quickly over the last two decades. The impact of this new but fast-growing credit derivative market has attracted considerable attention from financial researchers.

This thesis contains five chapters. Chapter 1 presents a brief introduction to CDSs and the research questions. Chapter 2 discusses the origins of CDS, the definition of CDS, the initiation of CDS through the over-the-counter market, the effect of CDS on creditor-debtor relationship and data sources for CDS inception.

Chapter 3 investigates how initiating a credit default swap (CDS) affects firm risk. Using the firm value volatility as a measure of firm risk, I document that firm risk decreases following the commencement of CDS trading. The CDS effect on firm risk is less pronounced for firms with more financial constraints and firms with a greater discrepancy between their bond and their CDS market.

[1] Credit events include bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring (ISDA, 2003).

My findings reveal a significant impact of financial innovation on firms' behavior, which supports the "empty creditor" hypothesis. I also document that reducing expenditure levels on hiring and investment is one channel through which this negative impact occurs.

Chapter 4 empirically investigates the impact of credit default swap (CDS) inception on corporate debt maturity profiles. I show a positive relationship between CDS inception and debt maturity dispersion. This positive relationship is stronger when the credit market condition is tighter, and more pronounced for less financially constrained or higher-quality firms. My results are robust to the endogeneity of CDS trading. The findings reveal a significant effect of financial innovation on the focal firm's debt structure.

Chapter 5 examines the impact of credit default swap (CDS) inception on debt specialization. I find that firms with CDS traded on their debts tend to increase their debt specification levels. CDS inception reduces the likelihood of a strategic default, so firms specialize in fewer debt types to decrease the probability of inefficient liquidation by creditors. The positive relationship between the CDS inception and debt specialization is more pronounced for firms facing higher expected bankruptcy costs. My results are robust to the endogeneity of CDS trading and the alternative measure of debt specialization.

Chapter 6 presents a summary of the findings in Chapter 3, Chapter 4, and Chapter 5 and concludes the thesis.

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Chapter 1

Introduction

A credit default swap (CDS) is an insurance contract under which buyers make periodic payments over the contract's life to insure against credit events related to the underlying entities.[1] As an efficient tool for lenders or bond investors to hedge the credit exposures associated with their investments in a firm while maintaining their control rights, the market for CDSs has developed quickly over the last two decades.[2] The impact of this new but fast-growing credit derivative market has attracted considerable attention from financial researchers. For example, Saretto and Tookes (2013), Subrahmanyam, Tang, and Wang (2014, 2017), Martin and Roychowdhury (2015), and Danis and Gamba (2018), among others, provide evidence showing how credit default swaps affect firm behavior. Understanding the effect of credit default swaps on firm behavior can help us not only to address the critical question of whether financial innovation benefits society (for an extensive review of this topic, see Zingales, 2015), but also to improve portfolio decision making.

[1] Credit events include bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring (ISDA, 2003).

[2] In March 2019, the CDS market's notional amount exceeded 10 trillion US dollars.(http://swapsinfo.org/swaps-notional-outstanding/).

In this thesis, I contribute to the literature on the CDS effect on firm behaviour by trying to provide a better understanding of how CDS inception affects firm risk and other aspects of debt structure.

In Chapter 2, I investigate how initiating a credit default swap (CDS) affects firm risk. Using firm value volatility as a measure of firm risk, I document that firm risk decreases following the commencement of CDS trading. The CDS effect on firm risk is less pronounced for firms with more financial constraints and firms with a greater discrepancy between their bond and their CDS market. My findings reveal a significant impact of financial innovation on firms' behavior, which supports the "empty creditor" hypothesis. I also document that reducing expenditure levels on hiring and investment is one channel that yields this negative impact.

In Chapter 3, I study the impact of credit default swap (CDS) inception on corporate debt maturity profiles. I show a positive relationship between CDS inception and debt maturity dispersion. This positive relationship is stronger when the credit market condition is tighter, and more pronounced for less financially constrained or higher-quality firms. My results are robust to the endogeneity of CDS trading. The findings reveal a significant effect of financial innovation on the focal firm's debt structure.

In Chapter 4, I examine the impact of credit default swap (CDS) inception on debt specialization. I find that firms with CDSs traded on their debts tend to increase their debt specification levels. CDS inception reduces the likelihood of a strategic default, so firms specialize in fewer debt types to decrease the probability of inefficient liquidation by creditors. The positive relationship between CDS inception and debt specialization is more pronounced for firms facing higher expected bankruptcy costs. My results are robust to the endogeneity of CDS trading and other alternative measures of debt specialization.

Chapter 2

Institutional background and data source for credit default swap

2.1 Institutional background

2.1.1 The origins of CDS

Credit default swaps were invented by JP Morgan, an American multinational investment bank and financial services holding company, in the 1990s to provide the buyer with protection from default risk (Tett, 2009). According to Tett (2009), the opportunity for JP Morgan to initiate a credit derivative happened in 1993 when Exxon, an American multinational oil and gas corporation, obtained a loan with a value of $4.8 billion from JP Morgan and Barclays to cover the $5 billion fine as a result of the Exxon Valdez spill. This loan put JP Morgan into trouble in terms of capital requirements and internal credit limits. However, JP Morgan is not willing to sell the loan to a third party because it might break the commitment to Exxon which was the bank's long-standing customer. In

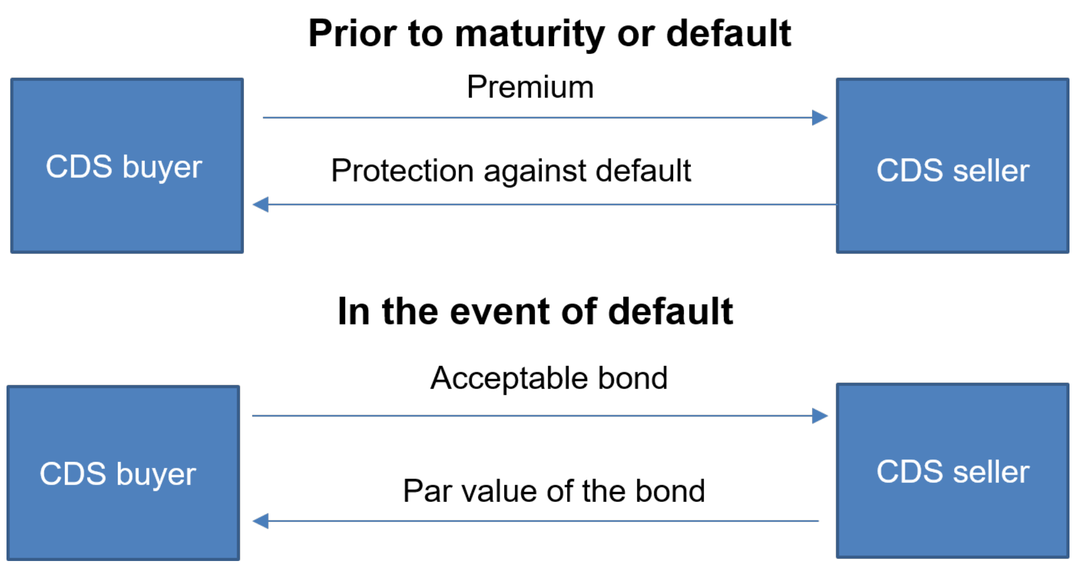
1994, JP Morgan negotiated with the European Bank of Reconstruction and Development (EBRD) to share the credit risk induced by the Exxon loan without selling the loan. In particular, JP Morgan agreed to pay an annual fee for EBRD, in exchange, receive the insurance from EBRD against credit events related to the Exxon loan. JP Morgan would expect to receive compensation for the loss from EBRD in Exxon's event of default. If Exxon did not default, EBRD would earn a good profit. EBRD accepted the deal since it was interested in expanding its credit portfolio to firms with high credit ratings like Exxon, and making investments with high returns. EBRD also assessed that the default probability of Exxon was low and the fee received from JP Morgan was high enough to compensate for the risk. Consequently, Exxon did not default, and the Exxon deal was considered as the first credit default swap.

2.1.2 The definition of CDS

The credit default swap (CDS) is the fundament of the credit derivatives market (JPMorgan, 2006). A credit default swap (CDS) is an insurance contract under which buyers make periodic payments (premium) over the contract's life to insure against credit events related to the underlying entities. Credit events include bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring (ISDA, 2003).

In Figure 2.1, I suppose that the CDS buyer hold bonds in the reference company and/or are concerned about the default risk of that company. The CDS buyer could insure her credit risk associated with the bonds by entering a credit default swap contract. It means that the CDS buyer needs to paid a premium (periodic fee) for the CDS seller during the specified duration of the contract. This fee is calculated by multiplying the notion amount of the CDS contract and the CDS spread, which is the market price of the CDS. CDS spreads are quoted in basis points, and are

Figure 2.1: Credit Default Swaps



measured based on the reference entity's credit risk (JPMorgan, 2006). In the event of default, the CDS buyer receives compensation (typically the face value of the bond) and the CDS seller obtain the defaulted bond. If there is no physical bond to deliver, the CDS seller will receive the bond's market value in cash.

2.1.3 How CDS is initiated through over-the-counter market

Credit default swap contracts are traded over the counter, "a market where traders in different locations communicate and make deals by phone and through electronic messages." (Stulz, 2010). In this section, I follow Stulz (2010) to describe how a CDS is initiated and traded through the over-the-counter market.

Suppose that a bondholder K is concerned about the default risk of the bonds issued by company

Z. The bondholder K then would like to buy a CDS on company Z. The bondholder K contact dealers, for example, JP Morgan, Goldman Sachs, Deutsche Bank to get quotes. The bondholder K finds that Deutsche Bank offers the best quote and agree with the deal from this bank. The bondholder is expected to make a quarterly payment with the annual rate of 120 basis points based on the notional amount of $8 million. Prior to 2009, the CDS spread is determined so that the present value of the expected spread payments paid by the bondholder B (Fee Leg) equals the present value of the payment paid by Deutsche Bank on the default event of company Z (Contingent Leg) (JPMorgan, 2006). In the effort to reduce the operational risks regarding CDS trading, the market standardized CDS contracts. Since March 2009, the market moved to use the fixed payment for North American CDS trades (100 basis points or 500 basis points) with an upfront payment from the buyer to the seller, or vice versa. Given the fixed CDS spread, the upfront payment makes the expected present value of Fee Leg equal to the expected present value of Contingent Leg (Boyarchenko, Gupta, Steele, and Yen, 2018). After bondholder K buy the CDS, Goldman Sachs has to bear credit risk exposure to company Z. Goldman Sachs need to find ways to hedge this risk exposure. It could buy other CDS from other dealers and aim to hedge for its whole CDS portfolio rather than each individual CDS.

Bondholder K have several ways to exit its position of CDS (Stulz, 2010). First, K could call up Goldman Sachs and negotiate terms for termination. The termination may incur payments subject to the change in the market since the CDS contract was made. Second, bondholder K could offset her original contract by entering into a contract to sell protection. Third, bondholder K negotiate with another dealer to paid appropriate payments in exchange for transferring the obligation regarding the CDS contract with Goldman Sachs. This agreement needs to be approved by Goldman Sachs.

2.1.4 The effect CDS on creditor-debtor relationship

The literature provides empirical and theoretical evidence for the effect of CDS on debtor-creditor relationship. In particular, CDS could affect monitoring incentives, risk sharing, creditors' bargaining power and credit supply.

First, much research documents the effect of CDS on the creditors' monitoring incentives risk sharing. Morrison (2005) argue that the neglect of using bank debt as a monitoring device for low-quality credit incurs the challenge for the risk-sharing rationale of credit derivatives. The authors provide the theoretical evidence that the inception of credit derivatives reduce the advantages of bank monitoring for the bondholders. A reduction in welfare could occur when the bank do not have an incentive to monitor. Parlour and Winton (2013) find the evidence of monitoring is excessive for riskier credits and it is insufficient for safer credits due to credit risk transfer through loan sales or CDSs. This effect is stronger when banks' cost of equity capital increases. CDSs are more likely to be used as a means of risk transfer for safer credits while loan sales are more likely to be used for riskier credits. In addition, they argue that CDS could support better monitoring for the safer credits while remain the efficiency of risk-sharing. Stulz (2010) argues that CDSs are not the main reason for the credit crisis, much of the crisis is due to the declines in the housing market.

Second, CDS could incur an empty creditor problem."Empty creditor" means that the debt holder has no desire to preserve a company to which she provides funds. Bolton and Oehmke (2011) show that, in theory, this problem arises when creditors have over-insured their credit risk by buying CDSs but still hold the control rights of the firms. With the credit insurance obtained through the CDS market, creditors have more bargaining power over borrowers in debt renegotiations. The author also discusses several cases as anecdotal evidence that CDS are more likely to increase bargaining power for the creditors. For example, Mirant Corporation, an energy company based in Atlanta, had to file for chapter 11 because it was not able to negotiate with its creditors, particularly Citigroup. It was suspected that this bank rejected Mirant's reorganization plan because the former had bought credit default swaps against the latter. A committee that was formed by the bankruptcy judge indicated that "there was a reasonable chance that the reorganization value would be high enough to give equity holders a positive claim after paying off all creditors." An increase in creditors' bargaining power could lead to an increase in the threat that the borrowing firms will be unable to refinance their debt. Consistent with this idea, Clark, Donato, Francis, and Shohfi (2020) show that CDS inception decreases the probability of "amendments, restatements, and rollovers to existing lenders of bank loans".

Finally, the CDS market could positively affect the credit supply. Hirtle (2009) show limited evidence for an increase in the credit supply when the bank use credit derivatives to receive incremental credit protection. In particular, banks that obtain credit protection via credit derivatives are more likely to issue new loans to large term borrowers. Saretto and Tookes (2013) document that CDSs could also affect firms' financing decisions through the credit supply channel because the CDS market increases the ability of capital suppliers to hedge their risks, thus reducing the friction on the supply side. They argue that creditors like banks and insurance companies have the opportunity to reduce the regulatory capital requirements by buying CDS to hedge their credit risks. The reduction in such requirements could increase the creditors' lending capability. As a result, the supply of credit to firms could rise if market segmentation exists between creditors who would like to lend more and CDS providers who are willing to hold credit risk. They also document that CDSs allows banks to provide debt while mitigating the portfolio risk for the purpose of maintaining client relationships. Moreover, the existence of the CDS market could make holding corporate debt (credit risk) more attractive to creditors (bond investors) since such a market provides creditors with a liquid resale option.

2.2 Data sources for CDS inception

In literature, the popular data sources used to identify the CDS initiation consist of the Markit CDS database, Credit Market Analytics (CMA), the GFI Group and CreditTrade. Markit CDS data is available from 2001, CMA data is available from 2001, GFI data is available from 2002 and CreditTrade data is from June 1997 to March 2006. Among these sources of data, only CreditTrade data allows tracing the inception of CDS back to 1997 when the broad CDS market commenced Subrahmanyam et al. (2014). However, since CreditTrade data is a proprietary database, access to this data is limited. Markit CDS data has been widely used in the literature (see, for example, Ashcraft and Santos (2009), Jorion and Zhang (2009), Zhang, Zhou, and Zhu (2009), Martin and Roychowdhury (2015), and Oehmke and Zawadowski (2017)) . The disadvantage of this source of data is that it is only available from 2001. This might cause uncertainty regarding the inception of a firm's CDS trading.

I follow the literature to use data from Markit to identify the inception of CDS trading, defined as the date on which the focal firm's CDS spread quote first appears in Markit. In line with the figures reported by Subrahmanyam et al. (2017), CDS inception occurs more frequently before 2005. Whereas 88% of total CDS inceptions happened before 2005, only 12% did so after 2005. There is a small number of CDS inceptions (about 2%) after 2007 in our sample. My sample ends in 2012 to allow the observation window of five years after the majority of CDS inceptions occur to investigate its potential effects. In addition, I follow Ashcraft and Santos (2009) to remove firms that begin trading in the first month of 2001, when the Markit data commence, to mitigate the problem of the uncertainty about the CDS inception of these firms. Hence, my sample of CDS inception covers the period between 2001 and 2012.

Chapter 3

Credit Default Swaps and Firm Risk

3.1 Introduction

Fast-growing financial innovations, particularly credit default swaps, have obtained significant attention during the recent financial crisis. A credit default swap (CDS) is an insurance contract under which buyers make periodic payments (a coupon, spread, or premium) over the contract's life to ensure against credit events related to the underlying entities.[1] As an efficient tool for lenders or bond investors to hedge the credit exposures associated with their investments in the firm while maintaining their control rights, credit default swaps have a substantial effect on the credit market and firm behavior. For example, Saretto and Tookes (2013), Subrahmanyam et al. (2014, 2017), Martin and Roychowdhury (2015), and Danis and Gamba (2018), among others, provide evidence on how credit default swaps affect firm behavior. Not only does understanding the effect of credit default swaps on firm behavior help us address the critical question of whether financial innovation bene-

[1]Credit events include bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring (ISDA, 2003).

fits society (for an extensive review of this topic, see Zingales, 2015), it also can improve portfolio decision making. While there exists extensive literature investigating the impact of CDS inception on various firm behavior,[2] how these behaviors overall affect firm risk remains an under-explored question.

There are two alternatives effects through which CDS inceptions could affect the risks taken by firms. By introducing an empty creditor, CDS inception increases the negotiation power of creditors and imposes a tougher condition to the firms, which will make them become more conservative to reduce the risk. On the other hand, by introducing hedge against default risk, CDS reduces the monitoring incentive of creditors and thus makes room for firms to engage in more risky projects that benefit the equity investors.[3] These two effects generate opposite predictions on firm risk and which effect dominates is an empirical question.

My study assesses the effect of CDS inception on firm risk. Firm risk provides an overall assessment for the firm's risk-taking behaviors because it reveals the net effect of all corporate risk-taking activities (Low, 2009). Low (2009) argues that using cash flow volatility to measure firm risk is problematic, and Choi and Richardson (2016) demonstrate that a firm's value volatility is fundamentally different from its equity volatility.[4] Furthermore, firm value volatility plays a vital role in the valuation of capital structure and in the risk–return trade-offs associated with the independence of firm leverage (Choi and Richardson, 2016). A firm's level of risk also bears crucial implications for its hiring and investment behavior and other economic activities. For instance,

[2] Saretto and Tookes (2013) find that firms involved with CDS trading have higher leverage ratios and longer debt maturities. Subrahmanyam et al. (2014) show that a firm is more likely to declare bankruptcy after engaging in CDS trading. Martin and Roychowdhury (2015) document a decrease in borrowing firms' reporting conservatism (i.e., their asymmetry in recognition of losses versus gains) after the initiation of CDS trading. Subrahmanyam et al. (2017) show that firms increase their cash holdings after CDS trading on their debt has commenced.

[3] I discuss in more detail the empty creditor effect and the monitoring effect in Section 3.2.

[4] In addition, Doshi, Jacobs, Kumar, and Rabinovitch (2019) identify significant differences in the behavior of unlevered asset returns versus levered stock returns.

Bloom (2009) shows that (a) firms prefer to delay both hiring and investment during periods of higher uncertainty and (b) increased firm risk due to uncertainty shocks leads to an overshoot in output, employment, and productivity. I follow the studies in using firm value volatility—rather than volatility in the firm's equity or cash flow—to measure firm risk.[5]

I use the structural model of Merton (1974) to estimate firm value volatility. Since the measure that Merton uses incorporates information on both equity and debt, it differs from equity volatility in being better able to capture a firm's overall level of risk. I follow Vassalou and Xing (2004) and Bharath and Shumway (2008) in employing an iterative procedure to estimate firm value volatility. To address the issue of endogeneity, I use both propensity score matching and an instrumental variable approach.

I document several interesting findings. First, I find that firm value volatility decreases after the introduction of CDS trading. When my regressions feature CDS firms matched up against their closest one (i.e., the most similar) non-CDS counterparts, firm value volatility declines by about 5.20% following CDS inception; similar results are obtained when I use other matched samples. This negative effect amounts to some 12.50% when assessed via an instrumental variable approach. These results suggest that firms become more conservative about their risk-taking behavior once CDS trading begins, which is consistent with Bolton and Oehmke's (2011) empty creditor hypothesis.

Second, I find that the effects of CDS inception depend on the focal firm's characteristics. I use both the index developed by Whited and Wu (2006)—hereafter the WW index—and the dividend payer indicator as proxies for financial constraints to show that the CDS effect on firm value volatility is less pronounced for firms that are more financially constrained. The finding suggests

[5] In Appendix 2.2, I show that the relationship between firm value volatility and equity volatility is uncertain.

that the monitoring effect is stronger for firms that face stricter financing conditions.

Using the absolute value of a firm's CDS–bond basis to measure the price discrepancy between the corporate bond and the CDS market, I establish that the effect of CDS trading is weaker on firms for which that price discrepancy is greater. Since a more pronounced price discrepancy is indicative of more arbitrage limitations and also of less integration between the CDS and the corporate bond market, this finding provides empirical evidence that market frictions influence the extent to which financial innovation affects society, which supports the notion that policymakers should be willing to limit such frictions as needed to improve social welfare.

Furthermore, I provide evidence that reducing expenditure levels on hiring and investment is one channel through which the inception of CDS trading affects firm behavior in ways that reduce firm value volatility. Particularly, I find that the inception of CDS trading leads to a reduction in focal firms' employment growth and investment rates. On the other hand, I do not find significant change of focal firms' operating leverage after their CDS inceptions. The results suggest that the decrease in firm value volatility after CDS inception could be partially attributed to the reduced expenditure level, but not the reduced expenditure leverage.

To check the robustness of my results, I run several tests: using the alternative asset volatility measure of Choi and Richardson (2016), using a different propensity score matched sample, using data that exclude financial firms, and using data collected at a different frequency. In each case, I find that firm value volatility declines after the inception of CDS trading. Thus the negative effect of credit default swaps on firm value volatility is robust not only to the choice of data but also to the measure adopted to analyze such volatility.

Subrahmanyam et al. (2014), Narayanan and Uzmanoglu (2018b), Danis (2017), and Colonnello, Efing, and Zucchi (2019) investigate the impact of CDS inception on default risk, yet my paper differs in several respects. First, I instead examine how CDS inception affects firm value volatility. Bankruptcy risk and firm value volatility are, of course, important (and related) dimensions of firm risk that are prominently in the literature. Second, the structural model of Merton (1974) posits that default risk depends not only on firm value volatility but also on firm leverage. Shumway (2001) and Correia, Kang, and Richardson (2018) document that firm risk has a significant effect on the likelihood of bankruptcy; in addition, those papers find a positive relationship between leverage and the probability of bankruptcy. Saretto and Tookes (2013) and Subrahmanyam et al. (2017) also provide evidence that the inception of CDS trading increases leverage—a finding that clearly distinguishes firm value volatility from default risk. A third difference is this: the results reported here suggest that firms *reduce* their risk level after the inception of their CDS trading, whereas Subrahmanyam et al. (2014) document an *increase* in default risk under the same circumstances. Since the CDS inception reduces the firm value volatility but increases firm leverage, it is possible to observe both decline of firm value volatility and increase of default risk if the impact on firm leverage is greater than that on firm value volatility. My results thus do not challenge but supplement the findings of Subrahmanyam et al. (2014).

This paper makes several contributions to the literature. First, my study significantly extends the literature on how CDS trading affects firm behaviour by providing the empirical evidence on how overall it affects risk at the firm level. The literature has documented mixed findings about how the CDS inception affects various decisions that influence firm risk. Some researches show that firms undertake more conservative or risk averse activities after their CDS inceptions. For example, Subrahmanyam et al. (2017) show that firms increase their cash holdings following CDS inception. Kim, Shroff, Vyas, and Wittenberg-Moerman (2018) establish that managers voluntarily disclose more information after CDS inception. Others, on the other hand, document that firms engage in more risky activities. For example, Saretto and Tookes (2013) find that firms involved with CDS trading have higher leverage ratios. Martin and Roychowdhury (2015) find a decrease in borrowing firms' reporting conservatism after the initiation of CDS trading. Chang, Chen, Wang, Zhang, and Zhang (2019) document that the start of CDS trading encourages the firm to take risks, which results in increased innovation output. It is not clear how overall these different activities affect firm risk. My study sheds light on this important question. My research also complements recent studies including Danis and Gamba (2018) and Narayanan and Uzmanoglu (2018a) that investigate how overall CDS inception affects values at the firm level.

Second, my study helps explain variation in levels of firm risk and identifies a channel through which CDS inception affects firm behavior. Previous studies have documented several determinants of firm volatility: firm leverage (Black, 1976), research and development (R&D) expenses (Comin and Philippon, 2005; Comin and Mulani, 2009), firm age (Davis, Haltiwanger, Jarmin, and Miranda, 2006), and firm size (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2018). I offer a novel perspective to explain firm risk—namely, by identifying a key link between the inception of CDS trading and firm value volatility. Also adding to the literature, I find that firms significantly reduce their expenditure levels on hiring and investment after their CDS inceptions. These findings extend the studies of Arellano, Bai, and Kehoe (2019), Baker, Bloom, and Davis (2016), Narayanan and Uzmanoglu (2018a), and Colonnello et al. (2019).

Third, I contribute to the ongoing debate over the impact of financial innovation, especially the effect of credit default swaps on social welfare. I find that CDS trading reduces firm risk as measured by firm value volatility, providing evidence of the social effects of such innovation. This finding supports the view that finance affects society (see e.g. Myers and Majluf, 1984; Guiso, Sapienza, and Zingales, 2004; Levine, 2004; Zingales, 2015). I investigate the effect of financial market information on firms' decisions and thus also contribute to the literature that addresses the link between asset pricing and corporate finance.

The rest of this paper proceeds as follows. In Section 3.2, I review the relevant literature and develop my hypotheses. Section 3.3 details my empirical methodology. Section 3.4 describes the data, and Section 3.5 presents my empirical results. In Section 3.6, I conduct several robustness tests. I conclude in Section 3.7 with a summary of my findings and a suggestion for future research.

3.2 Literature review and hypotheses development

3.2.1 Empty creditor effect versus monitoring effect

The literature has documented two primary mechanisms by which CDS inception affects firm behavior: the empty creditor effect and the monitoring effect.

An *empty creditor* is a debt holder that has no interest in preserving the company to which it provides funds. This problem arises when a creditor has overinsured its credit risk by purchasing credit default swaps yet still holds the firm's control rights. With credit insurance obtained through the CDS market, creditors have more bargaining power than do borrowers in any renegotiation that follows a "strategic" default—as when the borrower benefits more from defaulting than not (Bolton and Oehmke, 2011). In order to avoid a renegotiation in which the lenders have relatively more bargaining power, the borrowers tend to make more prudent decisions on investment and other corporate finance activities. For example, Subrahmanyam et al. (2017) demonstrate empirically that firms increase their cash holdings once CDS trading on their debt commences, which accords with Bolton and Oehmke's hypothesis. In other words, the empty creditor effect could drive the relationship between CDS inception and firm value volatility. This empty creditor effect results in reduced volatility in the focal firm's value following the inception of CDS trading on its debt.

At the same time, the CDS market gives banks and bond investors an efficient way to hedge the credit risks associated with their investment in the borrowing firms. This credit risk transfer could reduce a lender's monitoring incentive; the implication is that the credit risk transfer resulting from CDS purchases results in borrowing firms being monitored to a lesser extent—an outcome that Morrison (2005) documents. In such cases, borrowing firms are more tolerant of risk and so tend to engage in higher-risk projects. In line with this hypothesis, Martin and Roychowdhury (2015) find a decrease in borrowing firms' reporting conservatism after the initiation of CDS trading. Chang et al. (2019) document that the start of CDS trading encourages the firm to take risks, which results in increased innovation output. A firm's risk-shifting behavior could lead to an increase in the volatility of its value following the commencement of CDS trading. I refer to this dynamic as the *monitoring effect* of credit default swaps on firm value volatility.

My aim is to determine which effect dominates: the empty creditor effect or the monitoring effect. Hence I test the following hypothesis.

Hypothesis 1a. *If the empty creditor effect dominates the monitoring effect, then firm value volatility will* decrease *after the inception of CDS trading.*

Hypothesis 1b. *If the monitoring effect dominates the empty creditor effect, then firm value volatility will* increase *after the inception of CDS trading.*

3.2.2 CDS inception and financial constraint

Eisdorfer (2008) finds that risk-shifting incentives are stronger for more financially constrained firms. It follows that the risk-shifting incentives due to reduced creditor monitoring may be stronger for firms that are more financially distressed. Parlour and Winton (2013) show that credit risk transfer through loan sales (CDS purchases) tends to increase (decrease) the incentive to monitor riskier (safer) borrowers. As a result, the use of CDS for credit risk transfer engenders a reduced level of monitoring and the monitoring effect of CDS inception on firm value volatility is stronger for firms that are more financially constrained. If this is the case, then the negative association between CDS inception and firm value volatility is weaker for firms that are more financially constrained. These considerations lead to my second hypothesis, as follows.

Hypothesis 2. *The negative effect of CDS inception on firm value volatility is less pronounced for more financially constrained firms.*

3.2.3 CDS inception and the CDS–bond pricing discrepancy

The absolute value of the CDS–bond basis, or the absolute difference between the CDS spread and yield spreads of a par bond with the same maturity as the CDS, measures the price discrepancy between CDS and its reference corporate bond. Shleifer and Vishny (1997), Pontiff (2006), and Mitchell and Pulvino (2012) show that this price discrepancy could indicate the existence of limits to arbitrage, which might occur when a security's transaction costs and risk are both high. Thus a higher absolute value of the CDS–bond basis could indicate a higher transaction cost and risk of CDS trading. Moreover, a greater price discrepancy suggests that a firm's CDS market and corporate bond market are less integrated, which means that the CDS spread is less informative. These conditions may reduce a creditor's incentives to use credit default swaps as a tool for transferring credit risk, in which case the CDS effect would be weaker. So as a framework in which to study the relationship between price discrepancies in the credit market and the effect of CDS inception on firm value volatility, I propose the following hypothesis.

Hypothesis 3. *The effect of CDS inception on firm value volatility is less pronounced in firms for which the CDS–bond basis is of higher absolute value.*

3.3 Empirical specification

3.3.1 Firm value volatility

Firm value is not directly observable, which makes it difficult to estimate its volatility. Merton (1974) proposes a structural model and shows both equity and debt are options of firm value. Equity is a call option on the firm's value and could be priced using the Black–Scholes option pricing formula. Since the market reveals a firm's equity price, I can combine that equity information with the Black–Scholes formula to estimate the firm's value as well as its volatility.

According to Merton (1974), the equity value of a firm is expressed as a function of firm value:

$$E = VN(d_1) - e^{-rT} FN(d_2); \tag{3.1}$$

here E is the market value of the firm's equity, V is the firm value, F is the face value of the firm's debt, r is the risk-free interest rate, T is the debt maturity, and $N(\cdot)$ is the cumulative distribution function of a standard normal random variable. The term d_1 is given by

$$d_1 = \frac{\ln(V/F) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{3.2}$$

where σ_V is the firm value's volatility and $d_2 = d_1 - \sigma_V \sqrt{T}$.

Under Merton's (1974) assumptions, the link between firm value volatility σ_V and equity value volatility σ_E can be written as follows:

$$\sigma_E = (V/E)N(d_1)\sigma_V. \tag{3.3}$$

Eq. (3.3) shows that the relationship between σ_E and σ_V is nonlinear. Moreover, it is unclear whether they move in the same direction. For brevity, I only show the proof in Appendix 2. To estimate V and σ_V, I need not only equity information but also the face value and maturity of the focal firm's debt. Following Vassalou and Xing (2004) and Bharath and Shumway (2008), I assume a debt maturity of one year and a face value equal to short-term debt plus half of long-term debt.

In a structural model, default risk can be measured by the *distance to default* (DD):

$$\mathrm{DD} = \frac{\ln(V/F) + (\mu - \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{3.4}$$

where μ is the expected return of V. According to this expression, σ_V is a major determinant of DD. Furthermore, Eq. (3.4) shows that default risk is affected also by the firm's financial leverage and the expected return on its assets, which also makes the relationship between default risk and firm risk uncertain.

One could, in theory, use Eqs. (3.1) and (3.3) to calibrate V and σ_V, respectively. In practice, however, market leverage is far too variable for Eq. (3.3) to yield reliable results (Crosbie and Bohn, 2003). Following Vassalou and Xing (2004) and Bharath and Shumway (2008), I adopt an iterative procedure—using information that pertains to the previous year—when estimating each month's firm value volatility. The procedure consists of five steps.

1. Estimate the volatility from a time series of equity price over the past year, and use it as the initial estimate (σ_{V0}) of firm value volatility.

2. Plug σ_{V0} into Eq. (3.1) in order to calculate the time series of V.
3. Estimate the volatility from the time series of V, and use it as the second estimate (σ_{V1}) of firm value volatility.
4. Replace σ_{V0} with σ_{V1} and then repeat steps 2–4 until a convergence criterion is met.[6]
5. Use the last value so obtained for σ_{V1} as the estimate of σ_V.

3.3.2 Determinants of firm value volatility

I use a regression model to examine the effect of CDS inception on firm value volatility. The dependent variable is firm value volatility, which is estimated using the structural model of Merton (1974).[7] Following Ashcraft and Santos (2009) and Subrahmanyam et al. (2014), I use an indicator variable of CDS trading to estimate the impact of CDS inception on firm value volatility; thus *CDS_trading* is a dummy set equal to 1 if the firm has experienced CDS trading on its debt one year before time t (and set to 0 otherwise). I regress firm value volatility on CDS trading as well as on other control variables that, in the literature, have been viewed as possible determinants of firm value volatility. The regressions also incorporate firm and time fixed effects. There is an unobserved firm effect for any firm whose residuals are correlated across years; similarly, there is a time effect when a given year's residuals may be correlated across firms (Petersen, 2009). Because there could be unobserved time and firm effects that are fixed in my panel data, I control for both firm and time fixed effects in years. To increase the robustness of my statistical results, I cluster standard errors

[6]The absolute value of the difference between σ_{V0} and σ_{V1} is less than 0.001.

[7]For one of my robust checks, I instead use Choi and Richardson's (2016) asset volatility measure; see Section 3.6.1.

at the firm level. My regression model is written as follows:[8]

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t} + \varepsilon_{i,t}, \tag{3.5}$$

where *CDS_trading* is the main independent variable; recall that $CDS\_trading = 1$ (0) if the firm did (did not) have CDS trading on its debt one year before time t. The vector $X_{i,t}$ represents my control variables; firm and year fixed effects are included in the regression model. I use the log transformation to reduce the skewness of firm value volatility.[9] Finally, β captures the effect of CDS inception on that volatility.

The literature has documented many variables that can affect firm value volatility. For example, Black (1976) finds that changes in leverage (as defined below) drive the change in firm value volatility. Comin and Mulani (2009) use total R&D expenses divided by total sales as a proxy for R&D innovation and investigate the extent to which such innovation increases the volatility of a firm's value; these authors find that an increase in R&D intensity leads to an increase in firm value volatility because the former causes "turnover in the market leader". This evidence is consistent with the findings of Comin and Philippon (2005). Davis et al. (2006) analyze the effect of firm age on firm value volatility and report that the latter falls as the former rises. In light of the studies cited here, my study uses the following control variables.

- *Leverage*: the ratio of book value of debt to the sum of that value and market equity, where

[8] The equation for a typical difference-in-differences (DiD) regression would be $\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} \times Post_{i,t} + \beta_1 \times Post_{i,t} + \beta_2 \times CDS\_traded_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}$; here *CDS_traded* is a dummy variable set to 1 if the firm has CDS traded on its debt any time during my sample period (and set to 0 otherwise) and the indicator variable *Post* is set to 1 for observations after the inception of CDS (and to 0 otherwise). However, neither *CDS_traded* nor *Post* is actually required here because the model includes both firm and year fixed effects. Eq. (3.5) is thus equivalent to a DiD model in which *CDS_trading* represents the interaction term *CDS_traded* × *Post*.

[9] Using the logarithm also makes it easier to interpret the economic significance of my results. The effect of CDS inception on firm value volatility is given as a *percentage* when the log change is measured—that is, rather than as a *level* when the variable itself changes.

"book value of debt" is itself the sum of short-term debt and a half of long-term debt and where "market equity" is equal to the number of common shares outstanding multiplied by the stock price.

- *Firm_age*: the natural logarithm of the number of years since the firm first appeared in the Compustat database.
- *R&D_ratio*: the ratio of R&D expenses to total sales.
- *Excess_return*: the firm's return in excess of the market's return over the past year.
- *MB_ratio*: the market value of a firm's assets divided by its total assets, where market value of assets (MVA) is the sum of debt in current liabilities (dlcq), long-term debt (dlttq), preferred stock (pstkq), and market value of equity *minus* balance sheet deferred taxes and investment tax credits (txditcq).
- ln(*Equity*): the natural logarithm of the firm's equity market value, which is used as a proxy for firm size.

Appendix 3.1 gives a detailed description of all variables used in the paper.

3.3.3 Endogeneity

3.3.3.1 Propensity score matching

Roberts and Whited (2013) show that, although propensity score (PS) matching may not solve endogeneity and self-selection problems in every context, it can mitigate some biases caused by these problems. I shall therefore calculate the propensity scores for all firms and then use those scores to match CDS firms with their non-CDS counterparts. In this procedure, I adopt the method of Roberts and Whited (2013) and conduct the matching "with replacement", which means that a non-CDS firm may be used more than once for matching purposes. I also employ several alternative methods for choosing matches, as described next, to assemble four different matched samples for analysis.

- "Closest one" sample: for each CDS firm, I choose the single non-CDS firm whose propensity score is the closest.
- "Closest two" sample: for each CDS firm, I choose the two non-CDS firms whose propensity scores are closest to the focal firm's score.
- "Closest one with PS difference less than 1%" sample: for each CDS firm, I choose the single non-CDS firm whose propensity score is the closest *provided that* the difference between these scores is less than 1%.
- "Closest two with PS difference less than 1%" sample: for each CDS firm, I choose the two non-CDS firms whose propensity scores are closest to the focal firm's score *provided that* the difference between that firm's score and both of the non-CDS firms' score is less than 1%.

A central challenge of propensity score matching is to find an appropriate model to estimate the propensity score. Ashcraft and Santos (2009) propose such a model that addresses the endogeneity problem and that is further developed by Saretto and Tookes (2013), Subrahmanyam et al. (2014), and Martin and Roychowdhury (2015). Following Subrahmanyam et al. (2014) and Martin and Roychowdhury (2015), I use a probit model to estimate the probability of CDS inception:

$$\Pr(CDS\_traded_{i,t} = 1) = \Phi(\alpha + \beta \times X_{i,t}). \tag{3.6}$$

In this expression, *CDS_traded* is a dummy variable set equal to 1 for firms whose credit default swaps are traded during my sample period (and set to 0 for other firms); X is a vector of covariates that could be determinants of CDS trading probability; industry-level and year fixed effects are included in the regression model. I use this probability of CDS trading to calculate the propensity scores when constructing the various matched samples.

3.3.3.2 Instrumental variable approach

I address the endogeneity problem not only by propensity score matching, as just described, but also by taking an instrumental variable approach. Following Saretto and Tookes (2013) and Subrahmanyam et al. (2014), I use *Lender_FX_hedging* as the instrumental variable. Minton, Stulz, and Williamson (2009) show that banks with a large amount of foreign exchange derivatives for hedging purposes are more likely to be net buyers of CDS. If so, then the implication is that banks tend to hedge more than one component of their portfolios. A bank's involvement with foreign exchange derivatives is unlikely to have a direct relationship with their borrowers' volatility. In fact, these two factors are more likely to be independent when the borrower and bank are in the same country.

Because the endogenous variable, *CDS_trading*, is an indicator, the conditional expectation function associated with the first stage is probably nonlinear. To preclude the problems that could arise from my using an incorrect nonlinear model at the first stage, I follow Angrist and Pischke (2008) and apply a three-stage procedure to estimate the coefficients. In the first stage, I use the following probit model to estimate the predicted value of *CDS_trading* (i.e., *CDS_trading_IV*). Thus I regress *CDS_trading* on control variables and the instrumental variable, *Lender_FX_hedging*:

$$CDS\_trading\_IV_{i,t} = \Phi(\alpha + \beta \times X_{i,t} + \gamma \times Z_{i,t}), \tag{3.7}$$

where Z is the instrumental variable (*Lender_FX_hedging*) and X is the vector of all control variables in Eq. (3.5). I also control for industry-level and year fixed effects in the regression model. In the next step, I use *CDS_trading_IV* as an instrument for *CDS_trading* in a conventional two-stage least-squares (2SLS) procedure.

3.4 Data

I use data from Markit to identify the inception of CDS trading, defined as the date on which the focal firm's CDS spread quote first appears in Markit. My CDS data cover the period from 2001 to 2012. The dependent variable is firm value volatility, which is based on Merton's structural model and estimated following an iterative procedure that is used in Vassalou and Xing (2004) and Bharath and Shumway (2008). The stock price and other financial information used to calculate firm value volatility and other variables are from the merged quarterly database of Compustat and the Center for Research in Security Prices (CRSP). The only firms I consider are those with stocks listed on the NYSE, AMEX, or Nasdaq. I use 6-digit numbers from the Committee on Uniform Securities Identification Procedures (CUSIP) to match CDS data from Markit with information from the Compustat–CRSP database. I start by using the whole sample.[10]

Panel A of Table 3.1 presents results for the whole sample, by year, between 2001 and 2012. The second column shows the total number of US companies included in my sample. The number of firms gradually decreases during this period: from 6,669 firms in 2001 to 4,227 firms in 2012. The table's third column reports the number of firms for which CDS trading was initiated during that year. In line with the figures reported by Subrahmanyam et al. (2017), CDS inception occurs more frequently before 2005. Whereas there were 674 CDS inceptions before 2005, only 88 firms did so after 2005. My final sample includes 762 firms for which CDS inception occurred within

[10]One of the robustness tests consists of comparing results when I remove financial firms from the sample; see Section 3.6.3.

the 2001–2012 period.

[INSERT Table 3.1 about Here]

Panel B of Table 3.1 gives summary statistics for variables capturing the firm characteristics of all firms, CDS firms, and non-CDS firms. I report results for $\ln(\sigma_V)$, σ_V, $\ln(Assets)$, *Leverage*, *Excess_return*, *Firm_age*, *R&D_ratio*, *MB_ratio*, $\ln(Equity)$, *Emp_growth*, *Investment_rate*, *Book_operating_leverage*, and *Market_operating_leverage*. For each variable, I report the number of observations (N), mean, standard deviation (S.D.), skewness, and kurtosis as well as the 25th, 50th, and 75th percentile values. All variables are winsorized at the 1st and 99th percentiles, a procedure that mitigates the impact of outliers. The reported figures establish that, as compared with non-CDS firms, CDS firms tend to exhibit less volatility in their firm value. In particular, the mean σ_V of non-CDS firms is 0.827 whereas that for CDS firms is only 0.511.

A key variable that I use in propensity score matching and also in my IV approach is *Lender_FX_hedging*, which measures the foreign exchange hedging activities of banks and underwriters. This variable is defined formally as (the average ratio of) the notional volume of FX derivatives used for hedging—and not trading—purposes *divided by* the total assets of all banks that have served the firm as either lenders or bond underwriters over the previous five years (Subrahmanyam et al., 2014). For each firm in my sample, I identify its main lenders and bond underwriters based on information from Dealscan and the Fixed Income Securities Database (FISD), respectively. For the lenders' information, I use Gvkey to match the Compustat and Dealscan data via the link provided by Chava and Roberts (2008). For the underwriters' information, I use 6-digit CUSIP numbers to match the data between Compustat and the FISD. Finally, I collect bank-related information—including total assets, activity in credit derivatives and/or FX hedging, and Tier-1 capital ratios—

from the US Federal Reserve's call report.[11] Call report data, Dealscan, and FISD do not have a common identifier, so I manually match their data by name, state, and other information of the relevant banks. I next turn to the empirical analysis.

3.5 Empirical results

3.5.1 CDS inception and firm value volatility: Whole sample

I start my empirical analysis using the whole sample to run the regression of Eq. (3.5). Table 3.2 reports the results. My variable of interest is the coefficient for *CDS_trading*, which measures the impact of CDS inception on firm value volatility.

[INSERT Table 3.2 about Here]

First, I use only the *CDS_trading* variable in the panel regression and control for firm and year fixed effects; this is Model (1) in Table 3.2. The coefficient for *CDS_trading* is -0.046 and is significant at the 1% level. A coefficient with a negative value means that firm value volatility declines after the inception of CDS trading. Here, firm value volatility decreases by 4.60% after the CDS on its debt starts trading.

Next, I introduce other control variables into the regressions (Models (2) and (3) in the table). The coefficients for *CDS_trading* continue to be significantly negative: -0.066 in Model (2) and -0.073 in Model (3)—with both values significant at the 1% level [12]. These results suggest that

[11] Because the Compustat and Federal Reserve call reports are updated quarterly, I calculate the variables based on them in each quarter and then interpolate those variables in order to match my monthly updates of firm value volatility. All other variables are calculated on a monthly basis.

[12] The standard errors are clustered at firm level since the CDS trading varies at the firm level. The results are similar if I cluster the standard errors by firm and month

CDS trading's reduction of firm value volatility is robust to controlling for other firm characteristics, which supports Hypothesis 1a.[13]

3.5.2 Endogeneity

3.5.2.1 Propensity score matching

Propensity score matched sample

I use Eq. (3.6) to estimate the probability of CDS inception, which is then used as my propensity score for constructing the matched samples. First, I follow Subrahmanyam et al. (2014) and use the following covariates: $\ln(Assets)$, *Leverage*, *ROA*, *Excess_return*, *Equity_volatility*, *Tangibility*, *Sales_ratio*, *EBIT_ratio*, *WCAP_ratio*, *RE_ratio*, *Cash_ratio*, *CAPX_ratio*, *SP_rating*, *Unsecured_debt*, *Lender_FX_hedging*, *Lender_Tier1_capital*, *Lender_credit_derivative*, and *Lender_size*. This model underlies my primary method of constructing the matched samples.

Panel A of Table 3.3 reports my propensity score regression results. Most of the explanatory variables have a significant effect on the probability of CDS trading. For example, the coefficient for $\ln(Assets)$—a proxy for firm size—is significantly positive with a value of 0.762, which suggests that CDS trading is more likely to involve large firms than small ones. In addition, firms with higher excess stock returns are more likely to have credit default swaps being traded on their debt. The regression results also indicate that CDS trading is more likely to occur for firms with a relatively higher tangible asset ratio, sales-to-assets ratio, and/or profitability. The probability of CDS initiation is greater for rated firms and for firms with a higher unsecured debts–total assets ratio.

[13] The number of observations is not constant across model specifications owing to the missing values of some variables. I obtain close results when using only those observations for which there are no missing values.

[INSERT Table 3.3 about Here]

The coefficient for *Lender_FX_hedging* is 3.771 and significant at the 1% level when I control for other firm characteristics. This significantly positive coefficient establishes that credit default swaps are more likely to be traded on firms whose banks are relatively more involved in foreign exchange hedging activities—a result that accords with the findings of Saretto and Tookes (2013) and Subrahmanyam et al. (2014). The pseudo-R^2 of this regression is 0.587, which indicates that these variables could explain—to a reasonable extent—the probability of CDS trading.

I next examine the effectiveness of my matching procedure by testing the mean difference in the characteristics between CDS firms and their matched non-CDS peers *before* the inception of CDS. To simplify matters, I limit the comparison to my "Closest one" matched sample. I test the difference in means between the CDS and matched non-CDS firms by running the following regressions for each variable:

$$X_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} + \varepsilon_{i,t}, \tag{3.8}$$

where all variables are as defined previously; industry-level and year fixed effects are included.[14] In this expression, β captures the difference in means of each variable between CDS firms and the matched non-CDS firms. The variables I consider for firm characteristics include $\ln(\sigma_V)$, *Leverage*, *Excess_return*, *Firm_age*, *R&D_ratio*, *MB_ratio*, $\ln(Equity)$, $\ln(Assets)$, *Propensity_score*, and $\Delta\sigma_V$. The term *Propensity_score* is the probability of CDS inception as given by Eq. (3.6), and $\Delta\sigma_V$ represents monthly changes in firm value volatility. For each variable, the regressions use only the data *before* CDS inception.

[14] I do not include firm fixed effect in this regression since it will absorb $CDS\_traded_{i,t}$. Industry fixed-effects based on the Fama-French 48 industry classifications and year fixed-effects are included.

Panel B of Table 3.3 reports the results. Prior to CDS inception, there is no statistical difference between CDS firms and their matched non-CDS counterparts in terms of $\ln(\sigma_V)$, *Leverage*, *Excess_return*, *R&D_ratio*, *MB_ratio*, $\ln(\mathit{Equity})$, or $\ln(\mathit{Assets})$. Although the matched CDS and non-CDS firms differ to a statistically significant extent in terms of *Firm_age*, they are close to each other in the propensity scores with an insignificant mean difference. In other words: prior to any CDS trading, CDS firms and the matched non-CDS firms were similar in their respective likelihood of CDS trading. Hence I conclude (a) that no particular firm characteristic—including the probability of CDS trading—is likely to drive the difference in firm value volatility after CDS inception and (b) that my matching procedure is effective. I also test the mean difference of the changes in firm value volatility ($\Delta\sigma_V$) between the CDS and matched non-CDS firms before CDS inception; the difference is not statistically significant. So according to Roberts and Whited (2013), the matched sample satisfies the assumption of parallel trends.

Results

To illustrate the effect of CDS inception on firm value volatility, I compare changes in the volatility for the CDS firms and their "Closest one" matched non-CDS firms before and after the inception—at "date 0"—of CDS trading. I then calculate the mean changes in the logarithm of firm value volatility for the CDS firms and non-CDS firms starting from one year before CDS inception to zero $(-1,0)$, one $(-1,1)$, two $(-1,2)$, and three $(-1,3)$ years thereafter.

[INSERT Figure 5.1 about Here]

Figure 5.1 plots the results. Overall, the CDS and matched non-CDS firms exhibit a decreasing trend in firm value volatility. Yet there is a more significant decrease in firm value volatility for the CDS firms than that for the matched non-CDS firms. From year -1 to year 1, for example, the logarithm of firm value volatility of the CDS firms decreases by 0.19 on average while that for the matched non-CDS firms declines by only 0.13. Since the mean firm value volatility is about 0.78, this gap of 0.06 translates into a difference of about 4.68% in firm value volatility. I observe similar patterns for the other event windows. The results indicate also that CDS inceptions' dampening of firm value volatility persists over years. I next formally test this effect by running the regression of Eq. (3.5) with the propensity score matched sample.

Panel A of Table 3.4 reports the results for matched samples based on "Closest one" and "Closest one with PS difference less than 1%" (Closest one PS diff. $< 1\%$) as selecting criteria. When I use the "Closest one" matched sample and do not control for other variables, the coefficient for *CDS_trading* is -0.040 and is significant at the 5% level. This result is close to the one obtained when I use the full sample data (See Table 3.2), which suggests that my result concerning the effect of CDS inception on firm value volatility is robust to whether I use full sample data or matched sample data. When the variables for other firm characteristics are included, the coefficient for *CDS_trading* changes to -0.052 yet is still significant at the 1% level. That is, the inception of CDS trading reduces mean firm value volatility by about 5.20% on average. Since mean firm value volatility is around 0.78, it follows that the level of firm value volatility decreases by about 4.06% ($0.78 \times 5.20\%$) upon commencement of CDS trading. Results for the "Closest one with PS difference less than 1%" sample similarly indicate that CDS inception reduces firm value volatility.

[INSERT Table 3.4 about Here]

The coefficients for control variables are significant and have the expected signs. The coefficient for *Leverage* is positive, suggesting that an increase in financial leverage leads to an increase in firm value volatility—a result that is consistent with previous findings in the literature. The coefficient for *Firm_age* is significantly negative; its value is -0.187 if I use the "Closest one" matched sample and include all control variables (column (3) of Panel A of Table 3.4). This result accords with the findings of Davis et al. (2006) and suggests that firm value volatility declines with increasing firm age. Furthermore, the coefficient for *R&D_ratio* is 0.071 and significant at the 1% level if I use the "Closest one" matched sample and include all control variables. This result supports the findings of Chun, Kim, Lee, and Morck (2004), Comin and Philippon (2005), and Comin and Mulani (2009) that an increase in R&D intensity also increases firm value volatility. The coefficients for *Excess_return* and *MB_ratio* are -0.114 and 0.042, respectively, and are significant at the 1% level (column (3) of Panel A of Table 3.4). These results are indicative of historical stock returns and market-to-book ratios having statistically significant effects on firm value volatility.

Panel B of Table 3.4 reports the results for alternative matched samples using "Closest two" and "Closest two with PS difference less than 1%" (Closest two PS diff. $< 1\%$) as selecting criteria. The results reveal that the effect of CDS inception on firm value volatility is robust: in all models, the coefficients for *CDS_trading* are negative. For example, the coefficients in columns (3) and (6) of Panel B are -0.040 and -0.039 and are significant at the 1% and 5% levels, respectively. Overall, my results suggest that the negative relationship between CDS trading and firm value volatility is robust to the choice of sample used for the empirical analysis.

3.5.2.2 Instrumental variable approach

Next, I adopt an instrumental variable (IV) approach to mitigate the potential endogeneity problem of CDS trading. As mentioned in Section 3.3.3.2, I use *Lender_FX_hedging* as an instrumental variable (See Saretto and Tookes, 2013; Subrahmanyam et al., 2014). My analysis follows Angrist and Pischke's (2008) three-stage procedure. I estimate the predicted value of *CDS_trading*, *CDS_trading_IV*, by (i) using the probit model that regresses *CDS_trading* on the instrumental variable and all control variables in Eq. (3.7) and then (ii) using *CDS_trading_IV* as an instrument for *CDS_trading* in a conventional 2SLS procedure.

Table 3.5 reports the results of this IV approach. The table's left and right columns report results from my first-stage probit model and the 2SLS regression, respectively. To test the instrumental variable's significance, I report the F-statistic for the 2SLS regression's excluded instrument: F=2965, suggesting that *Lender_FX_hedging* is a strong instrumental variable.[15]

[INSERT Table 3.5 about Here]

In the 2SLS regression, the coefficient for *CDS_trading_IV* is negative and significant at the 1% level when I control for firm characteristics and for time and firm fixed effects.[16] These results are consistent with those of the propensity score matched sample. The significantly negative coefficient implies an inverse relationship between CDS inception and firm value volatility. I therefore conclude that firm value volatility decreases after CDS inception, which supports Hypothesis 1a that the empty creditor effect dominates the monitoring effect.

3.5.2.3 Lending bargaing power and the effect of CDS inception

Here I employ an alternative approach to test Hypothesis 1a by using *Lender_FX_hedging* as proxy for the lender bargaining power. The higher value of *Lender_FX_hedging* implies the higher level of the lender bargaining power. To test whether the effect of CDS inception on firm value volatility differs as a function of the lender bargaining power, I interact CDS trading with *Lender_FX_hedging*.

[15]According to Stock, Yogo, and Wright (2002) and Angrist and Pischke (2008), a significant IV is one for which $F > 10$.

[16]The results are similar if I measure firm size using $\ln(Asset)$. Additionally, since the literature documents the possible impact of CDS inception on *Leverage*, *MB_ratio*, and *R&D_ratio*, I run the regressions without controlling for these variables and find the results are robust. They are available upon request.

Table A7 presents the regression results. The coefficients for *CDS_trading* are negative and significant at the 1% level, suggesting that the inception of CDS trading reduces firm value volatility. The coefficients for the interaction terms involving *CDS_trading* $\times$ *Lender_FX_hedging* are -0.6 and significant at the 10% level. This negative coefficient indicates that firms with a higher *Lender_FX_hedging* exhibit a stronger negative CDS inception effect than do firms with a lower *Lender_FX_hedging*. In other words, the effect of CDS inception on firm value volatility is more pronounced for the firms with a higher level of lender bargaining powers, which support Hypothesis 1a.

3.5.3 CDS inception and financial constraints

I now study whether the effect of CDS inception on firm value volatility differs among firms under various levels of financial constraint. The literature shows that firms whose credit default swaps are traded tend to hold more cash (Subrahmanyam et al., 2017) and/or engage in more corporate innovation (Chang et al., 2019). However, the exact relationship between CDS effects and financial constraints has not been conclusively established. Subrahmanyam et al. (2017) document that the positive effect of CDS trading on cash holding is stronger for firms under *more* financial constraints; in contrast, Chang et al. (2019) show that the positive effect of CDS trading on firm innovation is greater for firms that are *less* financially constrained.

I use the financial constraints index developed by Whited and Wu (2006) (the WW index) and the dividend payer indicator as proxies for financial constraints. A higher level of the WW index corresponds to a tighter financial constraint, and firms that do not pay a dividend tend to be more financially constrained than firms that do. To test whether the effect of CDS inception differs as a function of firms' financial constraints, I interact CDS trading with the financial constraint indicators. If I use the WW index to proxy for financial constraint, then the following regression model applies:

$$\begin{aligned}\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t} \\ + \kappa \times CDS\_trading_{i,t-1} \times WW_{i,t} + \theta \times WW_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{3.9}$$

where WW is a dummy variable set equal to 1 if the WW index is above the cross-sectional median and set to 0 otherwise; firm and year fixed effects are included in the regression model.[17] A positive value of κ means that CDS trading's reduction in firm value volatility is less pronounced for firms that are more financially constrained.

If I instead use the dividend payer as my proxy for financial constraint, then the following regression is run:

$$\begin{aligned}\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t} \\ + \kappa \times CDS\_trading_{i,t-1} \times DV_{i,t} + \theta \times DV_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{3.10}$$

where DV is a dummy variable that takes the value 1 if the firm does not pays dividends (and otherwise takes the value 0); firm and year fixed effects are included in the regression model. A positive value of κ is another indication that CDS inception reduces firm value volatility to a lesser extent in the case of firms that are more financially constrained.

Table 3.6 presents the regression results. I compare the CDS firms with their "Closest one",

[17] It is common to have $WW_{i,t}$ as one independent variable when I consider the interaction effect. In my regression, this variable is absorbed by the firm fixed effect because I define it based on the WW index at the time of the CDS inception. As a result, the coefficient of this variable is omitted. The same rule applies for DV_{it} and ABS_{it} explained later.

"Closest one with PS difference less than 1%", "Closest two", and "Closest two with PS difference less than 1%" matched non-CDS firms. For all regressions, I include the same control variables as those used in column (3) of Panel A of Table 3.4. The left and right columns report results using the WW index and the dividend payment indicator, respectively.

[INSERT Table 3.6 about Here]

The coefficients for *CDS_trading* are negative for all model specifications, which strongly suggests that the inception of CDS trading reduces firm value volatility. The coefficients for the interaction terms involving $CDS\_trading \times WW$ are more than 0.126 and significant at the 1% level for all propensity score matched samples. These positive coefficients indicate that firms with a higher WW index exhibit a weaker negative CDS inception effect than do firms with a lower WW index. In other words, firm value volatility due to CDS inception is reduced to a lesser extent in firms that are more financially constrained.

The coefficient for $CDS\_trading \times DV$ is 0.131 for the "Closest one" and also the "Closest one with PS difference less than 1%" matched samples; the coefficients are 0.137 and 0.135 for the "Closest two" and "Closest two with PS difference less than 1%" matched samples, respectively. All of these values are significant at the 5% level or above. The significantly positive coefficients suggest that the negative effect of CDS trading is weaker for firms that do not pay a dividend and are viewed as being more financially constrained. Overall, the Table 3.6 results support Hypothesis 2: CDS inception reduces firm value volatility less in firms that are more financially constrained.

3.5.4 CDS inception and the CDS–bond basis

Here I investigate whether the price discrepancy between CDS and corporate bonds affects the extent to which CDS inception influences firm value volatility. Following the literature, I use the absolute value of the CDS–bond basis to proxy for this price discrepancy. A higher level of that absolute value points to the existence of a more severe price discrepancy between the CDS and corporate bond market. To estimate the CDS–bond basis, I use the par-equivalent CDS methodology developed by JP Morgan. Thus I calculate the absolute value of the CDS–bond basis as the absolute difference between the quoted 5-year CDS spread and the par-equivalent 5-year CDS (PECDS) spread on the same reference entity:

$$|Basis_{i,t}| = |CDS_{i,t} - PECDS_{i,t}|; \tag{3.11}$$

here $CDS_{i,t}$ and $PECDS_{i,t}$ are, respectively, the quoted and par-equivalent CDS spreads at time t. I follow the procedure outlined in Nashikkar, Subrahmanyam, and Mahanti (2011), Bai and Collin-Dufresne (2018), and Lin, Man, Wang, and Wu (2018) to calculate the PECDS spread. Given price information on a firm's corporate bonds at time t, I calibrate that firm's constant default intensity by minimizing the corporate bonds' pricing errors. The calibration is based on the bonds for each firm with a maturity between three and eight years. I then use the default intensity calibrated from bond prices to calculate the par-equivalent five-year CDS spread.[18] The par-equivalent CDS spread is set equal to the coupon rate that equates the expected value of the premium leg to that of its contingent leg. The recovery rate is set at 40%.

To assess how the effect of CDS inception on firm value volatility depends on the focal firm's

[18]The CDS spread information is from Markit, and data on corporate bond prices are obtained from the Trade Reporting and Compliance Engine (TRACE). Bond issuance information, including coupon rate and the maturity date, is from Mergent's Fixed Income Securities Database (FISD).

CDS–bond basis, I augment Eq. (3.5) with the interaction term $CDS\_trading \times ABS$:

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t} \\ + \kappa \times CDS\_trading_{i,t-1} \times ABS_{i,t} + \theta \times ABS_{i,t} + \varepsilon_{i,t}. \tag{3.12}$$

Here *ABS* is a dummy variable set equal to 1 if the absolute value of the firm's CDS–bond basis exceeds the cross-sectional median (and is set to 0 otherwise); firm and year fixed effects are included in the regression model. A positive value of κ indicates that the negative association between CDS trading and firm value volatility is less pronounced for firms whose CDS–bond basis has a higher absolute value. I only use the CDS firm and their matched non-CDS firm data since the CDS inception to run the panel regressions.

[INSERT Table 3.7 about Here]

Table 3.7 presents the results from regressions based on the "Closest one", "Closest one with PS difference less than 1%", "Closest two", and "Closest two with PS difference less than 1%" matched samples. For all regressions, I include the same control variables as those used in column (3) of Panel A of Table 3.4. The coefficients for *CDS_trading* are negative for all model specifications, which means that the inception of CDS trading does reduce firm value volatility. The coefficients for four interaction terms $CDS\_trading \times ABS$ are greater than 0.019 and significant at the 5% level. These positive coefficients indicate that firms with a higher absolute CDS–bond basis exhibit a weaker negative CDS inception effect than do firms for which that basis is lower. Thus my findings support Hypothesis 3: CDS inception's reduction of firm value volatility is less pronounced for firms with a higher absolute value of CDS–bond basis—my proxy for price discrepancy between CDS and corporate bonds.

3.5.5 Channels

My empirical results show that firms reduce their risk levels after the commencement of their CDS trading. It is thus of great interest to study the channels through which such impact arises. Since expenditure is one key activity for a firm, I focus on how a firm adjusts its expenditure after the CDS inception. Broadly speaking, there are two potential channels. One is to change the expenditure level and the other is to change the operating leverage ratio. Next, I empirically test them one by one.

3.5.5.1 Employment growth and investment

For a firm, hiring input is one important component of operating expense. Arellano et al. (2019) show that firms are likely to decrease their hiring inputs to reduce the risk of default and to lessen the volatility at the firm level. Baker et al. (2016) also document the negative association between uncertainty shocks and employment growth. On the other hand, investment is one major part of capital expenditure. Narayanan and Uzmanoglu (2018a) show that the inception of CDS trading significantly reduces investment. Colonnello et al. (2019) establish the negative association of CDS inception and firm investment, especially for the firms with powerful shareholders.

Following these studies, I investigate whether reducing expenditure levels on hiring and investment is one channel through which the inception of CDS trading affects firm behavior in ways that reduce firm value volatility. If this is the case, I would observe that the focal firms' hiring inputs and investment decrease after the commencement of CDS trading. To test the hypothesis, I use employment growth as a proxy for hiring inputs. I follow Baker et al. (2016) to measure the annual employment growth rate using the firms'number of employees (Emp) in one fiscal year:[19]

$$Emp\_growth_{i,t} = \frac{Emp_{i,t} - Emp_{i,t-1}}{0.5 \times Emp_{i,t} + 0.5 \times Emp_{i,t-1}}. \tag{3.13}$$

I measure the investment rates (*Investment_rate*) as the change in fixed assets, scaled by the fixed asset at the beginning of the period (See Kaplan and Zingales, 1997; Li, Lin, and Xu, 2019). I then use the following specification to evaluate the effect of CDS inception on employment growth and investment rates:

$$Y_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t} + \varepsilon_{i,t}, \tag{3.14}$$

where Y is either *Emp_growth* or *Investment_rate*. *CDS_trading* is the main independent variable. Following Gulen and Ion (2016), Jens (2017), and Li et al. (2019), I use the control variables ($X_{i,t}$) including $\ln(Assets)$, *Leverage_book_value*, *Profitability*, *Cash_ratio*, *Tangibility*, and *Sale_growth*. Firm and year fixed effects are included in the regression model. β captures the effect of CDS inception on employment growth or investment rates.

[INSERT Table 3.8 about Here]

Table 3.8 reports the regression results of both propensity score matching and the instrumental variable approach.[20] Panel A of Table 3.8 presents the results for the panel regressions in which the dependent variable is *Emp_growth*. The coefficients for *CDS_trading* are significantly negative in all regressions. For example, when I use the "Closest one" matched sample and control for other

[19]The results are similar if I measure employment growth as the change in the natural log of the number of employees in one fiscal year.

[20]The sample size is smaller in this table because Panel A uses yearly data and Panel B uses quarterly data.

firm characteristics, the coefficient for *CDS_trading* is -0.025 and is significant at the 1% level. The result suggests that the employment growth rate decreases by 0.025 on average after the inception of CDS trading. Since the sample mean and standard deviation of employment growth rate are around 0.023 and 0.233, respectively, as reported in Panel B of Table 3.1, such decrease in employment growth rate due to CDS inception is economically significant. Particularly, the inception of CDS trading reduces about 10.7% of a one-standard deviation of the employment growth rate on average. For other propensity score matching samples, those coefficients are -0.024, -0.026, and -0.025—all significant at the 1% level. Using the IV approach yields a coefficient for *CDS_trading_IV* of -0.050, which is also significant at the 1% level. These results establish the negative relation between CDS trading and the employment growth, supporting the hypothesis that the decrease in firm value volatility after the inception of CDS trading could be partially attributed to the reduced hiring inputs.

Panel B of Table 3.8 gives the results for the panel regressions in which the dependent variable is *Investment_rate*. The coefficients for *CDS_trading* are significantly negative in all regressions. Particularly, when I use the "Closest one" matched sample and control for other firm characteristics, the coefficient for *CDS_trading* is -0.006 and is significant at the 1% level. The result shows that the quarterly investment rates decrease by 0.006 on average after the inception of CDS trading. Since the sample mean of the quarterly investment rate is 0.016 as reported in Panel B of Table 3.1, this decrease in investment rates corresponds to a percentage impact of 37.7% and is economically significant. For other propensity score matching samples and the IV approach, those coefficients are -0.006, -0.006, -0.005, and -0.010—all significant at the 5% level or better. These results confirm the negative association between CDS trading and the investment rates, supporting the hypothesis that the decrease in firm value volatility after the inception of CDS trading could be partially attributed to the reduced investment rates.

3.5.5.2 Operating leverage

Operating leverage could be another channel through which the inception of CDS trading affects expenditure in ways that reduce firm value volatility. Lev (1974) defines operating leverage as a ratio of the fixed to variable operating costs. He finds a positive association between operating leverage and firm risk. A higher operating leverage could lead to a larger overall risk of the firm's stock. I base on this idea to examine whether the decrease in firm value volatility after the inception of CDS trading could be attributed to the reduced operating leverage. Specifically, I test if the focal firm reduces its operating leverage after the CDS inception. I follow Novy-Marx (2010) to measure operating leverage as the ratio of annual operating costs (cost of goods sold plus selling, general and administrative expenses) to either the book value (*Book_operating_leverage*) or the market value (*Market_operating_leverage*) of assets.

[INSERT Table 3.9 about Here]

Table 3.9 reports the regression results of both propensity score matching and the instrumental variable approach. Panels A and B report the results for the regressions in which the dependent variables are *Book_operating_leverage* and *Market_operating_leverage*, respectively. In both panels, columns (1)–(4) present results for a sample that includes CDS firms and their propensity score matched non-CDS firms, while column (5) gives the results when an instrumental variable approach is adopted. None of the coefficients for *CDS_trading* is significant at the 10% level or above. I do not find a significant change of operating leverage after the inception of CDS trading. These results suggest that reducing operating leverage is not a channel through which CDS inception affects firm behavior to reduce its risk.

3.6 Robustness tests

For my first robustness test, I check whether my results are robust to using the asset volatility measure of Choi and Richardson (2016). I then use a probit model with a set of covariates suggested by Martin and Roychowdhury (2015) to estimate each sample firm's propensity score, which is then used to select the matched non-CDS firm (or firms) for each CDS firm. The matching proceeds as described in Section 3.3.3.1. Third, I test the robustness of my results by excluding financial firms from the empirical analysis. Finally, I test for whether my results continue to hold when quarterly (rather than monthly) data are used in the panel regressions.

3.6.1 Alternative asset volatility measure

Although I strictly follow the literature, my estimate of firm value volatility is based on structural model with several strong assumptions. I assume a one-year debt maturity and the face value of debt is short term plus one-half of long term debt. I model the underlying firm value following Black and Scholes (1973) and Merton (1974) (BSM), but do not account for stochastic volatility (Heston, 1993; Britten-Jones and Neuberger, 2000) or jump factors (Merton, 1976). These strong assumptions raise a concern about the estimation error of firm value volatility used in my analysis. To address this measurement issue, Choi and Richardson (2016) propose a different way to estimate asset volatility. Rather than estimating the non-observable asset value and its volatility from the observable stock price information, they directly calculate a firm's asset and its returns using the observable information on the firm's equity, bonds, and outstanding loans; then asset volatility is estimated by fitting an EGARCH$(1,1)$ model to the asset returns. Choi and Richardson (2016) show that their findings of the relationship between asset volatility, leverage, and equity volatility are similar when using either the structural model or their method. Here I see whether my results are robust to the estimation error using this alternative measure of asset volatility.[21]

[INSERT Table 3.10 about Here]

Table 3.10 reports the regression results of both propensity score matching sample and the instrumental variable approach.[22] The coefficients for *CDS_trading* continue to be significantly negative in all regressions; for the different propensity score matching samples, those coefficients are −0.021, −0.019, −0.020, and −0.018—all significant at the 10% level or better. Using the IV approach yields a coefficient for *CDS_trading_IV* of −0.077, which is significant at the 1% level. These results establish that the negative relation between CDS trading and firm value volatility is robust to using this alternative measure of asset volatility.

3.6.2 Alternative propensity score matching model

Table 3.11 presents my estimates of the effect of CDS inception on firm value volatility when the CDS firms and non-CDS firms are matched by the propensity scores derived using the Martin and Roychowdhury (2015) model.

[INSERT Table 3.11 about Here]

Panel A of the table reports the results of propensity score modeling. The variables include lagged values of ln(*Equity*), *Investment_grade*, *SP_rating*, *Leverage_book_value*, *Net_income_ratio*, *Equity_volatility_year*, and *MB_ratio_equity*. The results are similar to those reported by Subrahmanyam et al. (2014). Credit default swaps are more likely to involve firms that are larger and/or

[21] I thank Jaewon Choi for making the data publicly available (https://sites.google.com/site/jaewchoi1203).

[22] The sample used in Choi and Richardson (2016) includes the firms with at least $100 million of market assets. As a result, there are only 519 CDS firms in their sample.

with a better credit rating, greater financial leverage, higher profitability, and lower market-to-book ratio. The pseudo-R^2 of this regression is 0.625, which is slightly higher than the value in Subrahmanyam et al. (2014).

Panel B of Table 3.11 gives the panel regression results, which differ little from those (reported in Table 3.4) based on firms matched by the propensity scores calculated under the Subrahmanyam et al. (2014) model. The inception of CDS trading still reduces firm value volatility to a significant extent. In particular: the coefficients for *CDS_trading* in columns (1)–(4) of Panel B of Table 3.11 are—depending on the matched sample used—−0.026, −0.025, −0.024, and −0.025. They are all significant at the 10% level. These results confirm that firm value volatility declines with the commencement of CDS trading. Thus the effect of CDS inception on firm value volatility is robust to using a different model to estimate the propensity score.

3.6.3 Excluding financial firms

The sample used for my main analysis includes financial firms, which is consistent with the study conducted by Subrahmanyam et al. (2017). To test for whether my results are robust to the choice of sample firms, I adopt the approach of Ashcraft and Santos (2009), Saretto and Tookes (2013), and Martin and Roychowdhury (2015): using a sample that consists only of *non*-financial firms. Thus I exclude financial firms from my analysis and re-run the regression of Eq. (3.5).[23]

[INSERT Table 3.12 about Here]

Table 3.12 reports the regression results. I find that, when control variables are included, *CDS_trading* continues to have a significantly negative effect: the coefficients for this variable (see columns (1)–

[23] There are 92 financial and 670 non-financial CDS firms, respectively, in the whole sample. I exclude the 92 financial CDS firms in this analysis.

(4) of Table 3.12) are -0.044, -0.046, -0.037, and -0.040; all are significant at the 5% level or above. The corresponding value estimated when I take the instrumental variable approach is -0.106, which is significant at the 1% level. These estimation results are also close to those obtained when using all the firms (see Tables 3.4 and 3.5). The sign and significance of other control variables' coefficients are consistent with those in the main analysis. These results provide empirical evidence that the negative relationship between CDS trading and firm value volatility is robust to samples that exclude financial firms.

3.6.4 Quarterly regression results

Most of my explanatory variables in my empirical analysis are updated quarterly; however, as explained in Section 3.4, I interpolated the quarterly values in order to match my monthly updates of asset volatility. To check for whether the results might have been affected by that data "expansion", I re-run the panel regressions while using quarterly data.

[INSERT Table 3.13 about Here]

Table 3.13 reports the regression results for the propensity score matched sample and for the instrumental variable approach. My findings continue to hold. All the *CDS_trading* coefficients are negative and significant at the 1% or 5% level for the four different propensity score matched samples, and *CDS_trading_IV* is negative and significant at the 1% level under the IV approach. Thus I find that CDS trading's reduction of firm asset volatility is robust to my use of quarterly instead of monthly data.

3.6.5 Financial constraints, CDS–bond basis, and CDS inception

I now test the robustness of Hypothesis 2 and Hypothesis 3. Toward that end, I run regressions of Eq. (3.9), Eq. (3.10), and Eq. (3.12) while alternately using (a) the propensity score matching model of Martin and Roychowdhury (2015), (b) the sample that excludes financial firms, and (c) the alternative asset volatility measure of Choi and Richardson (2016).

[INSERT Table 3.14 about Here]

Table 3.14 reports the regression results—here, for only the "Closest one" propensity score matched sample.[24] The significantly positive coefficients for $CDS\_trading \times WW$ and $CDS\_trading \times DV$ amount to robust evidence that the negative effect of CDS inception is less pronounced for firms that are more financially constrained. Similarly, the coefficients for $CDS\_trading \times ABS$ are significantly positive when I use the sample excluding financial firms. Although this coefficient is no longer significant when I use either the propensity score matching model of Martin and Roychowdhury (2015) or the asset volatility measure of Choi and Richardson (2016), it does still have a positive sign. These results also support Hypothesis 3: the reduced firm value volatility due to CDS trading is less pronounced for firms with a higher absolute value of the CDS–bond basis.

3.7 Conclusion

This paper offers empirical evidence that the inception of CDS trading leads to a decrease in firm risk. I use firm value volatility, which incorporates information on equity and corporate debt, as a proxy for firm risk. My finding is robust to whether the potential endogeneity problems associated

[24] Results for the other three propensity score matched samples are qualitatively similar and available upon request.

with CDS trading are addressed by using propensity score matching or instead via an instrumental variable approach.

I find also that the CDS-induced decrease in firm value volatility is less pronounced for more financially constrained firms. This finding indicates that the monitoring effect is stronger for firms that are more financially constrained. In addition, I document that the negative effect of CDS inception on firm value volatility is less pronounced for firms characterized by a greater price discrepancy between credit default swaps and the corporate bond. My results reveal that market frictions influence how much financial innovation affects society, from which it follows that policymakers should seek to control those frictions.

My findings support the hypothesis that, with regard to firm value volatility, the empty creditor effect of CDS trading dominates the monitoring effect. This paper contributes to the literature addressing the effect of CDS markets on firm behavior. One question of interest involves the particular *channels* through which CDS inception could affect firm behavior in ways that reduce firm value volatility. I find that the firms' expenditure levels on hiring and investment decrease after the inception of CDS trading, but their operating leverages do not change significantly. The results suggest that the decrease in firm value volatility after CDS inception could be partially attributed to the reduced hiring input or/and investment rates, but not operating leverage. Another question is that there are two possible ways to reach my results. One is both the empty creditor effect and the monitoring effect exist, but the empty creditor effect is stronger. The alternative way is only the empty creditor effect exists. My results are more likely to support the first possibility as I find that the monitoring effect is stronger—for firms that are more financially constrained. It will be interesting to see more evidence of the existence of both the empty creditor effect and the monitoring effect. These topics would be fruitful ones for future research.

3.8 Appendices, tables and figures

Appendix 3.1: Description of variables

This appendix lists the variables used in my analysis and explains how they are constructed.

Variable	**Definition**
CDS_trading	Dummy variable set to 1 if the firm has credit default swaps traded on its debt one year before time *t* (and set to 0 otherwise)
$\ln(\sigma_V)$	The natural logarithm of firm value volatility, which is estimated using the model proposed in Vassalou and Xing (2004)
Leverage	The ratio of book value of debt to the sum of book value of debt and market equity, where book value of debt is the sum of short-term debt and a half of long-term debt and where market equity is the number of common shares outstanding multiplied by the stock price
Firm_age	The natural logarithm of the number of years from the first time the firm appeared in the Compustat database
R&D_ratio	The ratio of R&D expenses to total sales. Missing R&D expenses are treated as zeros
Excess_return	The firm's return in excess of the market over the past year
MB_ratio	The ratio of market value of assets to total assets, where market value of assets is the sum of debt in current liabilities, long-term debt, preferred stock, and market value of equity *minus* balance sheet deferred taxes and investment tax credit
ln(*Equity*)	The natural logarithm of the firm's equity market value
CDS_traded	Dummy variable set equal to 1 if the firm has CDS traded on its debt during the sample period (and set to 0 otherwise)
ln(*Assets*)	The natural logarithm of the firm's total assets
ROA	The firm's return on assets
Equity_volatility	The natural logarithm of the firm's annualized equity volatility
Tangibility	The ratio of property, plant, and equipment to total assets
Sales_ratio	The ratio of sales to total assets
EBIT_ratio	The ratio of earnings before interest and taxes to total assets
WCAP_ratio	The ratio of working capital to total assets
RE_ratio	The ratio of retained earnings to total assets
Cash_ratio	The ratio of cash to total assets
CAPX_ratio	The ratio of capital expenditures to total assets
SP_rating	Dummy variable set to 1 if the firm is rated (and set to 0 otherwise)
Unsecured_debt	The ratio of unsecured debt to total debt
Lender_FX_hedging	The average of foreign exchange hedging activities relative to total assets across the firm's lending banks and underwriters
Lender_Tier1_capital	The average Tier-1 capital ratio of the firm's lenders
Lender_credit_derivative	The average of credit derivative activities relative to total assets across the firm's lending banks and underwriters
Lender_size	The average size of the focal firm's lending banks and underwriters as measured by the logarithm of total assets of those banks and underwriters
Investment_grade	Dummy variable set to 1 if a firm has a S&P credit rating above BB+ (and set to 0 otherwise)
Leverage_book_value	The ratio of book value of debt to book value of total assets
Net_income_ratio	The ratio of net income to total sales
Equity_volatility_year	The standard deviation of monthly stock return over the past year
MB_ratio_equity	The ratio of the market value of equity to the book value of equity
Profitability	The ratio of operating income before depreciation to total assets
Sale_growth	The natural logarithm of operating revenue divided by the operating revenue at the beginning of the year
WW	Dummy variable set equal to 1 if the firm has a WW index above the cross-sectional median (and set to 0 otherwise)
DV	Dummy variable set equal to 1 (0) for firms that do not (do) pay dividends
ABS	Dummy variable set equal to 1 if the absolute value of the focal firm's CDS–bond basis is above the cross-sectional median (and set to 0 otherwise)
Emp_growth	The annual employment growth rate using the firms' number of employees in one fiscal year
Investment_rate	The percentage change in fixed assets over the previous period
Book_operating_leverage	Cost of goods sold plus selling, general and administrative expenses, scaled by the book value of assets
Market_operating_leverage	Cost of goods sold plus selling, general and administrative expenses, scaled by the market value of assets

Appendix 3.2: Firm value volatility and equity volatility

Another popular risk measure—that is, besides firm value volatility—is *equity volatility*. Because equity is a call option on the firm's value, its volatility measures the risk of a call option whose underlying asset is the firm's value.

In theory, there is a *nonlinear* relationship between equity volatility and firm value volatility. Yet it is not clear whether reduced firm value volatility necessarily leads to a decline in equity volatility. There are two reasons for this uncertainty. First, by Eq. (3.3) I have

$$\frac{\partial \sigma_E}{\partial \sigma_V} = \frac{V}{E}\left(N(d_1) + \sigma_V N'(d_1)\frac{\partial d_1}{\partial \sigma_V}\right). \tag{A.1}$$

The sign of $\frac{\partial \sigma_E}{\partial \sigma_V}$ cannot be determined ex ante because

$$\frac{\partial d_1}{\partial \sigma_V} = -\frac{\ln(V/F) + rT}{\sigma_V^2\sqrt{T}} + \frac{1}{2}\sqrt{T} \tag{A.2}$$

could be either positive or negative. Second, the relationship between σ_E and σ_V is also affected by V/E, a measure of financial leverage. Choi and Richardson (2016) find a strong positive relationship between firm leverage and equity volatility, and both Saretto and Tookes (2013) and Subrahmanyam et al. (2017) document that the inception of CDS trading increases firm leverage. Hence the net impact of CDS trading on equity volatility is not clear.

Table 3.1: Summary statistics

This table presents summary statistics of firms in the whole sample. Panel A reports the number of firms and CDS trading inceptions, by year, between 2001 and 2012. The whole sample from the Compustat–CRSP merged database includes all firms traded on the NYSE, AMEX, and Nasdaq during the sample period 2001–2012. I merge the CDS data from Markit with the Compustat–CRSP data using the first 6 digits of CUSIP. The second column shows the total number of companies included in my analysis; the third column reports the number of firms for which CDS trading was initiated during that year (i.e., the year during which the focal firm's CDS spread quote first appeared in the database). The fourth column shows the cumulative number of CDS firms. Panel B gives summary statistics of the firm characteristic variables for all firms, CDS firms, and non-CDS firms. I report results for $\ln(\sigma_V)$, σ_V, $\ln(Assets)$, *Leverage*, *Excess_return*, *Firm_age*, *R&D_ratio*, *MB_ratio*, $\ln(Equity)$, *Emp_growth*, *Investment_rate*, *Book_operating_leverage*, and *Market_operating_leverage*. For each variable, I report the number of observations (N), mean, standard deviation (S.D.), skewness, kurtosis, and the 25th, 50th, and 75th percentile values. All variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. See Appendix 3.1 for additional details.

Panel A: CDS firms in the sample

Year	**Number of CRSP–Compustat firms**	**New CDS firms**	**Cumulative number of CDS firms**
2001	6,669	2	2
2002	5,978	394	396
2003	5,584	118	514
2004	5,419	115	629
2005	5,376	45	674
2006	5,283	30	704
2007	5,276	34	738
2008	4,969	7	745
2009	4,677	1	746
2010	4,528	5	751
2011	4,354	8	759
2012	4,227	3	762

(*continued*)

Table 3.1 (*continued*)

Panel B: Summary statistics

ALL FIRMS	*N*	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
$\ln(\sigma_V)$	586,339	−0.459	0.643	0.099	2.619	−0.908	−0.481	−0.019
σ_V	586,339	0.778	0.542	1.668	6.007	0.403	0.618	0.981
ln(*Assets*)	697,320	6.065	2.096	0.192	2.664	4.563	6.042	7.453
Leverage	693,307	0.191	0.223	1.335	4.033	0.008	0.106	0.300
Excess_return	667,649	−0.083	0.566	−0.605	4.925	−0.328	−0.040	0.223
Firm_age	696,294	2.405	0.905	−0.410	2.791	1.792	2.485	3.045
R&D_ratio	682,527	0.260	1.299	7.117	55.530	0.000	0.000	0.060
MB_ratio	697,320	1.474	1.503	2.644	11.460	0.596	1.008	1.750
ln(*Equity*)	700,139	5.683	2.071	0.198	2.616	4.171	5.611	7.085
Emp_growth	53,076	0.023	0.233	−0.302	7.366	−0.055	0.019	0.110
Investment_rate	222,350	0.016	0.127	2.578	16.320	−0.026	−0.000	0.035
Book_operating_leverage	57,068	0.843	0.779	1.557	5.860	0.263	0.659	1.180
Market_operating_leverage	57,067	0.903	1.178	2.837	12.501	0.204	0.480	1.083
CDS FIRMS	*N*	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
$\ln(\sigma_V)$	90,770	−0.823	0.528	0.436	3.453	−1.173	−0.850	−0.516
σ_V	90,770	0.511	0.336	2.856	15.500	0.310	0.427	0.597
ln(*Assets*)	92,703	8.971	1.307	0.133	2.355	7.973	8.884	9.941
Leverage	92,557	0.233	0.198	1.332	4.429	0.088	0.173	0.326
Excess_return	91,778	−0.027	0.411	−0.844	7.546	−0.192	−0.003	0.180
Firm_age	92,210	3.144	0.781	−0.998	3.805	2.639	3.367	3.761
R&D_ratio	92,554	0.027	0.171	43.050	2.478	0.000	0.000	0.003
MB_ratio	92,703	1.238	0.982	3.202	18.960	0.685	0.980	1.477
ln(*Equity*)	92,762	8.520	1.413	−0.390	3.136	7.610	8.523	9.566
Emp_growth	7,490	0.016	0.169	0.334	11.25	−0.045	0.005	0.068
Investment_rate	29,693	0.015	0.088	4.089	35.460	−0.013	0.006	0.027
Book_operating_leverage	7,659	0.764	0.694	2.033	8.276	0.282	0.596	0.993
Market_operating_leverage	7,659	0.805	0.946	3.243	17.061	0.258	0.508	0.959
NON-CDS FIRMS	*N*	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
$\ln(\sigma_V)$	495,569	−0.393	0.640	0.007	2.640	−0.833	−0.399	0.045
σ_V	495,569	0.827	0.558	1.546	5.480	0.435	0.671	1.046
ln(*Assets*)	604,617	5.620	1.820	0.076	2.767	4.334	5.682	6.845
Leverage	600,750	0.185	0.226	1.363	4.040	0.003	0.090	0.294
Excess_return	575,871	−0.092	0.587	−0.561	4.642	−0.355	−0.049	0.233
Firm_age	604,084	2.292	0.869	−0.440	2.839	1.792	2.398	2.890
R&D_ratio	589,973	0.297	1.392	6.601	47.940	0.000	0.000	0.075
MB_ratio	604,617	1.510	1.565	2.541	10.630	0.574	1.013	1.809
ln(*Equity*)	607,377	5.249	1.794	0.066	2.682	3.963	5.262	6.516
Emp_growth	45,586	0.024	0.242	−0.340	6.952	−0.058	0.023	0.118
Investment_rate	192,657	0.016	0.132	2.461	15.060	−0.030	−0.002	0.037
Book_operating_leverage	49,409	0.856	0.790	1.497	5.600	0.257	0.671	1.209
Market_operating_leverage	49,408	0.919	1.209	2.774	11.946	0.197	0.474	1.112

Table 3.2: CDS inception and firm value volatility: Whole sample

This table presents the effect of CDS inception on firm value volatility using the whole sample. I run the panel regressions of $\ln(\sigma_V)$ on *CDS_trading* and other control variables, including *Leverage*, *Firm_age*, *R&D_ratio*, *Excess_return*, *MB_ratio*, and $\ln(Equity)$; all the regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Appendix 3.1 gives a detailed description of the variables.

Variable	**(1)**	**(2)**	**(3)**
CDS_trading	-0.046^{***}	-0.066^{***}	-0.073^{***}
	(0.013)	(0.013)	(0.013)
Leverage		0.090^{***}	-0.253^{***}
		(0.023)	(0.026)
Firm_age		-0.104^{***}	-0.147^{***}
		(0.012)	(0.014)
R&D_ratio		0.009^{***}	0.007^{***}
		(0.002)	(0.002)
Excess_return			-0.061^{***}
			(0.004)
MB_ratio			0.060^{***}
			(0.003)
$\ln(Equity)$			-0.107^{***}
			(0.006)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj. R^2	0.255	0.262	0.290
N	586,339	571,677	552,808

Table 3.3: Propensity score modeling

This table presents the estimation results of propensity score matching. Panel A reports estimates of a probit model that regresses the probability of CDS trading on its determinants. The dependent variable, *CDS_traded*, is set to 1 if there is a CDS traded on the firm's debt during the sample period and is otherwise set to 0. I employ the same set of independent variables as used by Subrahmanyam et al. (2014). The sample period is 2001–2012. In Panel B, I examine the difference in means of firm characteristics—between the CDS and matched non-CDS firms before CDS inception—by running these regressions:

$$X_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} + \varepsilon_{i,t}.$$

Here the vector $X_{i,t}$ is my variable of interest; industry-level and year fixed effects are also included; and β captures the difference in means of each variable between the CDS firms and the matched non-CDS firms. I use the "Closest one" matched sample according to the propensity score derived with Subrahmanyam et al.'s (2014) model, and keep only the observations made prior to CDS inception. As before, *Propensity_score* is the probability of CDS inception and $\Delta\sigma_V$ represents monthly changes in firm value volatility. See Appendix 3.1 for descriptions of the other variables. Robust standard errors (S.E.) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Propensity score modeling			Panel B: Difference in means before CDS inception		
Variable	**Coefficient**	**S.E.**	**Variable**	β	**S.E.**
ln(*Assets*)	0.762***	(0.005)	$ln(\sigma_V)$	−0.021	(0.045)
Leverage	0.036	(0.030)	*Leverage*	−0.030	(0.025)
ROA	0.057	(0.161)	*Excess_return*	0.029	(0.024)
Excess_return	0.042***	(0.010)	*Firm_age*	0.214**	(0.098)
Equity_volatility	−0.091***	(0.009)	*R&D_ratio*	0.019	(0.013)
Tangibility	0.339***	(0.030)	*MB_ratio*	0.041	(0.091)
Sales_ratio	0.464***	(0.033)	ln(*Equity*)	0.090	(0.210)
EBIT_ratio	1.557***	(0.180)	ln(*Assets*)	−0.030	(0.165)
WCAP_ratio	−0.435***	(0.041)	*Propensity_score*	−0.004	(0.036)
RE_ratio	−0.063***	(0.009)	$\Delta\sigma_V$	−0.000	(0.002)
Cash_ratio	0.579***	(0.049)			
CAPX_ratio	−0.916***	(0.136)			
SP_rating	1.332***	(0.013)			
Unsecured_debt	0.679***	(0.016)			
Lender_FX_hedging	3.771***	(0.359)			
Lender_Tier1_capital	−0.018	(0.470)			
Lender_credit_derivative	−0.027***	(0.007)			
Lender_size	0.035***	(0.006)			
Industry fixed effects	Yes				
Year fixed effects	Yes				
Pseudo-R^2	0.587				
N	262,910				

Table 3.4: CDS inception and firm value volatility: Propensity score matched sample

This table presents the effect of CDS inception on firm value volatility using the sample that includes CDS firms and also their matched non-CDS firms. I follow Subrahmanyam et al. (2014) in estimating each firm's propensity score, which is then used to match the CDS firms. I run panel regressions of $\ln(\sigma_V)$ on *CDS_trading*, and on other control variables, while accounting for firm and year fixed effects. Panel A reports the results for my "Closest one" and "Closest one with PS difference less than 1%" (Closest one PS diff. $< 1\%$) matched samples; Panel B gives results for the "Closest two" and "Closest two with PS difference less than 1%" (Closest two PS diff. $< 1\%$) matched samples. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Detailed descriptions of the variables are provided in Appendix 3.1.

	Panel A: "Closest one" and "Closest one, PS diff. $< 1\%$" matched samples						Panel B: "Closest two" and "Closest two, PS diff. $< 1\%$" matched samples					
Variable	**(1) Closest one**	**(2) Closest one**	**(3) Closest one**	**(4) Closest one PS diff. $< 1\%$**	**(5) Closest one PS diff. $< 1\%$**	**(6) Closest one PS diff. $< 1\%$**	**(1) Closest two**	**(2) Closest two**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) Closest two PS diff. $< 1\%$**	**(6) Closest two PS diff. $< 1\%$**
CDS_trading	−0.040**	−0.052***	−0.052***	−0.039***	−0.051***	−0.051***	−0.024	−0.039**	−0.040***	−0.024	−0.039**	−0.039**
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)
Leverage		0.100	0.123		0.129**	0.120		0.089*	0.092		0.138***	0.112
		(0.066)	(0.083)		(0.064)	(0.082)		(0.052)	(0.068)		(0.052)	(0.069)
Firm_age		−0.171***	−0.187***		−0.177***	−0.190***		−0.217***	−0.240***		−0.210***	−0.233***
		(0.034)	(0.036)		(0.034)	(0.036)		(0.027)	(0.029)		(0.028)	(0.030)
R&D_ratio		0.073***	0.071***		0.072***	0.068***		0.071***	0.068***		0.070***	0.066***
		(0.015)	(0.014)		(0.014)	(0.014)		(0.014)	(0.014)		(0.014)	(0.013)
Excess_return			−0.114***			−0.112***			−0.107***			−0.105***
			(0.010)			(0.010)			(0.008)			(0.008)
MB_ratio			0.042***			0.044***			0.028***			0.032***
			(0.008)			(0.008)			(0.007)			(0.007)
ln(*Equity*)			0.025			0.015			0.026*			0.016
			(0.018)			(0.018)			(0.015)			(0.015)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.358	0.365	0.380	0.359	0.367	0.382	0.353	0.363	0.376	0.356	0.366	0.379
N	123,983	122,925	122,111	121,887	120,829	120,015	180,248	177,879	176,501	170,771	168,409	167,100

Table 3.5: CDS inception and firm value volatility: Instrumental variable approach

This table presents the effect of CDS inception on firm value volatility as estimated via an instrumental variable approach. I report results derived from the first-stage of a probit model and also from the 2SLS regression in the three-stage procedure. My instrumental variable is *Lender_FX_hedging*, which measures the foreign exchange hedging activities of the firm's banks and underwriters. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

	First-stage	**2SLS**
Variable	*CDS_trading*	$\ln(\sigma_V)$
CDS_trading_IV		-0.125^{***}
		(0.024)
Leverage	2.468^{***}	-0.182^{***}
	(0.280)	(0.032)
Firm_age	0.527^{***}	-0.216^{***}
	(0.050)	(0.019)
R&D_ratio	-0.614	0.013^{**}
	(0.388)	(0.005)
Excess_return	-0.140^{***}	-0.072^{***}
	(0.037)	(0.005)
MB_ratio	-0.371^{***}	0.061^{***}
	(0.044)	(0.004)
ln(*Equity*)	0.837^{***}	-0.091^{***}
	(0.039)	(0.007)
Lender_FX_hedging	4.196^{***}	
	(1.395)	
Industry fixed effects	Yes	
Firm fixed effects		Yes
Year fixed effects	Yes	Yes
F-statistic (excluded instrument)		2,965
Pseudo-R^2	0.561	
Adj. R^2		0.329
N	352,061	352,061

Table 3.6: Financial constraints and the effect of CDS inception

This table reports the effect of CDS inception on firm value volatility as a function of financial constraints. I use the financial constraints index proposed by Whited and Wu (2006) (the WW index), and also the dividend payer indicator, as proxies for financial constraints. A higher WW index means that financial constraints are tighter; and firms that do not pay a dividend tend to be more financially constrained. I use the interaction terms $CDS\_trading \times WW$ (Eq. (3.9)) and $CDS\_trading \times DV$ (Eq. (3.10)) to capture the difference in CDS effects between more and less financially constrained firms; here *WW* is an indicator set equal to 1 if the firm has a WW index above the cross-sectional median (and set to 0 otherwise), and *DV* is a dummy variable set equal to 1 (0) for firms that do not (do) pay dividends. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is given in Appendix 3.1.

	WW index				**Dividend payer indicator**			
Variable	**(1) Closest one**	**(2) Closest one PS diff. < 1%**	**(3) Closest two**	**(4) Closest two PS diff. < 1%**	**(1) Closest one**	**(2) Closest one PS diff. < 1%**	**(3) Closest two**	**(4) Closest two PS diff. < 1%**
CDS_trading	-0.132^{***}	-0.125^{***}	-0.115^{***}	-0.118^{***}	-0.173^{***}	-0.172^{***}	-0.166^{***}	-0.163^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.050)	(0.050)	(0.050)	(0.050)
$CDS\_trading \times WW$	0.139^{***}	0.132^{***}	0.126^{***}	0.139^{***}				
	(0.026)	(0.027)	(0.027)	(0.027)				
$CDS\_trading \times DV$					0.131^{**}	0.131^{**}	0.137^{***}	0.135^{***}
					(0.051)	(0.051)	(0.052)	(0.052)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.383	0.385	0.377	0.376	0.381	0.383	0.376	0.380
N	122,111	120,015	176,501	167,100	122,111	120,015	176,501	167,100

Table 3.7: CDS–bond basis and the effect of CDS inception

This table reports the effect of CDS inception on firm value volatility as a function of the absolute value of the CDS–bond basis. I use the interaction term $CDS\_trading \times ABS$ in the regressions to capture the difference in CDS effects between the CDS firms with high and low absolute values of the CDS–bond basis, where *ABS* is a dummy variable set equal to 1 if the absolute value of the focal firm's CDS–bond basis is above the cross-sectional median (and set to 0 otherwise). The CDS–bond basis is the difference between the quoted and par-equivalent CDS spread of a given reference entity. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**
CDS_trading	-0.073^{***}	-0.079^{***}	-0.089^{***}	-0.081^{***}
	(0.028)	(0.028)	(0.027)	(0.027)
$CDS\_trading \times ABS$	0.026^{**}	0.027^{**}	0.021^{**}	0.019^{**}
	(0.011)	(0.012)	(0.010)	(0.010)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.464	0.461	0.448	0.451
N	46,824	46,136	64,344	60,702

Table 3.8: CDS inception, employment growth and investment rates

This table reports the effect of CDS inception on employment growth and investment rates. Columns (1)–(4) present results for a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) gives the results when an instrumental variable approach is adopted. In panel A (panel B), I use firm-year (firm-quarter) observations to run the panel regressions of *Emp_growth* (*Investment_rate*) on *CDS_trading*, and on other control variables, while accounting for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A more detailed description of the variables is given in Appendix 3.1.

Panel A: CDS inception and *Emp_growth*

Variable	(1) Closest one	(2) Closest one PS diff. $< 1\%$	(3) Closest two	(4) Closest two PS diff. $< 1\%$	(5) IV approach
CDS_trading	-0.025^{***}	-0.024^{***}	-0.026^{***}	-0.025^{***}	
	(0.007)	(0.007)	(0.006)	(0.006)	
CDS_trading_IV					-0.050^{***}
					(0.009)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.248	0.246	0.250	0.250	0.228
N	10,053	9,888	14,412	13,661	31,094

Panel B: CDS inception and *Investment_rate*

Variable	(1) Closest one	(2) Closest one PS diff. $< 1\%$	(3) Closest two	(4) Closest two PS diff. $< 1\%$	(5) IV approach
CDS_trading	-0.006^{***}	-0.006^{**}	-0.006^{***}	-0.005^{***}	
	(0.002)	(0.002)	(0.002)	(0.002)	
CDS_trading_IV					-0.010^{***}
					(0.004)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.039	0.039	0.038	0.036	0.037
N	39,416	38,766	56,973	53,980	121,091

Table 3.9: CDS inception and operating leverage

This table reports the effect of CDS inception on operating leverage. Columns (1)–(4) present results for a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) gives the results when an instrumental variable approach is adopted. In panel A (panel B), I use firm-year observations to run the panel regressions of *Book_operating_leverage* (*Market_operating_leverage*) on *CDS_trading*, and account for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A more detailed description of the variables is given in Appendix 3.1.

Panel A: CDS inception and *Book_operating_leverage*

Variable	**(1) Closest one**	**(2) Closest one PS diff. < 1%**	**(3) Closest two**	**(4) Closest two PS diff. < 1%**	**(5) IV approach**
CDS_trading	−0.010	−0.009	−0.007	−0.005	
	(0.011)	(0.011)	(0.011)	(0.010)	
CDS_trading_IV					0.016
					(0.020)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.145	0.145	0.151	0.150	0.188
N	10,307	10,135	15,025	14,252	32,904

Panel B: CDS inception and *Market_operating_leverage*

Variable	**(1) Closest one**	**(2) Closest one PS diff. < 1%**	**(3) Closest two**	**(4) Closest two PS diff. < 1%**	**(5) IV approach**
CDS_trading	0.006	0.010	0.008	0.01	
	(0.027)	(0.027)	(0.024)	(0.024)	
CDS_trading_IV					0.054
					(0.042)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.073	0.071	0.078	0.076	0.093
N	10,307	10,135	15,025	14,252	32,904

Table 3.10: CDS inception and firm value volatility: Asset volatility measure of Choi and Richardson (2016)

This table reports the effect of CDS inception on firm value volatility as derived using the asset volatility measure of Choi and Richardson (2016). Columns (1)–(4) present results for a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) gives the results when an instrumental variable approach is adopted. I run the panel regressions of $\ln(\sigma_V)$ on *CDS_trading*, and on other control variables, while accounting for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A more detailed description of the variables is given in Appendix 3.1.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) IV approach**
CDS_trading	-0.021^{**}	-0.019^{*}	-0.020^{**}	-0.018^{*}	
	(0.010)	(0.010)	(0.009)	(0.009)	
CDS_trading_IV					-0.077^{***}
					(0.022)
Control variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.218	0.220	0.214	0.213	0.180
N	96,336	92,789	134,475	121,214	143,905

Table 3.11: CDS inception and firm value volatility: Propensity score matching model of Martin and Roychowdhury (2015)

This table reports the effect of CDS inception on firm value volatility for the sample that includes CDS firms and also their matched non-CDS firms. I follow Martin and Roychowdhury (2015) to estimate the propensity scores and select the matched non-CDS firms. Panel A reports the results of propensity score modeling, and Panel B presents the panel regression results. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are reported in parentheses. Detailed descriptions of the variables are provided in Appendix 3.1.

Panel A: Propensity score modeling		Panel B: Regression results				
Variable	**Coefficient**	**Variable**	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**
$\ln(Equity)$	0.610***	*CDS_trading*	−0.026*	−0.025*	−0.024*	−0.025*
	(0.004)		(0.014)	(0.014)	(0.013)	(0.013)
Investment_grade	0.401***	*Leverage*	−0.108	−0.103	−0.114*	−0.096
	(0.010)		(0.068)	(0.068)	(0.058)	(0.059)
SP_rating	1.276***	*Firm_age*	−0.156***	−0.153***	−0.162***	−0.168***
	(0.010)		(0.031)	(0.031)	(0.026)	(0.026)
Leverage_book_value	1.439***	*R&D_ratio*	0.024	0.024	0.052**	0.051**
	(0.025)		(0.020)	(0.020)	(0.026)	(0.026)
Net_income_ratio	0.019***	*Excess_return*	−0.129***	−0.130***	−0.125***	−0.127***
	(0.003)		(0.009)	(0.009)	(0.008)	(0.008)
Equity_volatility_year	0.132***	*MB_ratio*	0.080***	0.080***	0.076***	0.076***
	(0.008)		(0.007)	(0.007)	(0.007)	(0.007)
MB_ratio_equity	−0.067***	$\ln(Equity)$	−0.097***	−0.094***	−0.083***	−0.083***
	(0.001)		(0.014)	(0.014)	(0.012)	(0.013)
Industry fixed effects	Yes	Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Year fixed effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.625	Adj. R^2	0.400	0.399	0.396	0.394
N	612,305	N	154,544	152,959	222,420	213,645

Table 3.12: CDS inception and firm value volatility: Excluding financial firms

This table reports the effect of CDS inception on firm value volatility when I use the sample that excludes financial firms. Columns (1)–(4) present results based on a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) gives the results derived when using an instrumental variable approach. I run the panel regressions of $\ln(\sigma_V)$ on *CDS_trading*, and on other control variables, while accounting for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for more details about the variables.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) IV approach**
CDS_trading	-0.044^{***}	-0.046^{***}	-0.037^{**}	-0.040^{***}	
	(0.017)	(0.017)	(0.015)	(0.016)	
CDS_trading_IV					-0.106^{***}
					(0.025)
Leverage	0.273^{***}	0.265^{***}	0.232^{***}	0.238^{***}	-0.183^{***}
	(0.077)	(0.077)	(0.066)	(0.067)	(0.033)
Firm_age	-0.234^{***}	-0.233^{***}	-0.240^{***}	-0.238^{***}	-0.223^{***}
	(0.037)	(0.037)	(0.030)	(0.031)	(0.020)
R&D_ratio	0.047^{***}	0.046^{***}	0.008	0.008	0.009^{**}
	(0.013)	(0.013)	(0.020)	(0.020)	(0.004)
Excess_return	-0.104^{***}	-0.103^{***}	-0.091^{***}	-0.090^{***}	-0.067^{***}
	(0.009)	(0.010)	(0.008)	(0.008)	(0.005)
MB_ratio	0.029^{***}	0.031^{***}	0.031^{***}	0.033^{***}	0.055^{***}
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
ln(*Equity*)	0.055^{***}	0.048^{***}	0.037^{**}	0.030^{**}	-0.081^{***}
	(0.017)	(0.017)	(0.015)	(0.015)	(0.007)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.372	0.372	0.373	0.375	0.326
N	120,292	118,237	173,276	164,749	313,632

Table 3.13: CDS inception and firm value volatility: Quarterly data frequency

This table reports the effect of CDS inception on firm value volatility when using firm-quarter observations. Columns (1)–(4) present results based on a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) reports the results when adopting an instrumental variable approach. I run the panel regressions of $\ln(\sigma_V)$ on *CDS_trading*, and on other control variables, while accounting for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for additional details.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) IV approach**
CDS_trading	-0.045^{***}	-0.052^{***}	-0.031^{**}	-0.040^{***}	
	(0.016)	(0.016)	(0.015)	(0.015)	
CDS_trading_IV					-0.118^{***}
					(0.024)
Leverage	0.235^{***}	0.231^{***}	0.231^{***}	0.208^{***}	-0.172^{***}
	(0.085)	(0.085)	(0.069)	(0.071)	(0.032)
Firm_age	-0.194^{***}	-0.206^{***}	-0.229^{***}	-0.234^{***}	-0.217^{***}
	(0.031)	(0.032)	(0.024)	(0.025)	(0.018)
R&D_ratio	0.046	0.046	0.029	0.029	0.013^{**}
	(0.029)	(0.029)	(0.025)	(0.025)	(0.006)
Excess_return	-0.114^{***}	-0.112^{***}	-0.114^{***}	-0.114^{***}	-0.072^{***}
	(0.010)	(0.010)	(0.008)	(0.008)	(0.005)
MB_ratio	0.025^{***}	0.026^{***}	0.017^{***}	0.019^{***}	0.059^{***}
	(0.008)	(0.008)	(0.006)	(0.007)	(0.005)
	(0.004)				
ln(*Equity*)	0.053^{***}	0.048^{***}	0.071^{***}	0.063^{***}	-0.090^{***}
	(0.017)	(0.017)	(0.014)	(0.015)	(0.007)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.387	0.385	0.393	0.390	0.333
N	44,331	43,319	64,286	60,703	116,825

Table 3.14: Financial constraints, CDS–bond basis, and CDS trading effects

This table reports the effect of CDS inception on firm value volatility as a function of financial constraints, or the absolute value of the CDS–bond basis. I report results only for a sample that includes CDS firms and their "Closest one" propensity score matched non-CDS firms. I use the financial constraints index proposed by Whited and Wu (2006) (the WW index) and the dividend payer indicator as proxies for financial constraints, given that (a) a higher WW index signifies a tighter financial constraint and (b) firms that do not pay a dividend tend to be more financially constrained. The CDS–bond basis is the difference between the quoted and par-equivalent CDS spread on a given reference entity. As before, *WW* is an indicator set equal to 1 if the focal firm's WW index exceeds the cross-sectional median (and set to 0 otherwise); *DV* is a dummy variable set equal to 1 if the firm pays a zero dividend (and set to 0 otherwise); and *ABS* is a dummy variable set equal to 1 if the absolute values of the focal firm's CDS–bond basis is above the cross-sectional median (and is set to 0 otherwise). All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. All variables are defined in Appendix 3.1.

	Propensity score matching model of Martin and Roychowdhury (2015)			Excluding financial firms			Asset volatility measure of Choi and Richardson (2016)		
Variable	***WW***	***DV***	***ABS***	***WW***	***DV***	***ABS***	***WW***	***DV***	***ABS***
CDS_trading	-0.102^{***}	-0.160^{***}	-0.100^{***}	-0.121^{***}	-0.135^{***}	-0.062^{**}	-0.056^{***}	-0.084^{***}	-0.030^{*}
	(0.019)	(0.048)	(0.025)	(0.022)	(0.049)	(0.028)	(0.014)	(0.021)	(0.017)
CDS_trading × *WW*	0.125^{***}			0.131^{***}			0.059^{***}		
	(0.024)			(0.027)			(0.017)		
CDS_trading × *DV*		0.144^{***}			0.099^{**}			0.068^{***}	
		(0.049)			(0.050)			(0.022)	
CDS_trading × *ABS*			0.015			0.030^{***}			0.002
			(0.011)			(0.011)			(0.007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.402	0.401	0.454	0.374	0.372	0.453	0.220	0.219	0.196
N	154,544	154,544	59,749	120,292	120,292	45,918	96,336	96,336	37,515

Figure 3.1: Changes in firm value volatility following CDS inception.
This figure plots cross-sectional average changes in $\ln(\sigma_V)$ for the CDS firms and their "Closest one" matched non-CDS firms before and after the inception of CDS trading. I calculate the changes in $\ln(\sigma_V)$ from one year before the CDS inception to zero, one, two, and three years thereafter.

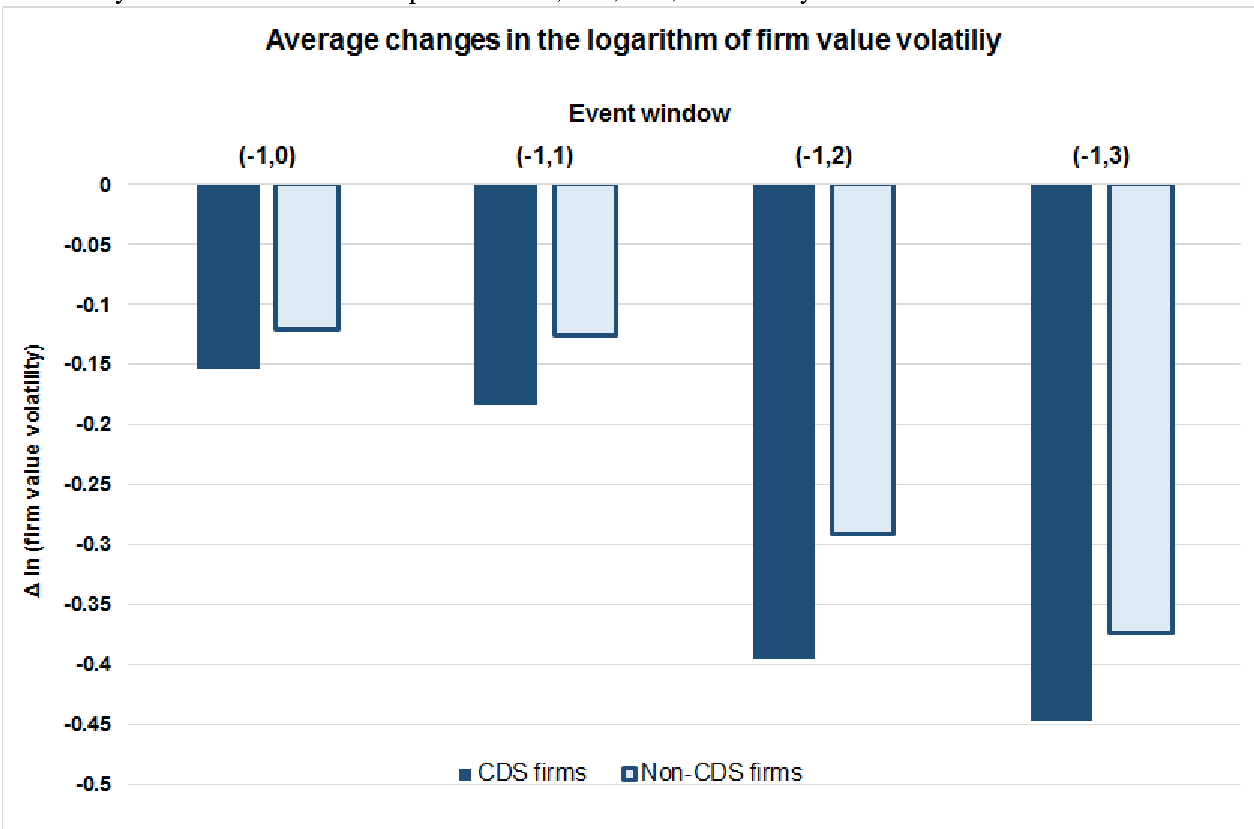


Table A1: Financial constraints and the effect of CDS inception: Propensity score matching model of Martin and Roychowdhury (2015)

This table reports the effect of CDS inception on firm value volatility as a function of financial constraints. I use the financial constraints index proposed by Whited and Wu (2006) (the WW index), and also the dividend payer indicator, as proxies for financial constraints. A higher WW index means that financial constraints are tighter; and firms that do not pay a dividend tend to be more financially constrained. I use the interaction terms $CDS\_trading \times WW$ and $CDS\_trading \times DV$ to capture the difference in CDS effects between more and less financially constrained firms; here WW is an indicator set equal to 1 if the firm has a WW index above the cross-sectional median upon inception of CDS (and set to 0 otherwise), and DV is a dummy variable set equal to 1 (0) for firms that do not (do) pay dividends when CDS trading begins. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is given in Appendix 3.1.

	WW index				**Dividend payer indicator**			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS Trading	-0.102^{***}	-0.101^{***}	-0.098^{***}	-0.094^{***}	-0.160^{***}	-0.158^{***}	-0.160^{***}	-0.159^{***}
	(0.019)	(0.020)	(0.019)	(0.019)	(0.048)	(0.048)	(0.0475)	(0.048)
$CDS\ Trading \times WW$	0.125^{***}	0.125^{***}	0.124^{***}	0.120^{***}				
	(0.024)	(0.024)	(0.024)	(0.024)				
$CDS\ Trading \times DV$					0.144^{***}	0.143^{***}	0.146^{***}	0.145^{***}
					(0.049)	(0.049)	(0.049)	(0.049)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.402	0.401	0.397	0.397	0.401	0.400	0.396	0.395
N	154,544	152,959	222,420	213,645	154,544	152,959	222,420	213,645

Table A2: Financial constraints and the effect of CDS inception: Excluding financial firms

This table reports the effect of CDS inception on firm value volatility as a function of financial constraints. I use the financial constraints index proposed by Whited and Wu (2006) (the WW index), and also the dividend payer indicator, as proxies for financial constraints. A higher WW index means that financial constraints are tighter; and firms that do not pay a dividend tend to be more financially constrained. I use the interaction terms $CDS\_trading \times WW$ and $CDS\_trading \times DV$ to capture the difference in CDS effects between more and less financially constrained firms; here WW is an indicator set equal to 1 if the firm has a WW index above the cross-sectional median upon inception of CDS (and set to 0 otherwise), and DV is a dummy variable set equal to 1 (0) for firms that do not (do) pay dividends when CDS trading begins. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is given in Appendix 3.1.

	WW index				**Dividend payer indicator**			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS Trading	-0.121^{***}	-0.124^{***}	-0.107^{***}	-0.117^{***}	-0.135^{***}	-0.138^{***}	-0.131^{***}	-0.134^{***}
	(0.022)	(0.022)	(0.021)	(0.020)	(0.049)	(0.049)	(0.049)	(0.049)
$CDS\ Trading \times WW$	0.131^{***}	0.133^{***}	0.118^{***}	0.135^{***}				
	(0.027)	(0.027)	(0.027)	(0.027)				
$CDS\ Trading \times DV$					0.099^{**}	0.100^{**}	0.102^{**}	0.102^{**}
					(0.050)	(0.050)	(0.050)	(0.051)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.374	0.375	0.375	0.374	0.372	0.372	0.374	0.375
N	120,292	118,237	173,276	164,749	120,292	118,237	173,276	164,749

Table A3: Financial constraints and the effect of CDS inception: The alternative asset volatility measure of Choi and Richardson (2016)

This table reports the effect of CDS inception on firm value volatility as a function of financial constraints. I use the financial constraints index proposed by Whited and Wu (2006) (the WW index), and also the dividend payer indicator, as proxies for financial constraints. A higher WW index means that financial constraints are tighter; and firms that do not pay a dividend tend to be more financially constrained. I use the interaction terms $CDS\_trading \times WW$ and $CDS\_trading \times DV$ to capture the difference in CDS effects between more and less financially constrained firms; here WW is an indicator set equal to 1 if the firm has a WW index above the cross-sectional median upon inception of CDS (and set to 0 otherwise), and DV is a dummy variable set equal to 1 (0) for firms that do not (do) pay dividends when CDS trading begins. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is given in Appendix 3.1.

	WW index				**Dividend payer indicator**			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS Trading	-0.056^{***}	-0.055^{***}	-0.053^{***}	-0.055^{***}	-0.084^{***}	-0.081^{***}	-0.082^{***}	-0.081^{***}
	(0.014)	(0.014)	(0.013)	(0.013)	(0.021)	(0.021)	(0.021)	(0.021)
$CDS\ Trading \times WW$	0.059^{***}	0.065^{***}	0.057^{***}	0.068^{***}				
	(0.017)	(0.017)	(0.017)	(0.017)				
$CDS\ Trading \times DV$					0.068^{***}	0.068^{***}	0.069^{***}	0.070^{***}
					(0.022)	(0.022)	(0.022)	(0.022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.220	0.222	0.216	0.218	0.219	0.221	0.215	0.214
N	96,336	92,789	134,475	121,214	96,336	92,789	134,475	121,214

Table A4: CDS-bond basis and the effect of CDS inception: Propensity score matching model of Martin and Roychowdhury (2015)

This table reports the effect of CDS inception on firm value volatility as a function of the absolute value of the CDS–bond basis. I use the interaction term *CDS_trading* $\times$ *ABS* in the regressions to capture the difference in CDS effects between the CDS firms with high and low absolute values of the CDS–bond basis, where *ABS* is a dummy variable set equal to 1 if the absolute value of the focal firm's CDS–bond basis is above the cross-sectional median (and set to 0 otherwise). The CDS–bond basis is the difference between the quoted and par-equivalent 5-year CDS spread of a given reference entity. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS Trading	-0.100^{***}	-0.097^{***}	-0.103^{***}	-0.103^{***}
	(0.025)	(0.025)	(0.025)	(0.025)
CDS Trading $\times$ *ABS*	0.015	0.016	0.011	0.015
	(0.011)	(0.010)	(0.009)	(0.010)
Control variables	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.454	0.451	0.448	0.444
N	59,749	59,094	81,494	77,817

Table A5: CDS-bond basis and the effect of CDS inception: Excluding financial firms

This table reports the effect of CDS inception on firm value volatility as a function of the absolute value of the CDS–bond basis. I use the interaction term $CDS\_trading \times ABS$ in the regressions to capture the difference in CDS effects between the CDS firms with high and low absolute values of the CDS–bond basis, where *ABS* is a dummy variable set equal to 1 if the absolute value of the focal firm's CDS–bond basis is above the cross-sectional median (and set to 0 otherwise). The CDS–bond basis is the difference between the quoted and par-equivalent 5-year CDS spread of a given reference entity. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS Trading	-0.062^{**}	-0.061^{**}	-0.079^{***}	-0.081^{***}
	(0.028)	(0.029)	(0.027)	(0.028)
$CDS\ Trading \times ABS$	0.030^{***}	0.031^{***}	0.029^{***}	0.030^{***}
	(0.011)	(0.012)	(0.009)	(0.010)
Control variables	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.453	0.451	0.442	0.441
N	45,918	45,065	62,953	59,664

Table A6: CDS-bond basis and the effect of CDS inception: The alternative asset volatility measure of Choi and Richardson (2016)

This table reports the effect of CDS inception on firm value volatility as a function of the absolute value of the CDS–bond basis. I use the interaction term $CDS\_trading \times ABS$ in the regressions to capture the difference in CDS effects between the CDS firms with high and low absolute values of the CDS–bond basis, where *ABS* is a dummy variable set equal to 1 if the absolute value of the focal firm's CDS–bond basis is above the cross-sectional median (and set to 0 otherwise). The CDS–bond basis is the difference between the quoted and par-equivalent 5-year CDS spread of a given reference entity. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
$CDS\ Trading$	-0.030^{*}	-0.023	-0.039^{**}	-0.036^{**}
	(0.017)	(0.017)	(0.016)	(0.017)
$CDS\ Trading \times ABS$	0.002	0.000	0.005	0.004
	(0.007)	(0.007)	(0.006)	(0.006)
Control variables	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
$Adj.\ R^2$	0.196	0.201	0.203	0.203
N	37,515	36,535	48,631	44,342

Table A7: Lender bargaining power and the effect of CDS inception

This table reports the effect of CDS inception on firm value volatility as a function of the lender bargaining power. I use the interaction term *CDS_trading* $\times$ *Lender_FX_hedging* in the regressions to capture the difference in CDS effects for the CDS firms with different levels of *Lender_FX_hedging*, where *Lender_FX_hedging* measures the foreign exchange hedging activities of the firm's banks and underwriters. The higher value of *Lender_FX_hedging* implies the higher level of the lender bargaining power. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 3.1 for a detailed description of the variables.

Variable	*CDS_trading*
CDS_trading	−0.0508***
	(0.0138)
CDS_trading $\times$ *Lender_FX_hedging*	−0.616*
	(0.334)
Lender_FX_hedging	0.0798
	(0.200)
Leverage	−0.178***
	(0.0338)
Firm_age	−0.191***
	(0.0191)
R&D_ratio	0.0129*
	(0.00696)
Excess_return	−0.0638***
	(0.00518)
MB_ratio	0.0627***
	(0.00465)
ln(*Equity*)	−0.0975***
Firm Fixed Effect	Yes
Year Fixed Effect	Yes
Adj. R^2	0.332
N	321,788

Chapter 4

Credit Default Swaps and Corporate Debt Maturity Profiles

4.1 Introduction

This paper studies the impact of CDS inception on debt maturity dispersion (or debt granularity). Debt maturity dispersion reflects the choice between dispersed and concentrated maturity structures and is an important aspect of the debt structure that affects the rollover risk. Choi, Hackbarth, and Zechner (2018, 2021) investigate the granularity of corporate debt both theoretically and empirically. Choi et al. (2018) show that the higher rollover risk after the event of the Ford/GM downgrade in 2005 led to the greater dispersion in new debt issuance, particularly for high-leverage firms. Choi et al. (2021) document a higher debt granularity for larger and more mature firms, for firms with higher leverage, and for firms with lower profitability. In addition, Huang, Oehmke, and Zhong (2019) develop a multi-period debt financing model and show that firms with high leverage, low profitability, and a large safe cash-flow component (e.g. mature firms) are more likely to choose dispersed maturity profiles. In the strand of literature regarding credit default swaps, Saretto and Tookes (2013) provide evidence of the impact of credit default swaps on corporate debt maturity. However, they only consider the average maturity of the focal firms' debt liabilities. Chen, Saffar, Shan, and Wang (2018) study the impact of CDS inception on the choice between public and private debt. No empirical research investigates whether firms manage the dispersion of their debt maturity profiles in response to the inception of CDS trading. Therefore, this study will fill this gap in the literature.

Both demand-side and supply-side theories explain the effect of CDS inception on firms' debt maturity dispersion. Demand-side effects stem from the empty creditor effect. Credit insurance makes the creditors empty in that they have no desire to preserve a company to which they provide funds, thus increasing their bargaining power. Such an increase could then lead to a more likely threat that the borrowing firms will be unable to refinance their debt. In the framework of Choi et al.'s (2018) model, [1] an increase in refinancing risk due to the increased bargaining power of creditors motivates CDS firms to choose a more dispersed debt maturity structure (the tougher creditor effect). On the supply side, CDS inception has two effects since it reduces the frictions of the credit supply. First, it enables creditors to lend more. This impact reduces the refinancing risk and decreases firms' motivation to spread out their debt maturities (the commitment effect). Second, CDS inception reduces the cost of diversifying debt portfolios. This effect will incentivize firms to shift towards a dispersed maturity structure (the cost reduction effect). In a nutshell, how CDS inception affects firms' debt maturity structure depends on the combination of the three potential effects.

[1] In Section 4.2, I discuss the framework in details.

I follow Choi et al. (2018) and measure maturity dispersion by grouping each firm's debt maturities into the nearest integer years and computing the fractions of amounts outstanding each year. I employ two measures of debt maturity dispersion: first, the inverse of the maturity profile's Herfindahl index based on these fractions; second, the average squared distance between a firm's actual maturity profile and its perfectly dispersed maturity profile of equal fractions maturing each year up to the longest maturity. Using these empirical measures of debt maturity dispersion, I investigate whether the inception of CDS trading affects the focal firm's maturity profile.

My baseline results using data from the whole sample suggest that corporate debt maturity dispersion increases after the introduction of CDS trading. The positive relationship between the inception of CDS trading and the dispersion of debt maturity is statistically and economically significant. After controlling for firm characteristics, including the market-to-book ratio, size, age, leverage, profitability, tangibility, cash flow risk, and debt maturity, the inception of CDS trading increases the focal firm's debt maturity dispersion by around 18.1% of one standard deviation. When I use the CDS firms with their closest one matched non-CDS firms in the regression, debt maturity dispersion increases by around 12.6% of one standard deviation after the CDS inception. I obtain similar results when using other matched samples. The positive impact is around 55.7% of one standard deviation if I use the instrumental variable approach. These results suggest that the focal firms tend to spread out their debt maturity after the inception of CDS trading, supporting the hypothesis that the *tougher creditor effect* and the *cost reduction effect* dominates the *commitment effect*.[2]

I also provide evidence that the credit supply is one channel through which the inception of CDS trading affects debt maturity dispersion. To disentangle this channel, I examine the CDS

[2] In Section 4.2, I discuss this hypothesis in details.

effect to determine whether it becomes stronger during times when credit market conditions tighten. I measure the credit market condition using the Federal Reserve's Senior Loan Officers Opinion Survey (SLOOS) responses to questions on loan spread increases and lending criteria tightening. A higher value of the SLOOS index implies increased tightening in the credit market condition. I document that the increased debt maturity dispersion due to CDS inception is stronger during periods of tighter credit market conditions. This finding is consistent with Saretto and Tookes's 2013 statement that CDS inception increases the credit supply.

Furthermore, I find that the impact of CDS inception on debt maturity dispersion exhibits heterogeneity for firms with different characteristics. Using the credit rating as the measure of firm quality, I find that the positive effect of CDS inception on maturity dispersion is more pronounced for high-quality firms. This result supports the hypothesis that higher–quality firms are more capable of spreading out their debt across maturities than lower-quality firms. The finding also reveals evidence that CDS inception affects debt maturity through the empty creditor channel.

My paper is close in spirit to that of Saretto and Tookes (2013) who investigate the effect of credit default swaps on firms' financing decisions including leverage and debt maturity, defined as the principal-weighted maturity of all debts. They show that firms are able to maintain a higher leverage ratio and longer debt maturity after credit default swaps have been traded on their debts. The positive relationship is stronger when the credit supply becomes tightened since borrowers benefit from a reduction in frictions on the supply side due to the increased ability of the capital supplier to hedge risk. In a recent study, Chen et al. (2018) find that firms use more public debt and less bank debt when CDSs are traded on their debts. My study extends those by Saretto and Tookes (2013) and Chen et al. (2018) by establishing the relationship between CDS inception and debt maturity dispersion, a new aspect of the debt structure. Second, while Saretto and Tookes (2013) focus on the change in credit supply as a channel for the effect of credit default swaps on firms' capital structure, I discuss a more comprehensive set of possibilities that covers both supply-side and demand-side economics. Third, I use a sample of all non-financial and non-utility firms for my analysis, which is also larger than the sample of non-financial firms in the S&P 500 index used by Saretto and Tookes (2013).

This paper contributes to two strands of the literature. First, it extends the extant literature on the impact of CDS trading on the corporate sector. Prior research documents the effects of CDS inception on firms' behaviors, including firm leverage and debt maturity (Saretto and Tookes, 2013), default risk (Subrahmanyam et al., 2014), reporting conservatism (Martin and Roychowdhury, 2015), cash holding (Subrahmanyam et al., 2017), firm value ((Danis and Gamba, 2018)), corporate innovation (Chang et al., 2019), and firm risk (Lin, Nguyen, Wang, and Zhang, 2019). I provide empirical evidence about the increase in debt maturity dispersion after the advent of CDS trading. The results show that firms manage their debt maturity profiles to deal with the precautionary change in the credit market due to the inception of CDS trading. My study also delivers more insights into the effect of CDS inception on the debt structure by expanding the findings of Saretto and Tookes (2013). While Saretto and Tookes (2013) concentrate on the impact of CDS trading on the average maturities of firms' debt, I document the positive impact of CDS inception on the dispersion of debt maturity. My findings suggest the importance of maturity dispersion as an aspect of the corporate debt structure and as a risk management tool.

Second, my study also helps to explain the variation in debt maturity dispersion. In the corporate finance literature, the debt maturity structure is a new research topic, which has just started to attract the attention of researchers. Several studies published in recent years document various determinants of debt maturity dispersion: rollover risk (Choi et al., 2018), firm size (Choi et al., 2018), leverage, and profitability (Choi et al., 2018; Huang et al., 2019), and cash flow risk (Huang et al., 2019). I contribute to this literature by establishing a link between the inception of CDS trading and the dispersion of debt maturity.

The rest of this paper proceeds as follows. In Section 4.2, I review the relevant literature and develop my hypotheses. Section 4.3 details my empirical methodology. Section 4.4 describes the data, and Section 4.5 presents my empirical results. In Section 4.6, I conduct several robustness tests. I conclude in Section 4.7 with a summary of my findings and a suggestion for future research.

4.2 Literature review and hypothesis development

4.2.1 Effect of CDS inception on debt maturity dispersion

I develop my main hypotheses using relevant theoretical models and empirical evidence from the literature. In particular, I discuss how the inception of CDS could affect debt maturity dispersion based on both demand- and supply-sides. I use the framework from Choi et al.'s (2018) model and other previous works in this field to support my economic intuition.

The demand-side argument focuses on the empty creditor effect, which could drive the relationship between CDS inception and debt maturity dispersion. "Empty creditor" means that the debt holder has no desire to preserve a company to which she provides funds. Bolton and Oehmke (2011) show that, in theory, this problem arises when a creditors have over-insured their credit risk by buying CDSs but still hold the control rights of the firms. With the credit insurance obtained through the CDS market, creditors have more bargaining power over borrowers in debt renegotiations. As I discussed earlier, an increase in creditors' bargaining power could lead to an increase in the threat that the borrowing firms will be unable to refinance their debt. Consistent with this idea, Clark et al. (2020) show that CDS inception decreases the probability of "amendments, restatements, and rollovers to existing lenders of bank loans". Choi et al. (2018) predict that firms will choose a more dispersed maturity structure due to an increase in refinancing risk. That is to say, the increase in refinancing risk due to the increased bargaining power of creditors motivates the CDS firms to choose a more dispersed debt maturity structure. I define this effect as the *tougher creditor effect* of CDS inception.

From the supply-side perspective, CDSs could also affect firms' financing decision through the credit supply channel. Saretto and Tookes (2013) argue that the CDS market increases the ability of capital suppliers to hedge their risks, thus reducing the friction on the supply side. They provide several reasons for this argument. First, creditors like banks and insurance companies have the opportunity to reduce the regulatory capital requirements by buying CDS to hedge their credit risks. The reduction in such requirements could increase the creditors' lending capability. As a result, the supply of credit to firms could rise if market segmentation exists between creditors who would like to lend more and CDS providers who are willing to hold credit risk. Second, for the purpose of maintaining client relationships, CDSs allows banks to provide debt while mitigating the portfolio risk. Finally, the existence of the CDS market could make holding corporate debt (credit risk) more attractive to creditors (bond investors) since such a market provides creditors with a liquid resale option.

Following Saretto and Tookes (2013), I expect that the frictions in the credit supply decline after the inception of CDSs. This reduction in the supply frictions may generate two effects. First, the increase in the credit supply may reduce the cost of debt insurance, which in turn decreases the cost of spreading out debt maturities.[3] Such a reduced cost will encourage firms to shift towards

[3]The cost occurs when a firm issue small, multiple debts instead of a big, single debt to achieve a more dispersed maturity structure (Choi et al., 2018).

a dispersed maturity structure. I present this effect as the *cost reduction effect* of CDS inception. Second, the increase in the ability of creditors to lend more after CDS inception could reduce firms' difficulty in refinancing their debt. This effect decreases firms' motivation to spread out their debt maturities. I define this effect as the *commitment effect* of CDS inception.

To summarize, the demand-side argument suggests the *tougher creditor effect* which predicts a positive relationship between CDS inception and maturity dispersion. Meanwhile, the supply-side argument implies the *cost reduction effect* and the *commitment effect*, which, respectively, predict the positive and negative associations between CDS inception and debt maturity dispersion. Hence, the net effect of CDS inception on debt maturity dispersion remains an empirical question. I formally test the following hypotheses:

Hypothesis 1a. If the combined effect from the *tougher creditor effect* and the *cost reduction effect* dominates the *commitment effect*, then the debt maturity dispersion will increase after the inception of CDS trading.

Hypothesis 1b. If the *commitment effect* dominates the combined effect from the *tougher creditor effect* and the *cost reduction effect* , then the debt maturity dispersion will decrease after the inception of CDS trading.

4.2.2 CDS inception and credit market conditions

Since the credit supply effect is more important for a firms when the credit market conditions are not favorable (Saretto and Tookes, 2013), I expect to find an association between the credit market conditions and the CDS effects. Although both the *cost reduction effect* and the *commitment effect* may become more pronounced during times of credit market tightening, the change in the net effect of CDS inception on maturity dispersion is not clear. Depending on which effect is more affected by the credit market conditions, I propose the following hypotheses:

Hypothesis 2a. During periods of a tightened credit market condition, if the *cost reduction effect* increases more than the *commitment effect* does, then the positive effect of CDS inception on debt maturity dispersion is stronger.

Hypothesis 2b. During periods of a tightened credit market condition, if the *cost reduction effect* increases less than the *commitment effect* does, then the positive effect of CDS inception on debt maturity dispersion is weaker.

4.2.3 CDS inception and firm quality

The *tougher creditor effect* suggests that the focal firm is more likely to increase its debt maturity dispersion after the inception of CDSs. Moreover, Servaes and Tufano (2006) argue that it is more affordable for higher–quality firms to spread out their debt maturities. Therefore, if the inception of CDSs affects the debt maturity dispersion through the tougher creditor channel, the positive effect of CDS inception on maturity dispersion is stronger for higher–quality firms. I thus propose the following hypothesis,

Hypothesis 3. *The positive effect of CDS inception on maturity dispersion is more pronounced for higher–quality firms.*

4.3 Empirical specification

4.3.1 Debt maturity dispersion measure

The dispersion of debt maturity contradicts the concentration of debt maturity, motivating me to use the Herfindahl index to measure the debt maturity dispersion. Following Choi et al. (2018), I employ my first measure of debt maturity dispersion using the Herfindahl index of the debt maturity structure. I define the Herfindahl index of firm i's debt maturity structure, $HERF_i$, as follows:

$$HERF_i = \sum_{j=1}^{N_i} w_{ij}^2, \tag{4.1}$$

where w_{ij} is the fraction of firm i's principal amounts maturing in each maturity bucket j and N_i is firm i's total number of maturity buckets. w_{ij} is given by

$$w_{ij} = \frac{x_{ij}}{\sum_{j=1}^{N_i} x_{ij}}. \tag{4.2}$$

where x_{ij} is firm i 's principal amounts maturing in maturity bucket j. To obtain the maturity buckets, I group bond maturities into the nearest integer years. $HERF_i$ measures the concentration of a firm's debt maturity structure. For example, if a firm's debt is all in maturity bucket k, then I have $w_{ij} = 1$ for $j = k$ and 0 otherwise. In this case, $HERF_i = 1$. If a firm's debt maturity is dispersed, $HERF_i$ will be much smaller than one. For a given $HERF_i$, the corresponding measure of debt maturity dispersion for firm i, DP_i, is given by:

$$DP_i = \frac{1}{HERF_i} = \frac{1}{\sum_{j=1}^{N_i} w_{ij}^2}. \tag{4.3}$$

Intuitively, the higher the value of DP, the more dispersed the debt maturity structure. It has a minimum value of one when the firm has only one debt maturity bucket. This means the firm's debt maturity structure is completely concentrated and the firm has the lowest level of maturity dispersion. An increase in the number of maturity buckets and a decrease in the principal amount maturing in each maturity bucket lead to a decrease in $HERF_i$ and an increase in DP_i.

Eq. (4.3) shows that the number of maturity buckets N also affects the calculation of DP. Choi et al. (2018) argue that the DP measure might reflect a firm's decision on both the maturity of debts and the dispersion of maturity. For example, if a firm can only issue debts with a maximum maturity of four years, its Herfindahl measure will be limited to 0.25, and then the value of DP will be constrained to 4. Generally, the value of DP_i is limited to the maximum maturity of debt that the firm could issue. To address this issue, Choi et al. (2018) propose an alternative measure of maturity dispersion that takes the firm's maximum debt maturity into consideration. This measure is based on the distance of a firm's actual maturity profile from the perfectly dispersed one. Specifically, I measure the distance for firm i, $DIST_i$, as follows:

$$DIST_i = \frac{1}{t_i^{max}} \sum_{j=1}^{t_i^{max}} (w_{ij} - \frac{1}{t_i^{max}})^2, \tag{4.4}$$

where t_i^{max} is firm i's maximum debt maturity proxied by the longest maturity of the outstanding debt at issuance. w_{ij} is the fraction of firm i's principal amounts maturing in maturity bucket j. If the firm's debt maturity is perfectly dispersed, I have $w_{ij} = \frac{1}{t_i^{max}}$ for all j and then $DIST_i = 0$. A higher value of $DIST_i$ means a more concentrated (less dispersed) debt maturity structure. I define my second measure of debt maturity dispersion, DP_dist_i, as follows:

$$DP\_dist_i = -\log(DIST_i). \tag{4.5}$$

I add a negative sign to reflect the fact that $DIST_i$ is negatively associated with debt maturity dispersion, and use the logarithm to reduce the skewness of $DIST_i$.[4] A higher value of DP_dist_i corresponds to a shorter distance from perfect dispersion and means a higher level of debt maturity dispersion. I use *DP* in my main analysis and *DP_dist* in my robustness test.

4.3.2 Determinants of debt maturity dispersion

I test the hypothesis in a panel regression framework. The dependent variable is the debt maturity dispersion measure as described in Section 4.3.1. I follow Ashcraft and Santos (2009) and Subrahmanyam et al. (2014) and use an indicator variable of CDS trading to estimate the impact of CDS trading on debt maturity dispersion. CDS trading is a dummy variable that equals 1 if a firm has CDS traded on its debt 1 year previously and 0 otherwise. I regress debt maturity dispersion on CDS trading and other control variables that are used as the determinants of debt maturity dispersion in the literature. I also account for firm and time effects. An unobserved firm effect occurs for a given firm when the residuals of the firm may be correlated across years, while a time effect occurs when the residuals of a given year may be correlated across different firms (Petersen, 2009). Assuming that there are unobserved time and firm effects that are fixed in my panel data, I control for both firm and time fixed effects. To provide more robust statistical results, I also cluster the standard errors at the firm level.

My regression model is written as follows:

$$DP_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \tag{4.6}$$

[4]Following Choi et al. (2018), I add 0.001 to DIST to avoid the case that DP_dist_i is negative infinity.

where $DP_{i,t}$ is the debt maturity dispersion measure that I use, $CDS\_trading$ is the key independent variable, which equals 1 if the firm has CDS traded on its debt 1 year previously and 0 otherwise, and $X_{i,t-1}$ is the vector of the control variable. β captures the impact of the inception of CDS trading on debt maturity dispersion.

I follow Choi et al. (2018) by including five fundamental determinants of debt maturity dispersion as my controlling variables. They are the market-to-book ratio (*MB_ratio*), firm size ($\ln(Assets)$), firm age (*Firm_age*), leverage (*Leverage*), and profitability (*Profitability*). I also control for the effect of pledgeability, the incremental effect of firm characteristics, and the effect of debt rollover ability by using tangibility (*Tangibility*), the average debt maturity (*DMAT*), and cash flow volatility (*CFV*), respectively. Appendix 4.1 provides a detailed description of the construction of these variables.

4.3.3 Endogeneity

An important concern about the CDS effect is that the inception of CDS trading might be endogenous in that the initiation of CDS trading on a firm's debt is not random. Such inception could be driven by the firm's characteristics including unobservable factors. At the same time, the firm might manage its debt maturity profiles in response to a change in unobservable factors that are correlated with the inception of CDS trading. The effect of CDS initiation on the dispersion of debt maturity could thus be spurious because of the omitted variable problem. To address this endogeneity problem, I follow Subrahmanyam et al. (2014), Martin and Roychowdhury (2015), and Lin et al. (2019) to employ a propensity score matching and an instrumental variable (IV) approach.

4.3.3.1 Propensity score matching

I first use the propensity score (PS) matched sample to reduce the impact of the endogeneity problem on my results since this approach can mitigate some biases caused by endogeneity (Roberts and Whited, 2013). I match the CDS firms and the non-CDS firms using propensity scores estimated using propensity score matching models. I form matched samples with the replacement approach, following Roberts and Whited (2013). In other words, each non-CDS firm may be used more than once for the matching purpose. Moreover, I use several alternatives for choosing matches. In particular, I use the following four matched samples in my analysis:

- "Closest one" sample: for each CDS firm, I choose the single non-CDS firm with the closest propensity score.
- "Closest two" sample: for each CDS firm, I choose the two non-CDS firms for which the propensity scores are the closest to the focal firm's score.
- "Closest one with a PS [propensity score] difference less than 1%"sample: for each CDS firm, I choose the single non-CDS firm for which the propensity score is the closest *provided that* the difference between these scores is less than 1%.
- "Closest two with a PS difference less than 1%" sample: for each CDS firm, I choose the two non-CDS firms with the closest propensity scores to the focal firm's score *provided that* the difference between that firm's score and both of the non-CDS firms' score is less than 1%.

Following Subrahmanyam et al. (2014) and Martin and Roychowdhury (2015), I use a probit model to estimate the probability of CDS inception:

$$\Pr(CDS\_traded_{i,t} = 1) = \Phi(\alpha + \beta \times X_{i,t}). \quad (4.7)$$

In this equation, *CDS_traded* is a dummy variable set equal to 1 for firms for which credit default swaps are traded during my sample period (and 0 for other firms); X is a vector of covariates that could be determinants of the CDS trading probability; and industry-level and year fixed effects are included in the regression. I use this probability of CDS trading to calculate the propensity scores when constructing the various matched samples.

4.3.3.2 Instrumental variable approach

I apply the instrumental variable approach by using an instrument that has a direct effect on the inception of CDS trading but no direct impact on the debt maturity dispersion. The instrumental variable is expected to affect the main variable of interest only indirectly through the inception of CDS trading. Following Saretto and Tookes (2013), Subrahmanyam et al. (2014), and Lin et al. (2019), I use *Lender_FX_hedging* as the instrumental variable. Given that *Lender_FX_hedging* measures the lenders' and underwriters' foreign exchange hedging activities, this instrument is valid for two reasons. First, *Lender_FX_hedging* could drive the inception of CDSs. Prior studies provide evidence that banks tend to hedge more than one component of their portfolios. For example, Minton et al. (2009) document that banks with a large notional volume of foreign exchange derivatives for hedging purposes are more likely to hedge credit risk by buying a CDS on a borrower's debt. This phenomenon induces the introduction of CDS trading on the borrower's debt. Second, the foreign exchange derivatives activities of banks are not likely to affect their borrower's debt structure decision directly. The intuition behind this is that the borrower and bank are usually in the same country while foreign exchange activities are more likely relevant to third parties in a foreign country. Because *CDS_trading* is a dummy variable, I use a probit model in the first stage. To avoid problems due to an incorrect nonlinear model in the first stage, I follow Angrist and Pischke (2008) and Lin et al. (2019) and apply a three-stage procedure to estimate the coefficients. In the first stage, I estimate the predicted value of $CDS\_trading$ ($CDS\_trading\_IV$) using the following probit model that regresses $CDS\_trading$ on the control variables and the instrumental variable, $Lender\_FX\_hedging$,

$$CDS\_trading\_IV_{i,t} = \Phi(\alpha + \beta \times X_{i,t-1} + \gamma \times Z_{i,t}), \tag{4.8}$$

where Z is the instrumental variable, $Lender\_FX\_hedging$. X is the vector of all control variables in Eq. (4.6). I also control for industry-level and year fixed effects in the regression model. In the next step, I use $CDS\_trading\_IV$ as an instrument for $CDS\_trading$ in a conventional two-stage least squares (2SLS) procedure.

4.4 Data

I use data from Markit to identify the inception of CDS trading, defined as the date on which the focal firm's CDS spread quote first appears in Markit. The primary dependent variable is the debt maturity dispersion measure, DP, which is estimated using the inverse of the maturity profile's Herfindahl index, as proposed by Choi et al. (2018). I use the Capital IQ database from Standard and Poor's and the merged database of Compustat and the Center for Research in Security Prices (CRSP) to calculate the annual maturity dispersion measure for the sample firms. My CDS data cover the period from 2002 to 2012 since the majority of CDS inceptions occur before 2013. The firms that I consider are those with stocks listed on the NYSE, AMEX, or Nasdaq. I use six-digit numbers from the Committee on Uniform Securities Identification Procedures (CUSIP) to match CDS data from Markit with information from the Compustat–CRSP database. I follow

Colla, Ippolito, and Li (2013) and Choi et al. (2018) to exclude financial firms (Standard Industrial Classification (SIC) codes 6000–6999) and utility firms (SIC codes 4900–4999).

Panel A of Table 4.1 presents the number of firms for the whole sample between 2001 and 2012. The second column shows the total number of US companies included in the sample. The number of firms gradually decreases during this period: from 3,604 firms in 2001 to 3,076 firms in 2012. The table's third column reports the number of non-financial and non-utility firms for which CDS trading was initiated during that year. In line with the figures reported by Subrahmanyam et al. (2017), CDS inception occurs more frequently before 2005. Whereas 518 ($1+304+91+87+35$) firms undertook CDS trading before 2005, only 63 firms ($20+26+4+0+4+7+2$) did so after 2005. My final sample includes 581 firms for which CDS inception occurred within the 2001–2012 period.

[INSERT Table 4.1 about Here]

Panel B of Table 4.1 provide summary statistics for the variables capturing the firm characteristics of all firms, CDS firms, and non-CDS firms. I report the results for *DP*, *DP_dist*, *DMAT*, *MB_ratio*, ln(*Assets*), *Firm_age*, *Leverage*, *Profitability*, *Tangibility*, and *CFV*. For each variable, I report the number of observations (*N*), mean, standard deviation (S.D.), skewness, and kurtosis as well as the 25th, 50th, and 75th percentile values. All the variables are winsorized at the 1st and 99th percentiles, a procedure that mitigates the impact of outliers. The reported figures show that CDS firms tend to have greater dispersion of their debt maturity profiles than non-CDS firms. For example, the mean *DP* of CDS firms is 3.834 whereas that for non-CDS firms is only 1.742. Meanwhile, the mean *DP_dist* for the CDS and non-CDS firms is 4.163 and 2.498, respectively.

Lender_FX_hedging is a key variable that I use in propensity score matching and in my IV approach. It measures the foreign exchange hedging activities of banks and underwriters and is defined as the notional volume of FX derivatives used for hedging—and not trading—purposes *divided by* the total assets of all the banks that have served the firm as either lenders or bond underwriters over the previous 5 years (Subrahmanyam et al., 2014). For each firm in my sample, I identify its main lenders and bond underwriters based on information from (respectively) Dealscan and the Fixed Income Securities Database (FISD). For the lenders' information, I use Gvkey to match the Compustat and Dealscan data via the link provided by Chava and Roberts (2008). For the underwriters' information, I use 6-digit CUSIP numbers to match the data between Compustat and the FISD. Finally, I collect bank-related information—including the total assets, activity in credit derivatives and/or FX hedging, and Tier-1 capital ratios—from the US Federal Reserve's call report. The call report data, Dealscan, and FIDS do not have a common identifier, so I manually match their data by name, state, and other information of the relevant banks. I next turn to the empirical analysis.

4.5 Empirical results

4.5.1 CDS inception and debt maturity dispersion: Baseline model

I start my empirical analysis by runing the baseline regression of Eq. (4.6). Table 4.2 reports the results. My variable of interest is the coefficient for *CDS_trading*, which measures the impact of CDS inception on debt maturity dispersion.

[INSERT Table 4.2 about Here]

First, I use only the *CDS_trading* variable in the panel regression and control for firm and year fixed effects; this is Model (1) in Table 4.2. The coefficient for *CDS_trading* is 0.315 and is significant at the 1% level. A coefficient with a positive value means that the debt maturity dispersion increases after the inception of CDS trading. Specifically, after the CDS starts trading, debt maturity dispersion increases by 0.315, which corresponds to 19.1% of one standard deviation for the full sample (1.652 reported in Panel B of Table 4.1). Next, I introduce other control variables into the regressions (Models (2) and (3) in the table). The coefficients for *CDS_trading* continue to be significantly positive: 0.294 in Model (2) and 0.299 in Model (3), both of which are significant at the 1% level. The coefficient of 0.299 in Model (3) indicates that after I control for other variables, the *DP* increases by around 18.1% of one-standard-deviation after the CDS inception (0.299/1.652). These results suggest that the increase in debt maturity dispersion due to CDS trading is robust to controlling for other firm characteristics, which supports Hypothesis 1a. I also find that the control variables have significant impacts on the debt maturity dispersion. For example, the coefficient of *Leverage* is significantly positive in Models (2) and (3), which suggests that firms with higher leverage tend to have greater debt maturity dispersion. The significantly positive coefficient of ln(*Assets*) implies that lager firms tend to have greater debt maturity dispersion. These results are consistent with Choi et al.'s (2021) findings.

4.5.2 Endogeneity

4.5.2.1 Propensity score matching

4.5.2.1.1 Propensity score matched sample

I use Eq. (4.7) to estimate the probability of CDS inception, which I then use as my propensity score for constructing the matched samples. First, I follow Subrahmanyam et al. (2014) and use the following covariates: ln(*Assets*), *Leverage*, *ROA*, *Excess_return*, *Equity_volatility*, *Tangibility*, *Sales_ratio*, *EBIT_ratio*, *WCAP_ratio*, *RE_ratio*, *Cash_ratio*, *CAPX_ratio*, *SP_rating*, *Unsecured_debt*, *Lender_FX_hedging*, *Lender_Tier1_capital*, *Lender_credit_derivative*, and *Lender_size*.[5] This model underlies my primary method of constructing the matched samples. Also following Subrahmanyam et al. (2014), I use monthly data to run the propensity score regression.[6]

Panel A of Table 4.3 reports my propensity score regression results. Most of the explanatory variables have a significant effect on the probability of CDS trading. For example, the coefficient for ln(*Assets*) is significantly positive with a value of 0.760, suggesting that CDS trading is more likely to involve large firms than small ones. The regression results also indicate that firms with higher leverage are more likely to have credit default swaps being traded on their debt. CDS trading is more likely to occur for firms with a relatively higher tangible asset ratio, sales-to-assets ratio, and/or profitability. The probability of CDS initiation is greater for rated firms and for firms with a higher unsecured debts–total assets ratio.

[INSERT Table 4.3 about Here]

The coefficient for *Lender_FX_hedging* is 2.688, which is significant at the 1% level. This significantly positive coefficient shows that credit default swaps are more likely to be traded on firms with banks that are relatively more involved in foreign exchange hedging activities—a result that is consistent with the findings of Saretto and Tookes (2013) and Subrahmanyam et al. (2014). The pseudo-R^2 of this regression is 0.598, which indicates that these variables could explain the probability of CDS trading to a reasonable extent.

I next examine the effectiveness of my matching procedure by testing the mean difference in

[5] Appendix 4.1 explains how to construct these variables.

[6] Because the Compustat and Federal Reserve call reports are updated quarterly, I calculate the variables based on them in each quarter and then interpolate those variables to obtain the monthly data. All the other variables are calculated on a monthly basis.

the characteristics between CDS firms and their matched non-CDS peers *before* the inception of CDSs. To simplify matters, I limit the comparison to my "closest one" matched sample. I test the difference in means between the CDS and the matched non-CDS firms by running the following regression for each variable:

$$X_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} + \varepsilon_{i,t}, \tag{4.9}$$

where all the variables are as defined previously. I also include industry-level and year fixed effects in the regression. In this expression, β captures the difference in means of each variable between the CDS firms and the matched non-CDS firms. The variables that I consider for the determinants of debt maturity dispersion include the *MB_ratio*, $\ln(Assets)$, *Firm_age*, *Leverage*, *Profitability*, *Tangibility*, *CFV*, *DMAT*, *Propensity_score*, and ΔDP. *Propensity_score* is the probability of CDS inception as given by Eq. (4.7), and ΔDP represents changes in the debt maturity dispersion. For each variable, the regressions use only the data *before* the CDS inception.

Panel B of Table 4.3 reports the results. Prior to the CDS inception, none of the differences between the CDS firms and their matched non-CDS counterparts in terms of all the considered determinants of debt maturity dispersion is significant at the 5% level or above. Specifically, the matched CDS and non-CDS firms are close to each other in the propensity scores with an insignificant mean difference. In other words, prior to any CDS trading, the CDS firms and the matched non-CDS firms were similar in their respective likelihood of CDS trading. Hence I conclude (a) that no particular firm characteristic—including the probability of CDS trading—is likely to be driving the difference in debt maturity dispersion after CDS inception and (b) that my matching procedure is effective. I also tested the mean difference of the changes in debt maturity dispersion (ΔDP) between the CDS and the matched non-CDS firms before CDS inception; the difference is not statistically significant. Therefore, according to Roberts and Whited (2013), the matched sample satisfies the assumption of parallel trends.

4.5.2.1.2 Results

To illustrate the effect of CDS inception on debt maturity dispersion, I compare the changes in *DP* for the CDS firms and their 'closest one" matched non-CDS firms before and after the inception—on "date 0"—of CDS trading. I then calculate the mean changes in *DP* for the CDS firms and non-CDS firms starting from 1 year before CDS inception to 0 $(-1,0)$, 1 $(-1,1)$, 2 $(-1,2)$, and 3 $(-1,3)$ years thereafter.

[INSERT Figure 4.1 about Here]

Figure 4.1 plots the results. From year -1 to year 1, the mean *DP* of the CDS firms increases by 0.97 on average while such dispersion for the matched non-CDS firms rises by only 0.51. Since the mean *DP* of all firms is about 2.18 as reported in Table 4.1, this gap of 0.46 translates into a difference of about 21.1% in debt maturity dispersion. I observe a similar change for the CDS firms during the other event windows $(-1,2)$, and $(-1,3)$. These results indicate that the increased debt maturity dispersion after the CDS inception persists over the years. On the other hand, the changes in *DP* for the non-CDS firms decline with years. The mean ΔDP for the non-CDS firms is only 0.25 during the window of $(-1,3)$ and much smaller than that during the window of $(-1,1)$. I next test for this effect formally by running the regression of Eq. (4.6) with the propensity score matched sample.

Panel A of Table 4.4 reports the results for the matched samples based on the "closest one" and "closest one with a PS difference less than 1%" as selection criteria. When I use the "closest one" matched sample and do not control for other variables, the coefficient for *CDS_trading* is 0.252 and significant at the 1% level. This result is close to the one obtained with the full sample data (Table 4.2), which suggests that my result concerning the effect of CDS inception on debt maturity dispersion is robust to the use of full sample data or matched-sample data. When the variables for the other firm characteristics are included, the coefficient for *CDS_trading* decreases slightly to 0.208, yet it is still significant at the 5% level. That is, the inception of CDS trading increases debt maturity dispersion by about 12.6% of one standard deviation (0.208/1.652). These results indicate that the effect of CDS inception on debt maturity dispersion is economically significant. The results for the "closest one with a PS difference less than 1%" sample similarly indicate that CDS inception increases debt maturity dispersion.

[INSERT Table 4.4 about Here]

The coefficients for the control variables are significant and have the expected signs. In column (3) of Table (4.4), the coefficient for *Leverage* is 1.602 and statistically significant at the 1% level, suggesting that an increase in financial leverage leads to an increase in debt maturity dispersion—a result that is consistent with the previous findings in the literature. In particular, Huang et al. (2019) and Choi et al. (2021) show a positive link between leverage and debt granularity, while Choi et al. (2018) find that the relationship between increased rollover risk and debt maturity management is stronger for firms with higher leverage. The coefficient for $\ln(Assets)$ is significantly positive with a value of 0.624, when I use the "closest one" matched sample and include all the control variables (column (3) in Panel A of Table 4.4). This result agrees with Choi et al.'s (2021) finding that small firms are less likely to spread out their debt maturity profiles due to high borrowing and illiquidity costs.

Panel B of Table 4.4 reports the results for the alternative matched samples using the "closest two" and "closest two with a PS difference less than 1%" as selection criteria. The results reveal that the effect of CDS inception on debt maturity dispersion is robust: in all the models, the coefficients for *CDS_trading* are significantly positive. For example, the coefficients in columns (9) and (12) are 0.269 and 0.258, respectively, and both are significant at the 1% level. Overall, my results suggest that the positive relationship between CDS trading and debt maturity dispersion is robust to the choice of sample used for the empirical analysis.

4.5.2.2 Instrumental variable approach

Next, I adopt an instrumental variable approach to mitigate the potential endogeneity problem of CDS trading. As mentioned in Section 4.3.3.2, I use *Lender_FX_hedging* as an instrumental variable (Saretto and Tookes, 2013; Subrahmanyam et al., 2014). My analysis follows Angrist and Pischke's (2008) three-stage procedure. I estimate the predicted value of *CDS_trading*, *CDS_trading_IV*, by (i) using the probit model, which regresses *CDS_trading* on the instrumental variable and all the control variables in Eq. (4.8) and then (ii) using *CDS_trading_IV* as an instrument for *CDS_trading* in a conventional 2SLS procedure.

Table 4.5 reports the results of this IV approach. The table's left and right columns contain the results from my first-stage probit model and the 2SLS regression, respectively. To test the instrumental variable's significance, I report the F-statistic for the 2SLS regression's excluded instrument, F=744.41, suggesting that *Lender_FX_hedging* is a strong instrumental variable.[7]

[INSERT Table 4.5 about Here]

In the 2SLS regression, the coefficient for *CDS_trading_IV* is positive and significant at the 1% level when I control for firm characteristics and for time and firm fixed effects. These results

[7] According to Stock et al. (2002) and Angrist and Pischke (2008), a significant IV is one for which $F > 10$.

are consistent with those of the propensity score matched sample. The significantly positive coefficient implies that CDS inception is positively associated with debt maturity dispersion. I therefore conclude that firms tend to their increase debt maturity dispersion after CDS inception, which supports Hypothesis 1a that the empty creditor effect dominates the monitoring effect. Regarding the economic significance, the coefficient of *CDS_trading_IV* is 0.920. This estimate coverts into an impact of about 55.7% of one standard deviation for the full sample.

It is noted that the coefficient in IV estimation (Table 4.5) is larger than the coefficient in OLS estimation (Table 4.4). This difference is difficult to be explained since the net effect of CDS inception on the outcome debt maturity dispersion is mixed up with many effects from the demand side and supply side. One possible reason is due to an omitted variable that could be negatively correlated with the inception of CDS and positively correlated with the dependent variable (or vice versa), leading to a downward bias in the OLS estimate of debt maturity dispersion. For example, a manager with less financial management skills could be a reason for CDS initiation on the firm's debt. Meanwhile, the manager with less financial skills might be not competent in employing debt maturity dispersion as a risk management tool. This case might lead to a low correlation (or negative) between CDS inception and debt maturity dispersion.

4.5.2.3 Lending bargaing power and the effect of CDS inception

In this section, I employ an alternative approach to provide a supplementary test for Hypothesis 1a by using *Lender_FX_hedging* as proxy for the lender bargaining power. The higher value of *Lender_FX_hedging* implies the higher level of the lender bargaining power. To test whether the effect of CDS inception on debt maturity dispersion differs as a function of the lender bargaining power, I interact CDS trading with *Lender_FX_hedging*. Table A8 presents the regression results. The coefficients for the interaction terms involving $CDS\_trading \times Lender\_FX\_hedging$ are positive and significant at the 1% level. This positive coefficient indicates that firms with a higher $Lender\_FX\_hedging$ exhibit a stronger positive CDS inception effect on debt maturity dispersion than do firms with a lower $Lender\_FX\_hedging$. In other words, the effect of CDS inception on debt maturity dispersion is more pronounced for the firms with a higher level of lender bargaining powers.

4.5.3 CDS inception and credit market conditions

Here I investigate whether the credit supply is a channel through which CDS inception affects focal firms' debt maturity dispersion. In other words, I test Hypothesis 2, which states that the positive effect of CDSs on debt maturity dispersion is stronger during periods of a tightened credit market condition.

I follow Mian and Santos (2018) by measuring the credit market condition using the Federal Reserve's Senior Loan Officers Opinion Survey (SLOOS) responses to questions on loan spread increases and lending criteria tightening. Specifically, $SLOOS\_spread$ presents the net percentage of domestic banks increasing the spreads of loan rates over banks' cost of funds to large-and middle-market firms, while $SLOOS\_tightening$ presents the net percentage of domestic banks tightening the standards for commercial and industrial loans to large-and middle-market firms. The value of these measures has a scale from -1 to 1 after dividing by 100. A higher value of either $SLOOS\_spread$ or $SLOOS\_tightening$ implies a tightened credit market condition. To test whether the effect of CDS inception varies with the credit cycle, I introduce the interaction terms of the CDS trading indicator and the measures of the credit market condition. If I use $SLOOS\_spread$ as the proxy for the credit market condition, I run the following regression model,

$$DP_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times SPR_{i,t} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \quad (4.10)$$

where $SPR_{i,t} = 1$ if *SLOOS_spread* is above the median and 0 otherwise. Similarly, if I use *SLOOS_tightening* as the proxy for the credit market condition, I run the following regression model,

$$DP_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times TIG_{i,t} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \quad (4.11)$$

where $TIG_{i,t} = 1$ if *SLOOS_tightening* is above the median and 0 otherwise. A positive value of κ in Eqs. (4.10) and (4.11) means that the positive effect of CDS inception on debt maturity dispersion is stronger during the period of tightened credit market conditions. I include firm and year fixed effects in these two regressions.[8]

Table 4.6 presents the results from the regressions based on the "closest one", "closest one with a PS difference less than 1%", "closest two", and "closest two with a PS difference less than 1%" matched samples. For all the regressions, I include the same control variables as those used in column (3) of Panel A in Table 4.4. The coefficients for the four interaction terms $CDS\_trading \times SPR$ are greater than 0.201 and significant at the 1% level. Similarly, the coefficients for the four interaction terms $CDS\_trading \times TIG$ are greater than 0.404 and significant at the 1% level. These positive coefficients indicate that the increased debt maturity dispersion after the CDS inception is positively associated with the credit market conditions. Thus my findings support Hypothesis 2:

[8] It is common to have $SPR_{i,t}$ or $TIG_{i,t}$ as one independent variable when I consider the interaction effect. In my regression, this variable is absorbed by the firm fixed effect so its coefficient is omitted. The same rule applies to $WW_{i,t}$ and $KZ_{i,t}$, which are explained later.

the positive effect of CDS inception on debt maturity dispersion is stronger during the period of a tightened credit market condition.

4.5.4 CDS inception and firm quality

To support further the hypothesis that the inception of CDSs affects debt maturity dispersion through the empty creditor channel, I consider whether the positive effect of CDS inception on maturity dispersion is stronger for higher–quality firms. I use the credit rating assigned by Standard & Poor's (S&P) to measure firms' overall quality.[9] I employ two approaches to test whether the effect of CDS inception differs between higher- and lower-quality firm. First, I run the following regression model,

$$DP_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times IG_{i,t} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \qquad (4.12)$$

where $IG_{i,t}$ is a dummy variable set equal to 1 if the focal firms have investment grade ratings (and 0 otherwise). A positive value of κ means that the positive impact of CDS inception on debt maturity dispersion is stronger for higher–quality firms. Second, I estimate the effect of CDS inception on debt maturity dispersion in different credit rating subsamples. Firms are separated into four categories, specifically *High yield*, *BBB*, *A*, and $AA - AAA$, based on their S&P credit rating.[10] I run Eq. (4.6) for the firms in each rating group separately. I include both firm and year fixed effects in these regressions.

Table 4.7 presents the results from the regressions based on the "closest one", "closest one

[9] Kisgen (2006) shows that the credit rating contains more information on the quality of a firm than other publicly available information.

[10] The *High yield* category consits of firms with credit ratings below *BBB*. I group firms with credit ratings of *AA* and *AAA* into the $AA - AAA$ category since the number of observations for *AAA* firms is very small.

with a PS difference less than 1%", "closest two", and "closest two with a PS difference less than 1%" matched samples. For all the regressions, I include the same control variables as those used in column (3) of Panel A of Table 4.4. Panel A of Table 4.7 shows that the coefficients for the interaction terms involving $CDS\_trading \times IG$ are about 0.37 and significant at the 5% level. These results suggest that the positive impact of CDS inception on debt maturity dispersion is stronger for firms with a better quality.

Panel B of Table 4.7 reports the results of $CDS\_trading$ for different rating groups. The significant results only appear for the firms with an A rating or above. Moreover, the coefficients for the $AA-AAA$ rating are much higher than those for $High\ yield$ and BBB firms. For example, the $CDS\_trading$ estimate for the $AA-AAA$ group is 0.526 and significant at the 5% level if I use the "closest one" matched sample and include all the control variables. The coefficient is only 0.079 for $High\ yield$ firms and 0.034 for BBB firms, neither of which is significant. The results of the other matched samples are similar. These results consistently indicate that the positive relationship between CDS inception and debt maturity dispersion is stronger for firms with higher credit ratings and firms that are viewed as higher quality. Overall, Table 4.7 supports Hypothesis 4: the positive effect of CDS inception on debt maturity dispersion is more pronounced for higher quality firms.

4.6 Robustness tests: An alternative measure of debt maturity dispersion

In this section, I check whether my results are robust to the use of DP_dist as an alternative measure of debt maturity dispersion. DP_dist is estimated based on the distance of a firm's actual maturity profile from the perfectly dispersed one (see Section 4.3.1). Using this measure enables me to address the concern that the possible maximum maturity of debt may affect the inverse Herfindahl index, which is my prime measure of debt maturity dispersion.

4.6.1 CDS inception and debt maturity dispersion

I first check whether the positive relationship between CDS inception and debt maturity dispersion is robust to the use of *DP_dist* as an alternative measure of debt maturity dispersion.

Table 4.8 reports the regression results of both the propensity score matching and the instrumental variable approach. The coefficients for *CDS_trading* continue to be significantly positive in all the regressions; for the four different propensity score matching samples, those coefficients are 0.093, 0.095, 0.113, and 0.112—all significant at the 10% level or better. Using the IV approach yields a coefficient for *CDS_trading_IV* of 0.251, which is significant at the 5% level. These results establish that the positive relationship between CDS trading and debt maturity dispersion is robust to the use of this alternative measure of debt maturity dispersion. My Hypothesis 1a still holds.

[INSERT Table 4.8 about Here]

4.6.2 Credit market conditions, firm quality and CDS trading effects

I now test the robustness of Hypothesis 2 and Hypothesis 3. With that aim, I run regressions of Eq. (4.10), Eq. (4.11), and Eq. (4.12) using *DP_dist* as the dependent variable.

Table 4.9 reports the regression results – here for only the "closest one" propensity score matched sample.[11] Panel A of Table 4.9 shows that the coefficient for $CDS\_trading \times SPR$ is 0.066 and significant at the 10% level. This result reveals that the positive effect of CDS inception on debt

[11] Results for the other three propensity score matched samples are similar and available upon request.

maturity dispersion is stronger during the period of tightened credit market conditions, which supports my Hypothesis 2. The coefficients for *CDS_trading* $\times$ *IG* reported in Panel A is significantly positive. Panel B of Table 4.9 shows that the results of the *CDS_trading* coefficients are much higher and more significant for the firms with credit ratings of A and above than for the firms with the ratings of *High yield* and *BBB*. These findings provide evidence supporting Hypothesis 4: An increase in the debt maturity dispersion due to CDS trading is more pronounced for higher quality firms.

[INSERT Table 4.9 about Here]

4.7 Conclusion

This paper provides empirical evidence that the inception of CDS trading leads to an increase in the dispersion of corporate debt maturity profiles. I employ two measures of maturity dispersion proposed by Choi et al. (2018). My finding is robust to the use of propensity score matching or instead instrumental variable approach to address the potential endogeneity problems associated with CDS trading.

I also find that the positive relationship between CDS inception and debt maturity dispersion is stronger during periods of increased tightening in the credit market condition. This finding indicates that the effect of CDS inception on debt maturity dispersion could be established through the credit supply channel. Furthermore, I document that the positive effect of CDS inception on debt maturity dispersion is more pronounced for higher–quality firms. These results support the idea that higher quality firms are more likely to use debt maturity dispersion as a risk management tool to cope with the threat from an empty creditor problem caused by CDS inception.

My findings support the hypothesis that, concerning debt maturity dispersion, the combined effect of the *tougher creditor effect* and the *cost reduction effect* dominates the *commitment effect*. One possible channel is through the shock in the credit supply due to the CDS inception. This paper contributes to the literature addressing the influence of the CDS market on a firms' financing decision and risk management and provides interesting implications regarding how financial market innovations interact with corporate behaviors.

4.8 Appendices, tables, and figures

Appendix 4.1: Description of variables

This appendix lists the variables used in my analysis and explains how they are constructed.

Variable	Definition
CDS_trading	A dummy variable set to 1 if the firm has credit default swaps traded on its debt 1 year before time *t* (and set to 0 otherwise)
DP	The inverse of the Herfindahl index of debt maturity fractions (see 4.3.1)
DP_dist	The negative value of log distance from the perfect maturity dispersion (see 4.3.1)
MB_ratio	The ratio of the market value of assets to the total assets, where the market value of assets is the sum of debt in current liabilities, long-term debt, preferred stock, and market value of equity minus the balance sheet deferred taxes and investment tax credit
$\ln(Assets)$	The natural logarithm of the firm's total assets
Firm_age	The number of years from the first time the firm appeared in the Compustat database
Leverage	The ratio of the book value of debt to the sum of the book value of debt and market equity, where the book value of debt is the sum of short-term debt and half of long-term debt and where market equity is the number of common shares outstanding multiplied by the stock price
Profitability	The ratio of operating income before depreciation to total assets
Tangibility	The ratio of property, plant, and equipment to total assets
CFV	The standard deviation of quarterly operating income over the previous 12 quarters scaled by the total assets
DMAT	The firms' mean debt maturities weighted by amounts
CDS_traded	A dummy variable set equal to 1 if the firm has CDS traded on its debt during the sample period (and set to 0 otherwise)
ROA	The firm's return on assets
Excess_return	The firm's return in excess of the market over the past year
Equity_volatility	The natural logarithm of the firm's annualized equity volatility
Tangibility	The ratio of property, plant, and equipment to total assets
Sales_ratio	The ratio of sales to total assets
EBIT_ratio	The ratio of earnings before interest and taxes to total assets
WCAP_ratio	The ratio of working capital to total assets
RE_ratio	The ratio of retained earnings to total assets
Cash_ratio	The ratio of cash to total assets
CAPX_ratio	The ratio of capital expenditures to total assets

(*continued*)

Variable	Definition
SP_rating	A dummy variable set to 1 if the firm is rated (and set to 0 otherwise)
Unsecured_debt	The ratio of unsecured debt to total debt
Lender_FX_hedging	The lenders' and underwriters' ratio of the total amount of foreign exchange hedging activities to the total assets over the previous 5 years
Lender_Tier1_capital	The Tier-1 capital ratio of the firm's lenders over the previous 5 years
Lender_credit_derivative	The lenders' and underwriters' ratio of the total amount of credit derivative activities to the total assets over the previous 5 years
Lender_size	The size of the focal firm's lending banks and underwriters as measured by the logarithm of the total assets of those banks and underwriters over the previous 5 years

Table 4.1: Summary statistics

This table presents the summary statistics of the firms in the whole sample. Panel A reports the number of firms and CDS trading inceptions, by year, between 2001 and 2012. The whole sample from the Compustat–CRSP merged database includes all non-financial and non-utility firms traded on the NYSE, AMEX, and Nasdaq during the sample period 2001–2012. I merge the CDS data from Markit with the Compustat–CRSP data using the first six digits of CUSIP. The second column shows the total number of companies included in my analysis; the third column reports the number of firms for which CDS trading was initiated during that year (i.e., the year during which the focal firm's CDS spread quote first appeared in the database). The fourth column shows the cumulative number of CDS firms. Panel B presents summary statistics of the firm characteristic variables for all firms, CDS firms, and non-CDS firms. I report the results for *DP*, *DP_dist*, *MB_ratio*, ln(*Assets*), *Firm_age*, *Leverage*, *Profitability*, *Tangibility*, *CFV*, and *DMAT*. For each variable, I report the number of observations (*N*), mean, standard deviation (S.D.), skewness, and kurtosis, and the 25th, 50th, and 75th percentile values. All the variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. See Appendix 4.1 for additional details.

Panel A: CDS firms in the sample

Year	**Number of CRSP–Compustat firms**	**New CDS firms**	**Cumulative number of CDS firms**
2001	3604	1	1
2002	3511	304	305
2003	3422	91	396
2004	3448	87	483
2005	3413	35	518
2006	3392	20	538
2007	3348	26	564
2008	3245	4	568
2009	3124	0	568
2010	3100	4	572
2011	3071	7	579
2012	3076	2	581

(*continued*)

Table 4.1 (*continued*)

Panel B: Summary statistics

ALL FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DP	19,529	2.176	1.652	2.189	8.445	1.000	1.606	2.667
DP_dist	19,529	2.843	1.476	−0.053	2.680	1.826	2.836	3.845
MB_ratio	18,701	1.532	1.236	2.955	14.916	0.808	1.160	1.788
ln(*Assets*)	18,701	6.444	1.955	0.061	2.638	5.048	6.469	7.766
Firm_age	18,701	19.914	15.485	0.965	2.852	8.000	15.000	29.000
Leverage	18,699	0.216	0.206	1.149	3.841	0.047	0.161	0.324
Profitability	18,671	0.087	0.174	−3.077	17.736	0.063	0.115	0.166
Tangibility	18,701	0.279	0.241	1.052	3.080	0.091	0.194	0.405
CFV	18,006	0.019	0.024	4.280	27.644	0.007	0.012	0.021
DMAT	15,045	6.574	6.607	5.147	70.053	2.674	5.000	8.035
CDS FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DP	4,046	3.834	2.262	0.941	3.244	2.060	3.284	5.143
DP_dist	4,046	4.163	1.103	−0.651	3.605	3.479	4.256	4.980
MB_ratio	4,006	1.356	0.928	3.117	18.042	0.801	1.096	1.589
ln(*Assets*)	4,006	8.717	1.159	0.374	2.927	7.847	8.606	9.490
Firm_age	4,006	32.878	17.643	−0.025	1.581	16.000	34.000	51.000
Leverage	4,006	0.274	0.187	0.908	3.393	0.132	0.230	0.378
Profitability	4,002	0.138	0.076	−0.290	7.720	0.094	0.134	0.177
Tangibility	4,006	0.319	0.238	0.753	2.511	0.125	0.251	0.483
CFV	3,953	0.011	0.013	5.781	54.081	0.005	0.008	0.013
DMAT	3,505	10.399	9.101	5.524	64.958	5.664	8.000	12.729
NON-CDS FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DP	15,483	1.742	1.095	2.591	13.053	1.000	1.265	2.003
DP_dist	15,483	2.498	1.362	0.045	3.065	1.671	2.497	3.341
MB_ratio	14,695	1.580	1.303	2.847	13.814	0.810	1.182	1.852
ln(*Assets*)	14,695	5.824	1.644	−0.003	2.886	4.671	5.908	6.941
Firm_age	14,695	16.380	12.728	1.196	3.741	7.000	13.000	22.000
Leverage	14,693	0.200	0.208	1.276	4.138	0.029	0.137	0.303
Profitability	14,669	0.073	0.190	−2.828	14.982	0.049	0.110	0.163
Tangibility	14,695	0.267	0.240	1.149	3.307	0.083	0.182	0.378
CFV	14,053	0.021	0.026	3.993	24.124	0.007	0.013	0.024
DMAT	11,540	5.413	5.096	3.459	28.289	2.000	4.150	6.916

Table 4.2: CDS inception and debt maturity dispersion: Baseline model

This table presents the effect of CDS inception on debt maturity dispersion using the whole sample. I run the panel regressions of *DP* on *CDS_trading* and other control variables lagged by one year, including *MB_ratio*, ln(*Assets*), *Firm_age*, *Leverage*, *Profitability*, *Tangibility*, *CFV* and *DMAT*; all the regressions control for firm and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Appendix 4.1 provides a detailed description of the variables.

Variable	**(1)**	**(2)**	**(3)**
CDS_trading	0.315***	0.294***	0.299***
	(0.071)	(0.070)	(0.078)
MB_ratio		0.006	0.002
		(0.012)	(0.017)
ln(*Assets*)		0.289***	0.330***
		(0.032)	(0.042)
Firm_age		−0.149*	−0.199**
		(0.076)	(0.097)
Leverage		0.501***	0.541***
		(0.083)	(0.109)
Profitability		−0.121	−0.119
		(0.077)	(0.102)
Tangibility			0.618**
			(0.278)
CFV			0.550
			(0.946)
DMAT			0.001
			(0.003)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj. R^2	0.0238	0.0457	0.0516
N	19,529	18,631	14,529

Table 4.3: Propensity score modeling

This table presents the estimation results of the propensity score matching. Panel A reports the estimates of a probit model that regresses the probability of CDS trading on its determinants. The dependent variable, *CDS_traded*, is set to 1 if CDS is traded on the firm's debt during the sample period and 0 otherwise. I employ the same set of independent variables as used by Subrahmanyam et al. (2014). The sample period is 2001–2012. Financial and utility firms are excluded. In Panel B, I examine the difference in means of firm characteristics—between the CDS and the matched non-CDS firms before CDS inception—by running the following regressions:

$$X_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} + \varepsilon_{i,t}.$$

Here the vector $X_{i,t}$ is my variable of interest; industry-level and time fixed effects are also included; and β captures the difference in means of each variable between the CDS firms and the matched non-CDS firms. I use the "closest one" matched sample according to the propensity score derived with Subrahmanyam et al.'s (2014) model, and keep only the observations made prior to CDS inception. As before, *Propensity_score* is the probability of CDS inception and ΔDP represents the yearly changes in the debt maturity dispersion. See Appendix 4.1 for descriptions of the other variables. Robust standard errors (S.E.) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Propensity score modeling			Panel B: Difference in means before CDS inception		
Variable	**Coefficient**	**S.E.**	**Variable**	β	**S.E.**
ln(*Assets*)	0.760***	(0.006)	*MB_ratio*	0.031	(0.153)
Leverage	0.257***	(0.036)	ln(*Assets*)	0.159	(0.116)
ROA	−0.139	(0.189)	*Firm_age*	1.462	(2.324)
Excess_return	0.005	(0.012)	*Leverage*	0.016	(0.035)
Equity_volatility	−0.086***	(0.011)	*Profitability*	−0.018*	(0.010)
Tangibility	0.375***	(0.036)	*Tangibility*	−0.019	(0.022)
Sales_ratio	0.386***	(0.036)	*CFV*	−0.002	(0.002)
EBIT_ratio	1.178***	(0.202)	*DMAT*	0.329	(1.103)
WCAP_ratio	−0.565***	(0.046)	*Propensity_score*	0.002	(0.038)
RE_ratio	−0.078***	(0.009)	ΔDP	−0.209	(0.132)
Cash_ratio	0.545***	(0.056)			
CAPX_ratio	−0.680***	(0.150)			
SP_rating	1.420***	(0.014)			
Unsecured_debt	0.721***	(0.017)			
Lender_FX_hedging	2.688***	(0.408)			
Lender_Tier1_capital	2.705***	(0.541)			
Lender_credit_derivative	−0.012*	(0.007)			
Lender_size	0.021***	(0.007)			
Industry fixed effects	Yes				
Year fixed effects	Yes				
Pseudo-R^2	0.598				
N	207,156				

Table 4.4: CDS inception and debt maturity dispersion: Propensity score matched sample

This table presents the effect of CDS inception on debt maturity dispersion using the sample that includes CDS firms and their matched non-CDS firms. I follow Subrahmanyam et al. (2014) in estimating each firm's propensity score, which is then used to match the CDS firms. I run panel regressions of *DP* on *CDS_trading*, and on other control variables lagged by one year, while accounting for firm and time fixed effects. Panel A reports the results for my "closest one" and "closest one with a PS difference less than 1%" matched samples; Panel B gives results for the "closest two" and "closest two with a PS difference less than 1%" matched samples. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Detailed descriptions of the variables are provided in Appendix 4.1.

	Panel A: "Closest one" and "Closest one, PS diff. < 1%" matched samples						Panel B: "Closest two" and "Closest two, PS diff. < 1%" matched samples					
Variable	**(1) Closest one**	**(2) Closest one**	**(3) Closest one**	**(4) Closest one PS diff. < 1%**	**(5) Closest one PS diff. < 1%**	**(6) Closest one PS diff. < 1%**	**(7) Closest two**	**(8) Closest two**	**(9) Closest two**	**(10) Closest two PS diff. < 1%**	**(11) Closest two PS diff. < 1%**	**(12) Closest two PS diff. < 1%**
CDS_trading	0.252***	0.182**	0.208**	0.253***	0.186**	0.211**	0.292***	0.233***	0.269***	0.285***	0.223***	0.258***
	(0.090)	(0.085)	(0.096)	(0.091)	(0.085)	(0.096)	(0.086)	(0.082)	(0.091)	(0.086)	(0.082)	(0.091)
MB_ratio		−0.129**	−0.120*		−0.134**	−0.129*		−0.168***	−0.151***		−0.129**	−0.106*
		(0.061)	(0.070)		(0.061)	(0.070)		(0.050)	(0.054)		(0.050)	(0.056)
ln(*Assets*)		0.692***	0.624***		0.684***	0.623***		0.564***	0.488***		0.625***	0.571***
		(0.094)	(0.113)		(0.094)	(0.113)		(0.082)	(0.099)		(0.081)	(0.098)
Firm_age		0.071	0.079		0.046	0.058		0.054	−0.016		0.043	0.000
		(0.206)	(0.253)		(0.209)	(0.254)		(0.152)	(0.190)		(0.156)	(0.194)
Leverage		1.304***	1.602***		1.285***	1.557***		1.378***	2.004***		1.343***	1.770***
		(0.218)	(0.289)		(0.221)	(0.292)		(0.176)	(0.250)		(0.185)	(0.257)
Profitability		−0.103	−0.043		−0.034	0.023		−0.313	−0.307		−0.320	−0.387
		(0.463)	(0.508)		(0.464)	(0.509)		(0.364)	(0.412)		(0.373)	(0.414)
Tangibility			0.408			0.469			0.274			0.383
			(0.751)			(0.752)			(0.610)			(0.613)
CFV			−9.847***			−8.896**			−9.647***			−9.518***
			(3.583)			(3.593)			(2.783)			(2.821)
DMAT			−0.005			−0.005			−0.005*			−0.004
			(0.003)			(0.003)			(0.003)			(0.003)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.103	0.168	0.178	0.0976	0.161	0.171	0.108	0.170	0.189	0.0932	0.159	0.172
N	5,844	5,779	4,999	5,751	5,687	4,926	8,343	8,231	7,010	7,640	7,546	6,448

Table 4.5: CDS inception and debt maturity dispersion: Instrumental variable approach

This table presents the effect of CDS inception on debt maturity dispersion as estimated via an instrumental variable approach. I report results derived from the first-stage of a probit model and also from the 2SLS regression in the three-stage procedure. My instrumental variable is *Lender_FX_hedging*, which measures the foreign exchange hedging activities of the firm's banks and underwriters. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 4.1 for a detailed description of the variables.

	First-stage	**2SLS**
Variable	*CDS_trading*	*DP*
CDS_trading_IV		0.920***
		(0.203)
MB_ratio	0.079	−0.053
	(0.067)	(0.049)
ln(*Assets*)	0.727***	0.568***
	(0.047)	(0.078)
Firm_age	0.635***	−0.134
	(0.067)	(0.193)
Leverage	0.983***	0.370*
	(0.255)	(0.194)
Profitability	0.707	−0.097
	(0.595)	(0.266)
Tangibility	0.039	0.401
	(0.278)	(0.495)
CFV	−0.934	−2.451
	(2.621)	(2.027)
DMAT	0.013**	−0.002
	(0.007)	(0.005)
Lender_FX_hedging	3.333**	
	(1.347)	
Industry fixed effects	Yes	
Firm fixed effects		Yes
Year fixed effects	Yes	Yes
F-statistic (excluded instrument)		744.41
Pseudo-R^2	0.531	
Adj. R^2		0.420
N	7,812	6,255

Table 4.6: Credit market conditions and the effect of CDS inception

This table reports the effect of CDS inception on debt maturity dispersion as a function of the credit market condition. I use the Federal Reserve's Senior Loan Officers Opinion Survey response (*SLOOS_spread* and *SLOOS_tightening*) as proxies for credit market conditions. A higher level of either *SLOOS_spread* or *SLOOS_tightening* implies an increased tightening in the credit market conditions. I use the interaction terms $CDS\_trading \times SPR$ (Eq. (4.10)) and $CDS\_trading \times TIG$ (Eq. (4.11)) to capture the variation in CDS effects with the credit cycle. $SPR = 1$ if *SLOOS_spread* is above the median (and 0 otherwise). $TIG = 1$ if *SLOOS_tightening* is above the median (and 0 otherwise). All the regressions control for firm and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is provided in Appendix 4.1.

	SLOOS_spread				*SLOOS_tightening*			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
CDS_trading	0.215**	0.218**	0.280***	0.270***	0.179*	0.181*	0.236***	0.226**
	(0.095)	(0.095)	(0.091)	(0.091)	(0.096)	(0.096)	(0.091)	(0.091)
$CDS\_trading \times SPR$	0.201***	0.208***	0.248***	0.257***				
	(0.067)	(0.067)	(0.062)	(0.062)				
$CDS\_trading \times TIG$					0.404***	0.412***	0.482***	0.476***
					(0.121)	(0.122)	(0.112)	(0.112)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.179	0.172	0.190	0.174	0.179	0.172	0.191	0.174
N	4,999	4,926	7,010	6,448	4,999	4,926	7,010	6,448

Table 4.7: Firm quality and the effect of CDS inception

This table reports the effect of CDS inception on debt maturity dispersion as a function of credit ratings. I use S&P credit ratings to measure firms' overall quality. In Panel A, I use the interaction term $CDS\_trading \times IG$ in the regressions to capture the difference in the CDS effects between the firms that do and those that do not have investment grade ratings. IG is a dummy variable set equal to 1 if the focal firms have investment grade ratings (and 0 otherwise). In panel B, I estimate the CDS effect in different credit rating subsamples. The firms are separated into four categories, consisting of $High\ yield$, BBB, A, and $AA-AAA$ based on their S&P credit rating. I run the regression of Eq. (4.6) for the four subsamples separately. All the regressions include the control variables used in column (3) of Table (4.2) and control for firm and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 4.1 for a detailed description of the variables.

Panel A: Investment grade and the effect of CDS inception

Variable	**Closest one**	**Closest one PS diff. < 1%**	**Closest two**	**Closest two PS diff. < 1%**
CDS_trading	−0.016	−0.013	0.040	0.026
	(0.146)	(0.146)	(0.150)	(0.147)
$CDS\_trading \times IG$	0.372**	0.372**	0.371**	0.378**
	(0.180)	(0.180)	(0.182)	(0.180)
Adj. R^2	0.180	0.173	0.190	0.173
N	4,993	4,920	6,998	6,436

Panel B: The effect of CDS inception in different credit rating subsamples

Variable	*High yield*	*BBB*	*A*	$AA-AAA$
B.1."Closest one" sample				
CDS_trading	0.079	0.034	0.288***	0.526**
	(0.087)	(0.075)	(0.097)	(0.241)
Adj. R^2	0.211	0.114	0.318	0.457
N	1,899	1,745	1,193	156
B.2."Closest one with PS difference less than 1%" sample				
CDS_trading	0.081	0.038	0.288***	0.526**
	(0.087)	(0.076)	(0.097)	(0.241)
Adj. R^2	0.200	0.103	0.318	0.457
N	1,850	1,725	1,189	156
B.3."Closest two" sample				
CDS_trading	0.116	0.047	0.345***	0.540**
	(0.088)	(0.070)	(0.092)	(0.252)
Adj. R^2	0.217	0.123	0.407	0.505
N	2,850	2,267	1,606	275
B.4."Closest two with PS difference less than 1%" sample				
CDS_trading	0.110	0.053	0.315***	0.527**
	(0.089)	(0.070)	(0.095)	(0.249)
Adj. R^2	0.197	0.117	0.342	0.492
N	2,629	2,194	1,374	239

Table 4.8: CDS inception and debt maturity dispersion: Alternative measure of debt maturity dispersion

This table reports the effect of CDS inception on debt maturity dispersion measured by *DP_dist*, which captures the distance of a firm's actual maturity profile from the perfectly dispersed one. Columns (1)–(4) present the results for a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) contains the results obtained when an instrumental variable approach is adopted. I run the panel regressions of *DP_dist* on *CDS_trading*, and on the other control variables lagged by one year, while accounting for firm and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A more detailed description of the variables is presented in Appendix 4.1.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) IV approach**
CDS_trading	0.093*	0.095*	0.113**	0.112**	
	(0.052)	(0.052)	(0.049)	(0.049)	
CDS_trading_IV					0.251**
					(0.107)
MB_ratio	−0.091***	−0.094***	−0.122***	−0.105***	−0.011
	(0.033)	(0.033)	(0.027)	(0.028)	(0.030)
ln(*Assets*)	0.353***	0.355***	0.225***	0.287***	0.401***
	(0.057)	(0.058)	(0.053)	(0.052)	(0.045)
Firm_age	0.237*	0.240**	0.242**	0.270***	0.070
	(0.121)	(0.122)	(0.095)	(0.096)	(0.108)
Leverage	0.588***	0.575***	0.778***	0.676***	0.386***
	(0.151)	(0.153)	(0.133)	(0.135)	(0.125)
Profitability	0.324	0.343	0.115	0.074	−0.097
	(0.255)	(0.256)	(0.229)	(0.230)	(0.205)
Tangibility	0.556*	0.581*	0.376	0.393	0.310
	(0.311)	(0.311)	(0.269)	(0.271)	(0.277)
CFV	−1.774	−1.610	−2.128**	−2.192**	−1.063
	(1.185)	(1.209)	(0.965)	(0.977)	(1.216)
DMAT	0.004***	0.004***	0.005***	0.005***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.115	0.113	0.110	0.106	0.501
N	4,982	4,909	6,990	6,428	6,104

Table 4.9: Credit market conditions, firm quality and CDS trading effects

This table reports the effect of CDS inception on debt maturity dispersion as a function of credit ratings, or credit market conditions. Here, I measure the maturity dispersion by using *DP_dist*. I report the results only for a sample that includes CDS firms and their "closest one" propensity score matched non-CDS firms. In panel A, I use (a) the Federal Reserve's Senior Loan Officers Opinion Survey response (*SLOOS_spread* and *SLOOS_tightening*) as proxies for credit market conditions and (b) S&P credit ratings as proxies for the firms' overall quality. As before, *SPR* is an indicator set equal to 1 if *SLOOS_spread* is above the time series median (and set to 0 otherwise); and *TIG* is an indicator set equal to 1 if *SLOOS_tightening* is above the time series median (and set to 0 otherwise); *WW* is an indicator set equal to 1 if the focal firm's WW index exceeds the cross-sectional median upon the inception of CDSs (and set to 0 otherwise); *KZ* is an indicator set equal to 1 if the firm's KZ index is above the cross-sectional median upon the inception of CDSs (and set to 0 otherwise); *IG* is a dummy variable set equal to 1 if the focal firms have investment grade ratings (set to 0 otherwise). In panel B, I estimate the CDS effect in different credit rating subsamples. The firms are separated into four categories including *High yield*, *BBB*, *A*, and $AA-AAA$ based on their S&P credit rating. I run the regressions of Eq. (4.6) using *DP_dist* as the dependent variable for the four subsamples separately. All the regressions include the control variables used in column (3) of Table (4.2) and control for firm and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. All the variables are defined in Appendix 4.1.

Panel A: Credit market conditions, firm quality and CDS trading effects

	Credit market conditions		**Firm quality**
Variable	***SPR***	***TIG***	***IG***
CDS_trading	0.095*	0.087	−0.034
	(0.052)	(0.053)	(0.075)
CDS_trading × *SPR*	0.066*		
	(0.035)		
CDS_trading × *TIG*		0.089	
		(0.063)	
CDS_trading × *IG*			0.210**
			(0.088)
Adj. R^2	0.115	0.115	0.117
N	4,982	4,982	4,976

Panel B: The effect of CDS inception in different credit rating subsamples

Variable	*High yield*	*BBB*	*A*	$AA-AAA$
CDS_trading	0.027	0.088	0.241**	0.742*
	(0.083)	(0.090)	(0.111)	(0.367)
Adj. R^2	0.177	0.0712	0.231	0.509
N	1,890	1,740	1,190	156

Figure 4.1: Changes in debt maturity dispersion following CDS inception.
This figure plots the cross-sectional average changes in *DP* for the CDS firms and their "closest one" matched non-CDS firms before and after the inception of CDS trading. I calculate the changes in *DP* from 1 year before the CDS inception to 0, 1, 2, and 3 years thereafter. For each CDS firm, I select a matched firm from the non-CDS firm sample based on propensity scores calculated as described in the model by Subrahmanyam et al. (2014).

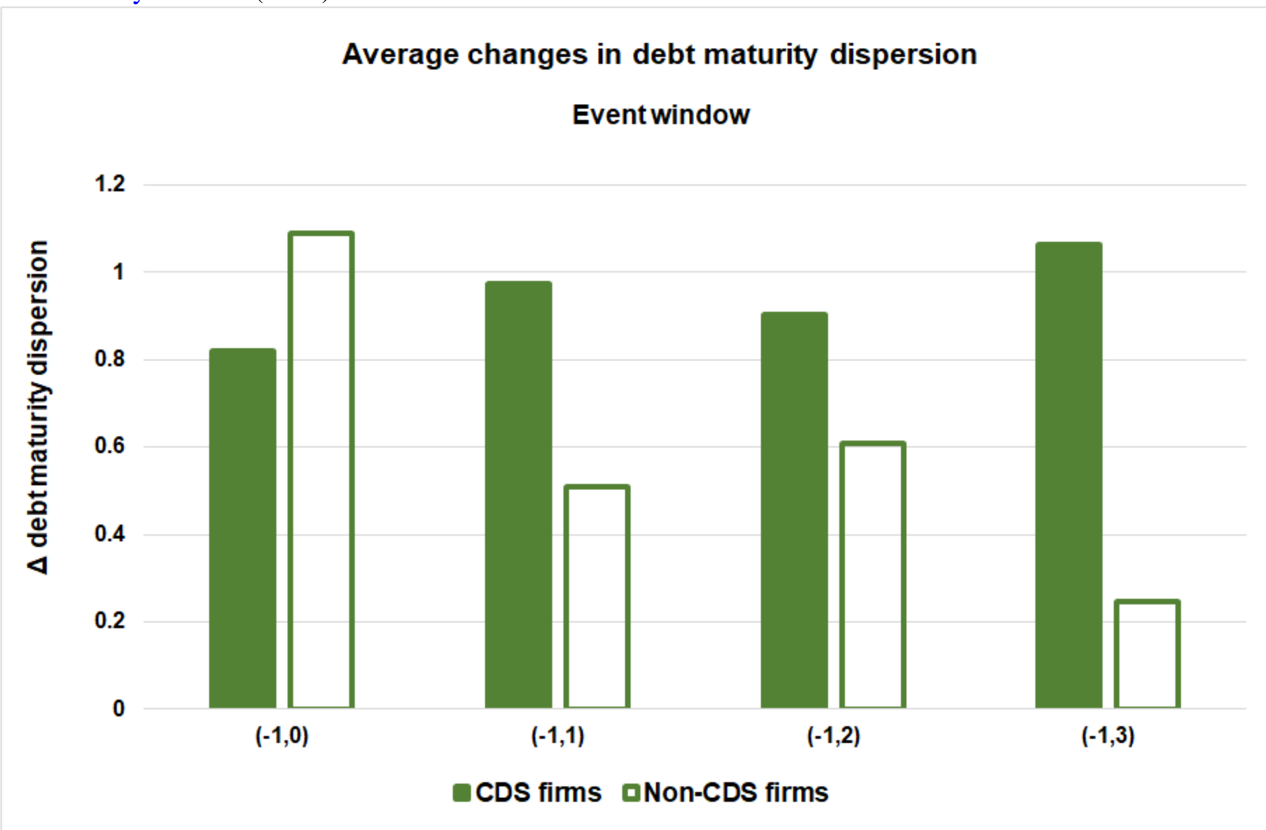


Table A8: Lender bargaining power and the effect of CDS inception on debt maturity dispersion

This table reports the effect of CDS inception on debt maturity dispersion as a function of the lender bargaining power. I use the interaction term *CDS_trading* $\times$ *Lender_FX_hedging* in the regressions to capture the difference in CDS effects for the CDS firms with different levels of *Lender_FX_hedging*, where *Lender_FX_hedging* measures the foreign exchange hedging activities of the firm's banks and underwriters. The higher value of *Lender_FX_hedging* implies the higher level of the lender bargaining power. All regressions control for firm and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 4.1 for a detailed description of the variables.

Variable	*CDS_trading*
CDS_trading	0.126
	(0.099)
CDS_trading $\times$ *Lender_FX_hedging*	7.613***
	(1.927)
Lender_FX_hedging	−2.983***
	(1.024)
MB_ratio	−0.050
	(0.049)
ln(*Assets*)	0.592***
	(0.079)
Firm_age	−0.216
	(0.189)
Leverage	0.429**
	(0.190)
Profitability	−0.124
	(0.258)
Tangibility	0.484
	(0.494)
CFV	−2.148
	(2.038)
DMAT	−0.002
	(0.005)
Firm Fixed Effect	Yes
Year Fixed Effect	Yes
Adj. R^2	0.0868
N	6,320

Chapter 5

Creditor protections and debt specialization: Evidence from credit default swaps

5.1 Introduction

One important aspect of the corporate capital structure is the way in which firms make their decisions on using different types of debts. Some studies try to understand such firm's debt structure better, for example, Rauh and Sufi (2010), Colla et al. (2013), Colla, Ippolito, and Li (2020), Zhong (2021). Among these studies, Colla et al. (2013) in particular explain why firms tend to use few types of debt. John, Kaviani, Kryzanowski, and Maleki (2018) find a positive association between country-level creditor protection and debt concentration. Since credit default swaps are considered as a form of credit protection for lenders or bond investors, it is of interest to investigate whether and to what extent the CDS inception affects firms' debt structure.

The literature provides both demand-side and supply-side channels, which generate different results regarding the association between CDS inception and the firms' debt specialization. On the one hand, the demand-side effect suggests a positive relationship between CDS inception and debt specialization. With the credit protection obtained through the CDS market, creditors have more bargaining power over borrowers in debt re-negotiations. The increase in the bargaining power of the lender can affect debt specialization in two ways. First, the increased bargaining power of creditors could lead to a decrease in the probability of strategic default, which will encourage firms to reduce their degree of debt specialization in response to the increased bargaining power of creditors. Second, when creditors have higher bargaining power induced by the CDS inception, the likelihood of bankruptcy is higher for the focal firms (Subrahmanyam et al., 2014). In response, the focal firms may reduce the complexity of their debt structure in an effort to negotiate with the creditors to mitigate the cost of bankruptcy. As a result, these firms are more likely to specialize in their debt structure.

On the supply side, the inception of CDSs reduces the frictions of the credit supply as documented by Saretto and Tookes (2013). The reduction in the supply frictions allows firms easier access to a variety of debt types and, in turn, a lower degree of debt specialization. Thus, the supply-side effect suggests a negative relationship between CDS inception and debt specialization. In sum, theoretically, the aggregate effects of CDS inception on debt specialization are ambiguous. Therefore, an empirical analysis is necessary to understand such important effects.

I follow Colla et al. (2013) in employing two measures of debt specialization. The first measure is the normalized Herfindahl-Hirschman Index (HHI) of the debt types that a firm uses. The second measure is a dummy variable that equals 1 if the focal firm has at least 90% of its debt from one type of debt, and equals 0 otherwise. My baseline results using all the sample data suggest that firms tend to increase their level of debt specialization after the introduction of CDS trading. This positive association between CDS inception and debt specialization is statistically and economically significant. After controlling for firm characteristics, the inception of CDS trading increases the focal firm's debt specialization by around 19.7% of one standard deviation. The effect is similar if I use the instrumental variable approach. When I use the CDS firms with their closest matched non-CDS firms in the regression, the debt specialization increases by around 29.16% of a one-standard-deviation after the CDS inception. These results suggest that firms tend to specialize their debt types after the inception of CDS trading, supporting the demand side argument.

Furthermore, I find evidence that the bankruptcy cost is one channel through which CDS inception affects focal firms' debt specialization. I investigate this channel by testing whether the positive effect of CDSs on debt specialization is stronger for firms facing a higher bankruptcy risk, and/or a liquidation cost. First, I use the $distance-to-default$ (DD) measure of Vassalou and Xing (2004) and the $Z-score$ proposed by Altman (1968) as proxies for bankruptcy risk. Second, I follow Garlappi and Yan (2011) and use $Intangibles$ to measure liquidation cost. A higher level of $Intangibles$ indicates a higher liquidation cost. I document that the positive impact of CDS inception on debt specialization is more pronounced for firms facing a higher bankruptcy risk or a higher liquidation cost.

This paper contributes to two strands of the literature. First, my study extends the extant literature on the impact of CDS trading on the corporate sector. Prior research documents the effects of CDS inception on firm behaviors, including firm leverage and debt maturity (Saretto and Tookes, 2013), default risk (Subrahmanyam et al., 2014), reporting conservatism (Martin and Roychowdhury, 2015), cash holding (Subrahmanyam et al., 2017), firm value (Danis and Gamba, 2018), corporate innovation (Chang et al., 2019), and firm risk (Lin et al., 2019). In a related study, Chen et al. (2018) find that firms use more public debt and less bank debt when there is CDS trading on their debt. My study supplements those by Saretto and Tookes (2013) and Chen et al. (2018) by establishing the relationship between CDS inception and debt specialization, an important aspect of the debt structure. Second, my study also helps to explain the variation in debt specialization. I extend the studies by Colla et al. (2013), Colla et al. (2020), and John et al. (2018) by investigating an important determinant of debt specialization, the inception of CDS trading.[1]

The rest of this paper proceeds as follows. In Section 5.2, I review the relevant literature and develop my hypotheses. Section 5.3 details my empirical methodology. Section 5.4 describes the data, and Section 5.5 presents my empirical results. In Section 5.6, I conduct several robustness tests. I conclude in Section 5.7 with a summary of my findings.

5.2 Literature review and hypothesis development

5.2.1 Effect of CDS inception on debt specialization

I develop my main hypotheses using the theoretical and empirical evidence on the effect of CDS inception on firm behavior on both the demand and the supply side. The demand-side effect comes from the empty creditor effect, while the supply-side effect occurs mainly through the impact on the credit supply.

[1] My paper is close to that of Donato (2016) in that both examine the effects of CDS on debt specialization. My paper differs in several ways. First, I use a larger sample since my study covers 581 CDS firms while Donato (2016) include only 239 CDS firms. Second, I thoroughly consider both the demand-side and the supply-side effects of CDS inception. Third, I address the endogeneity problem using both propensity score matching and the instrumental variable approach. Fourth, I identify the bankruptcy cost as one channel through which the CDSs impose an impact on debt specialization.

5.2.1.1 Demand-side effect: Empty creditors with a reduced probability of strategic defaut

The empty creditor effect could drive the relationship between CDS inception and debt specialization. The empty creditor effect means that debt holders have no desire to preserve a company that they provide with funds. This problem arises when creditors have over-insured their credit risk by buying CDSs but still hold the control rights in the firms (Bolton and Oehmke, 2011). With the credit insurance, the creditors have more bargaining power over the borrowers in the re-negotiations that follows a "strategic" default—such as when the borrower benefits more from defaulting than from not defaulting. The increase in lenders' bargaining power might affect debt specialization in two ways. First, the increased bargaining power of creditors could lead to a decrease in the probability of strategic default which might affect firms' decision when seeking the optimal debt structure. Firms not only decide on the optimal leverage ratios but also choose the number of different types of debt and their amounts. In this sense, firms will select the degree of debt specialization in response to the increased bargaining power of the creditors. Second, when creditors' bargaining power is high due to the inception of CDSs, the likelihood of bankruptcy is higher for the focal firms (Subrahmanyam et al., 2014). In response, firms may reduce the complexity of the debt structure in an effort to negotiate with the creditors to mitigate the expected cost of bankruptcy. Thus, firms are more likely to specialize in their debt structure to seek coordination among creditors, helping to reduce the chance of inefficient liquidation. This idea is consistent with John et al.'s (2018) finding that credit protection leads to more specialized debt structures to mitigate the inefficient liquidation. Research also shows evidence of the negative association between debt specialization and costs of bankruptcy. For example, Gilson, John, and Lang (1990) find that firms that use fewer debt types are more likely to succeed in Chapter 11 negotiations. Ivashina, Iverson, and Smith (2016) show that firms with more concentrated debt structures have a higher probability of reducing the time involved in the restructuring process along with higher recovery rates.

5.2.1.2 Supply-side effect: Credit supply

CDSs could also affect firms' financing decision through the credit supply channel. Saretto and Tookes (2013) argue that the CDS market increases the ability of capital suppliers to hedge their risks, thus reducing the friction on the supply side. They provide several reasons for this argument. First, creditors, like banks and insurance companies have the opportunity to reduce the regulatory capital requirements by buying CDSs to hedge their credit risk. The reduction in such requirements could increase the creditors' capability of lending. As a result, the supply of credit to firms could rise if market segmentation exists between the creditors who would like to lend more and the CDS providers who are willing to hold credit risk. Second, for the purpose of maintaining client relationships, CDSs allow banks to provide debt while mitigating the portfolio risk. Finally, the existence of the CDS market could make holding corporate debt (credit risk) more attractive to creditors (bond investors) by providing creditors with a liquid resale option. [2]

Following Saretto and Tookes (2013), I expect that the frictions in the credit supply decline after the inception of CDSs. The reduction in the supply frictions provides firms with easier access to a variety of debt types which, in turn, might lead to a lower degree of debt specialization. This argument is consistent with Colla et al.'s 2013 finding that firms with highly constrained access to capital (measured by a unrated dummy) are more likely to increase their debt specialization. In other words, firms with easy access to capital tend to employ a lower level of debt specialization. Thus, the supply-side effect suggests a negative relationship between CDS inception and debt

[2] Third, if treasuries are in short supply, the existence of CDS markets can make holding corporate debt more attractive to a broad group of potential investors

specialization.

I investigate whether the demand-side effect dominates the supply-side effect on the choice of debt specialization by testing the following hypotheses:

Hypothesis 1a. *If the demand-side effect dominates the supply-side effect, then debt specialization will increase after the inception of CDS trading.*

Hypothesis 1b. *If the supply-side effect dominates the demand-side effect, then debt specialization will decrease after the inception of CDS trading.*

5.2.2 CDS inception, bankruptcy risk, and liquidation cost

The demand-side effect suggests that firms are more likely to increase their debt specialization after the inception of CDSs due to an increase in the expected bankruptcy cost. If this is the case, I expect the focal firms that have a higher cost of bankruptcy to be more likely to increase their debt specialization levels in response to the CDS inception. In other words, the CDS effect is expected to be stronger for the firms with a higher ex-ante cost of bankruptcy. Altman (1984) shows that the bankruptcy risk and liquidation cost are the key determinants of the expected bankruptcy cost. Following this, I hypothesize that the CDS effect on debt specialization is more pronounced for the firms with a higher ex-ante bankruptcy risk and liquidation cost.

Hypothesis 2. *If the demand-side effect works through the expected bankruptcy cost, the positive effect of CDS inception on debt specialization is stronger for firms with a higher bankruptcy risk and/or a higher liquidation cost.*

5.3 Empirical specification

5.3.1 Debt specialization measure

I follow Colla et al. (2013) in using two measures of debt specialization. The first measure is the normalized Herfindahl-Hirschman Index (HHI) of the debt types that the firms use. I use Capital IQ data to decompose the total debt (TD) into seven mutually exclusive types of debt. These debt types include commercial papers (CP), drawn credit lines (DC), term loans (TL), senior bonds and notes (SBN), subordinated bonds and notes (SUB), capital leases (CL), and other debt types (Other).[3] I first calculate the sum of the square of the debt type ratio and then compute the normalized HHI, *DS*:

$$\begin{aligned} SS_{i,t} = & \left(\frac{CP_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{DC_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{TL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SBN_{i,t}}{TD_{i,t}}\right)^2 \\ & + \left(\frac{SUB_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{CL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{Other_{i,t}}{TD_{i,t}}\right)^2, \end{aligned} \tag{5.1}$$

$$DS_{i,t} = \frac{SS_{i,t} - 1/7}{1 - 1/7}, \tag{5.2}$$

Here, a higher value of *DS* means a higher degree of debt specialization. *DS* has a value between 0 and 1. *DS* takes a value of one when the firm has only a single debt type and a value of 0 when the firm is financed with all seven types of debt with equal weights. I follow Colla et al. (2013) and assume that different debt types are more likely to be held by different creditors; then, *DS* can act as a proxy for creditors concentration.

[3]Most other debt types are unclassified borrowings.

Eq. (5.1) and Eq. (5.2) show that the number of debt types affects the calculation of *DS*. To mitigate the impact of the number of debt types on the degree of debt specialization, I calculate an alternative measure of debt concentration, $ODT90$. I follow Colla et al. (2013) in defining $ODT90$ as a dummy variable that equals 1 if the focal firm has at least 90% of its debt from one type of debt, and 0 otherwise.

5.3.2 Determinants of debt specialization

I test the hypothesis in a panel regression framework. The dependent variable is the debt specialization measure described in Section 5.3.1. I follow Ashcraft and Santos (2009) and Subrahmanyam et al. (2017) and use an indicator variable of CDS trading to estimate the impact of CDS trading on debt specialization. *CDS_trading* is a dummy variable that equals 1 if the firm has CDSs traded on its debt 1 year previously and 0 otherwise. I regress debt specialization on CDS trading and other control variables that are used as the determinants of debt specialization in the literature. Specifically, I follow Colla et al. (2013) by applying the Tobit model and include the fundamental determinants of debt specialization in my controlling variables. They are the firm size (ln(*Assets*)), profitability (*Profitability*), dividend payer indicator (*Div_payer*), tangibility (*Tangibility*), cash flow volatility (*CFV*), *R&D_ratio*, credit rated firms indicator *Rated*, and market-to-book ratio (*MB_ratio*). I also control for industry, and year effects and cluster standard errors at the firm level to provide more robust statistical results. Appendix 5.1 provides a detailed description of construction of these variables.

My Tobit regression model is written as follows,

$$DS_{i,t} = \alpha \; + \; \beta \times CDS\_trading_{i,t-1} \; + \gamma \times X_{i,t-1} \; + \; \varepsilon_{i,t}, \tag{5.3}$$

where $DS_{i,t}$ is the debt specialization measure that I use, $CDS\_trading$ is the key independent variable which equals 1 if the firm has CDS traded on its debt 1 year earlier and 0 otherwise, and $X_{i,t-1}$ is the vector of the control variable. β captures the impact of the inception of CDS trading on debt specialization.

5.3.3 Endogeneity

The effect of CDS initiation on debt specification could be spurious because of the omitted variable problem. Since the inception of CDS trading might be endogenous in that the initiation of CDS trading on a firm's debt is not random, it could be driven by the firm's characteristics including unobservable factors. At the same time, the firm might manage its debt specification in response to a change in the unobservable factors, which are correlated with the inception of CDS trading. To address this endogeneity problem, I follow Subrahmanyam et al. (2014), Martin and Roychowdhury (2015), and Lin et al. (2019) by employing a propensity score matching and an instrumental variable (IV) approach.[4] For the propensity score matching, I form four matched samples, consisting of "Closest one", "Closest two", "Closest one with PS difference less than 1%", and "Closest two with PS difference less than 1%". Adopting the instrumental variable (IV) approach, I follow Saretto and Tookes (2013), Subrahmanyam et al. (2014), and Lin et al. (2019), and use $Lender\_FX\_hedging$ as the instrumental variable. Since my model is a Tobit regression, it is not appropriate to apply a three-stage procedure as in Section 3.3.3.2 of Chapter 1. I instead follow Roodman (2011) and Subrahmanyam et al. (2014) in using the the full-information maximum likelihood (FIML) estimation and regressing the dependent variables on $CDS\_trading$ with the instrumental variable and all the control variables.

[4] In section 3.3.3.1 and 3.3.3.2, I discuss the endogeneity of CDS trading in more details.

5.4 Data

I use data from Markit to identify the inception of CDS trading, defined as the date on which the focal firm's CDS spread quote first appears in Markit. The primary dependent variable is the debt specialization measure, *DS*, which is estimated using the Herfindahl index of debt type proposed by Colla et al. (2013). I use the Capital IQ database from Standard and Poor's to calculate the annual debt specialization measure for the sample firms. My CDS data cover the period from 2002 to 2012 since the majority of CDS inception occurs before 2013. The firms that I consider are those with stocks listed on the NYSE, AMEX, or Nasdaq. I use 6-digit numbers from the Committee on Uniform Securities Identification Procedures (CUSIP) to match the CDS data from Markit with information from the Compustat–CRSP database. I follow Colla et al. (2013) and exclude financial firms (Standard Industrial Classification (SIC) codes 6000–6999) and utility firms (SIC codes 4900–4499).

Table 5.1 presents summary statistics for the variables capturing the firm characteristics of all firms, CDS firms, and non-CDS firms. I report the results for *DS*, *ODT90*, $\ln(Assets)$, *Profitability*, *Div_payer*, *Tangibility*, *CFV*, *R&D_ratio*, *Rated*, and *MB_ratio* . For each variable, I report the number of observations (*N*), mean, standard deviation (S.D.), skewness, and kurtosis as well as the 25th, 50th, and 75th percentile values. All the variables are winsorized at the 1st and 99th percentiles, a procedure that mitigates the impact of outliers. The reported figures show that CDS firms tend to have lower degree of debt specification than non-CDS firms. For example, the mean *DS* of CDS firms is 0.678 whereas that for non-CDS firms is 0.736. Meanwhile, the mean *ODT90* for the CDS and non-CDS firms is 0.048 and 0.541, respectively.

[INSERT Table 5.1 about Here]

I use *Lender_FX_hedging* as the main covariate in the propensity score matching model and as an instrumental variable. I define *Lender_FX_hedging* as the foreign exchange hedging activities by banks and underwriters. This variable is calculated as the average of the ratio of the notional volume of foreign exchange derivatives used for hedging (not trading) purposes to the total assets "across the banks that have served as either lenders or bond underwriters for the firm over the previous five years" (Subrahmanyam et al., 2014). For each firm in my sample, I use data from Dealscan and the Fixed Income Securities Database (FISD) to identify its main lenders and bond underwriters, respectively. For the lenders information, I match the data from Compustat and Dealscan by Gvkey using the link provided by Chava and Roberts (2008). For the underwriter information, I use the 6-digit CUSIP to match the data from Compustat and FISD. The data on FX activities and other fundamental information of the banks are obtained from the Federal Reserve call report. Since there is no common identifier between Dealscan, FISD, and call report data, I perform hand-matching by using the name, state and other information of the relevant banks.

5.5 Empirical results

5.5.1 CDS inception and debt specialization: Baseline model

I start my empirical analysis by runing the baseline regression of Eq. (5.3). Table 5.2 reports the results. My variable of interest is the coefficient for *CDS_trading*, which measures the impact of CDS inception on debt specialization.

[INSERT Table 5.2 about Here]

First, I use the Tobit model to regress *DS* on the *CDS_trading* variable. Here I control for

CDS_Firm, other firm characteristics, and year fixed effects; this is Model (1) in Table 5.2. The coefficient for *CDS_trading* is 0.049 and is significant at the 1% level. The positive coefficient estimate of $CDS_t rading$ means that debt specialization increases after the inception of CDS trading. Particularly, after a CDS starts trading, debt specialization increases by 0.049, which corresponds to 18.6% of one standard deviation for the full sample (0.264 reported in Table 5.1). Next, I introduce industry fixed effects into the regression (Models (2) in the table). The coefficients for *CDS_trading* continue to be significantly positive: 0.052 in Model (2) —with values that are significant at the 1% level. The coefficient of 0.052 in Model (2) indicates that after I control for industry fixed effects, *DS* increases by around 19.7% of one-standard-deviation after the CDS inception ($0.052 \div 0.264$). These results suggest that the increase in debt specialization due to CDS trading is robust to controlling for other firm characteristics, which supports Hypothesis 1a.[5] I also find that the control variables have significant impacts on debt specialization. For example, the coefficient of *Profitablility* is significantly positive in both specifications, which suggests that firms with higher profitability tend to have higher debt specialization. The significantly negative coefficient of $\ln(Assets)$ implies that lager firms tend to have a lower degree of debt specialization. These results are consistent with Colla et al.'s (2013) findings.

We follow Colla et al. (2013) to use the Tobit specification with industry fixed effect since our sample consists of a large number of firms (about 25%) that have a maximum value of debt specialization. To examine if our results are robust to specification with a firm fixed effect, we employ OLS regression. Column (3) in Table 5.2 report the results for this OLS regression with

[5] When I control for *Leverage*, along with the other control variable in Model (2), the coefficient of *CDS_trading* is 0.37 and significant at the 1% level. However, since the literature documents the effect of CDS inception on leverage (for example, see Saretto and Tookes (2013)), one may argue that it is problematic to include affected outcome variables as control variables. This results implies that the positive effect of CDS inception on debt concentration is robust to different degrees of leverage. To mitigate this concern, I exclude leverage from my main model.

firm fixed effect. The coefficient *CDS_trading* remain positive and significant at the 5% level. The result suggests that the increase in debt specialization due to CDS trading is robust to the specification of firm fixed effect.

5.5.2 Endogeneity

5.5.2.1 Propensity score matching

5.5.2.1.1 Propensity score matched sample

I use Eq. (3.6) to estimate the probability of CDS inception, which I then use as my propensity score for constructing the matched samples. First, I follow Subrahmanyam et al. (2014) and use the following covariates: ln(*Assets*), *Leverage*, *ROA*, *Excess_return*, *Equity_volatility*, *Tangibility*, *Sales_ratio*, *EBIT_ratio*, *WCAP_ratio*, *RE_ratio*, *Cash_ratio*, *CAPX_ratio*, *SP_rating*, *Unsecured_debt*, *Lender_FX_hedging*, *Lender_Tier1_capital*, *Lender_credit_derivative*, and *Lender_size*.[6] I run this model using the sample excluding financial firms and utility firms to construct the matched samples. Also following Subrahmanyam et al. (2014), I use monthly data to run the propensity score regression.[7]

Panel A of Table 5.3 reports my propensity score regression results. Most of the explanatory variables have a significant effect on the probability of CDS trading. For example, the coefficient for ln(*Assets*) is significantly positive with a value of 0.76, suggesting that CDS trading is more likely to involve large firms than small ones. The regression results also indicate that firms with higher leverage are more likely to have CDS being traded on their debt. CDS trading is more

[6] Appendix 5.1 explains how to construct these variables.

[7] Because the Compustat and Federal Reserve call reports are updated quarterly, I calculate the variables based on them in each quarter and then interpolate those variables to obtain the monthly data. All other variables are calculated on a monthly basis.

likely to occur for firms with a relatively higher tangible asset ratio, sales-to-assets ratio, and/or profitability. The probability of CDS initiation is greater for rated firms and for firms with a higher unsecured debts–total assets ratio.

[INSERT Table 5.3 about Here]

The coefficient for *Lender_FX_hedging* is 2.747 and significant at the 1% level. This significantly positive coefficient shows that credit default swaps are more likely to be traded for firms with banks that are relatively more involved in foreign exchange hedging activities—a result that is consistent with the findings of Saretto and Tookes (2013) and Subrahmanyam et al. (2014). The pseudo-R^2 of this regression is 0.598, which indicates that these variables could explain the probability of CDS trading to a reasonable extent.

I next examine the effectiveness of my matching procedure by testing the mean difference in the characteristics between CDS firms and their matched non-CDS peers *before* the inception of CDSs. To simplify matters, I limit the comparison to my "Closest one" matched sample. I test the difference in means between the CDS and the matched non-CDS firms by running the following regressions for each variable:

$$X_{i,t} = \alpha + \beta \times CDS\_Firm_{i,t} + \varepsilon_{i,t}, \tag{5.4}$$

where all the variables are as defined previously.I also include industry-level and year fixed effects in the regression. In this expression, β captures the difference in means of each variable between CDS firms and the matched non-CDS firms. The variables that I consider for the determinants of debt specialization include *DS*, *ODT90*, $\ln(Assets)$, *Profitability*, *Div_payer*, *Tangibility*, *CFV*, *R&D_ratio*, *Tangibility*, *Rated*, *Propensity_score*, and ΔDS. *Propensity_score* is the probability of

CDS inception, and ΔDS represents changes in debt specialization. For each variable, the regressions use only the data *before* CDS inception.

Panel B of Table 3.3 reports the results. Prior to CDS inception, none of the differences between CDS firms and their matched non-CDS counterparts in terms of all the considered determinant of debt specialization is significant at the 10% level or above. Specifically, the matched CDS and non-CDS firms are close to each other in the propensity scores with an insignificant mean difference. In other words, prior to any CDS trading, the CDS firms and the matched non-CDS firms were similar in their respective likelihood of CDS trading. Hence I conclude (a) that no particular firm characteristic—including the probability of CDS trading—is likely to be driving the difference in debt specialization after CDS inception and (b) that my matching procedure is effective. I also tested the mean difference of the changes in debt specialization (ΔDS) between the CDS and the matched non-CDS firms before CDS inception; it is not statistically significant. Hence, according to Roberts and Whited (2013), the matched sample satisfies the assumption of parallel trends.

5.5.2.1.2 Results

To illustrate the effect of CDS inception on debt specialization, I compare changes in *DS* for the CDS firms and their "Closest one" matched non-CDS firms before and after the inception—at "date 0"—of CDS trading. I then calculate the mean changes in *DS* for the CDS firms and non-CDS firms starting from one year before CDS inception to 0 $(-1,0)$, 1 $(-1,1)$, 2 $(-1,2)$, and 3 $(-1,3)$ years thereafter.

[INSERT Figure 5.1 about Here]

Figure 5.1 plots the results. From year -1 to year 1, the mean *DS* of the CDS firms increases by 0.06 on average, while the degree of debt specialization for the matched non-CDS firms reduces by 0.03. Since the mean DS of all the firms is about 0.74 as reported in Table 5.1, this gap of 0.09 translates into a difference of about 12.1% in debt specialization. I observe a similar pattern for the CDS firms during the other event windows $(-1,2)$, and $(-1,3)$. The gap between the mean ΔDS fore CDS firms and non-CDS firms is 0.06, and it is 0.08 for the event windows $(-1,2)$, and $(-1,3)$, respectively. These results indicate that the increased debt specialization after the CDS inception persists over years. I next test formally for this effect by running the regression of Eq. (5.3) with the propensity score matched sample.

Panel A of Table 5.4 reports the results for matched samples based on the "Closest one" and "Closest one with PS difference less than 1%" as selection criteria. When I use the "Closest one" matched sample and control for $\ln(Assets)$, and *CDS_Firm*, the coefficient for *CDS_trading* is 0.073 and is significant at the 1% level. This result is close to the one obtained when using the full sample data (Table 5.2), which suggests that my result concerning the effect of CDS inception on debt specialization is robust to whether I use the full sample data or the matched sample data. When the variables for the other firm characteristics are included, I still obtain a positive coefficient of 0.077, which is significant at the 1% level. That is, the inception of CDS trading increases debt specialization by about 29.16% of one standard deviation ($0.077 \div 0.264$). This coefficient is even larger when I suppress *CDS_Firm*. These results indicate that the effect of CDS inception on the debt specialization is economically significant. Results for the "Closest one with PS difference less than 1%" sample similarly indicate that CDS inception increases debt specialization.

[INSERT Table 5.4 about Here]

The coefficients for the control variables are significant and have the expected signs. In column (2) of Table (5.4), the coefficients for *CFV*, and *R&D_ratio* are significantly positive with the values of 0.923, and 1.200, respectively . This result accords with Colla et al.'s (2013) finding that a positive and significant relationship exists between debt specialization and either expected bankruptcy costs or information asymmetry. Additionally, the coefficient for *Rated* is -0.071 and statistically significant at the 1% level when I use the "Closest one" matched sample and include all the control variables (column (2) in Panel A of Table 5.4). This result indicates that rated firms, which might have more capital accessibility than unrated firms tend to diversify their debt type. In sum, this finding supports the hypothesis that firms that face more difficulty in accessing capital are likely to choose a higher degree of debt specialization (Colla et al., 2013).

Panel B of Table 5.4 reports the results for the alternative matched samples using the "Closest two" and "Closest two with PS difference less than 1%" as selection criteria. The results reveal that the effect of CDS inception on debt specialization is robust: in all the models, the coefficients for *CDS_trading* are significantly positive. For example, the coefficients in columns (8) and (11) are 0.077 and 0.072, respectively, and both are significant at the 1% level. Overall, my results suggest that the positive relationship between CDS trading and debt specialization is robust to the choice of sample used for the empirical analysis.

5.5.2.2 Instrumental variable approach

Next, I adopt an instrumental variable approach to mitigate the potential endogeneity problem of CDS trading. As mentioned in Section 5.3.3, I use *Lender_FX_hedging* as an instrumental variable (Saretto and Tookes, 2013; Subrahmanyam et al., 2014). My analysis follows Roodman (2011), and Subrahmanyam et al. (2014) in using the full-information maximum likelihood (FIML) estimation, which regresses the dependent variables on *CDS_trading* with the instrumental variable and all the control variables.

Table 5.5 reports the results of this IV approach. The table's left and right columns report the results from the first-stage and the last-stage of the full-information maximum likelihood (FIML) estimation, respectively. The positive and significant coefficient of 4.904 suggests that *Lender_FX_hedging* is significantly correlated with *CDS_trading*.

[INSERT Table 5.5 about Here]

The coefficient for *CDS_trading_IV* is positive and significant at the 1% level when I control for firm characteristics and include time and industry fixed effects. These results are consistent with those of the propensity score matched sample. The significantly positive coefficient implies that CDS inception is positively associated with debt specialization. I therefore conclude that firms tend to increase their debt specialization after CDS inception, which supports Hypothesis 1a's assertion that firms prefer a higher degree of debt specialization in response to the reduced likelihood of strategic default due to CDS inception. Regarding the economic significance, the coefficient of *CDS_trading_IV* is 0.052. This estimate translates into an impact of about 19.7% of one-standard-deviation of the full sample.

5.5.3 CDS inception, bankruptcy risk and liquidation cost

Here I investigate whether the expected bankruptcy cost is a channel through which CDS inception affects focal firms' debt specialization. In other words, I test the hypothesis that the positive effect of CDS on debt specialization is stronger for the firms facing a higher bankruptcy risk, and/or liquidation cost.

I use the *DD* measure used in Vassalou and Xing (2004), and Altman's $Z-score$ (**Altman, 1968**) as proxies for bankruptcy risk. A lower level of either *DD* or $Z-score$ indicates a higher bankruptcy risk. To measure the liquidation cost, I follow Garlappi and Yan (2011) and use

$Intangibles$. A higher level of $Intangibles$ indicates a higher liquidation cost. To test whether the impact of CDS inception is a function of firm's bankruptcy risk, I introduce the interaction terms of the CDS trading indicator and bankrupt risk indicator. If I use the DD measure as the proxy for bankruptcy risk, I run the following regression model,

$$DS_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times DD_i + DD_i + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \quad (5.5)$$

where DD_i is an indicator variable that takes the value of 1 if the firm has a DD below the cross-sectional median upon the inception of a CDS (and set to 0 otherwise). Similarly, if I use the $Z-score$ as the proxy for bankruptcy risk, I run the following regression,

$$DS_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times ZS_i + ZS_i + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \quad (5.6)$$

where ZS_i is an indicator variable that takes the value 1 if the firm has a $Z-score$ less than 3 (and 0 otherwise).[8] To test whether the impact of CDS inception on debt specialization differs between firms with a low and a high liquidation cost, I use the interaction term of the CDS trading indicator and $Intangibles$, and run the following regression,

$$DS_{i,t} = \alpha + \beta \times CDS\_trading_{i,t-1} + \kappa \times CDS\_trading_{i,t-1} \times INTA_i + ZS_i + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \quad (5.7)$$

where $INTA_i$ is an indicator variable that takes the value 1 if the firm has $Intangibles$ above the cross-sectional median upon the inception of CDS (and 0 otherwise). A positive value of κ in Eqs. (5.5) and (5.6) means that the positive impact of CDS inception on debt specialization is more

[8] According to (CFI, 2021), firms that have an $Altman's\ Z-score$ below 3 are considered to be outside safe zone. Additionally, the median of $Altman's\ Z-score$ for firms with a BBB credit rating is around 3 (Altman, 2017).

pronounced for firms facing a higher bankruptcy risk. A positive value of κ in Eq. (5.7) means that the positive impact of CDS inception on debt specialization is more pronounced for firms that have higher liquidation cost. I apply FIML estimation and include all the control variables, industry, and year fixed effects in these two regressions.

Table 5.6 presents the results from the regressions based on the "Closest one", "Closest one with PS difference less than 1%", "Closest two", and "Closest two with PS difference less than 1%" matched samples. For all the regressions, I include the same control variables as those used in column (3) of Panel A of Table 5.4. The coefficients for the four interaction terms $CDS\_trading \times DD$ are greater than 0.078 and significant at the 1% level. Similarly, the coefficients for the four interaction terms $CDS\_trading \times ZS$ are greater than 0.097 and significant at the 1% level. These positive coefficients indicate that the increased debt specialization after the CDS inception is positively associated with the bankruptcy risk. Thus my findings support Hypothesis 2: the positive effect of CDS inception on debt specialization is pronounced for the firms with a higher bankruptcy risk.

[INSERT Table 5.6 about Here]

Table 5.7 presents the CDS effect for firms with different level of liquidation cost. The coefficients for the four interaction terms $CDS\_trading \times INTA$ are greater than 0.099 and significant at the 1% level. These results indicate that the effect of CDS inception on debt specialization is positively associated with the liquidation cost. In other words, my findings support Hypothesis 2: the positive effect of CDS inception on debt specialization is stronger for firms with a higher liquidation cost.

[INSERT Table 5.7 about Here]

5.6 Robustness tests: An alternative measure of debt specialization

In this section, I check whether my results are robust to the use of *ODT90* as an alternative measure of debt specialization. *ODT90* is a dummy variable set equal to 1 if the focal firms have at least 90% of their debt from one type of debt (set to 0 otherwise) (see Section 5.3.1).

5.6.1 CDS inception and debt specialization

First, I examine whether the positive relationship between CDS inception and debt specialization is robust to the use of *ODT90* as an alternative measure of debt specialization.

Table 5.8 reports the regression results when employing both the propensity score matching and the instrumental variable approach. The coefficients for *CDS_trading* continue to be significantly positive in all the regressions; for the four different propensity score matched samples, those coefficients are 0.351, 0.326, 0.358, and 0.332—all significant at the 1% level. Using the IV approach yields a coefficient for *CDS_trading_IV* of 0.274, which is significant at the 5% level. These results establish that the positive relationship between CDS trading and debt specialization is robust to the use if this alternative measure of debt specialization. My Hypothesis 1a still holds.

[INSERT Table 5.8 about Here]

5.6.2 Expected bankruptcy cost and CDS trading effects

I now test the robustness of Hypothesis 2. I run regressions of Eq. (5.5), Eq. (5.6) and Eq. (5.7) using *ODT90* as the dependent variable. Table 5.9 reports the regression results for the propensity score matched samples. Table 5.9 shows that the coefficients for *CDS_trading* $\times$ *DD* are greater than 0.584 and significant at the 1% level. Meanwhile, the coefficients for *CDS_trading* $\times$ *ZS* are greater than 0.441 and significant at the 1% level. This result reveals that the positive effect of CDS inception on debt specialization is stronger for the firms facing a higher bankruptcy risk, which supports my Hypothesis 2.

[INSERT Table 5.9 about Here]

Similarly, Table 5.9 shows that the coefficients for *CDS_trading* $\times$ *INTA* are greater than 0.561 and significant at the 1% level. This result suggests that the positive effect of CDS inception on debt specialization is stronger for the firms that have a higher liquidation cost, also supporting my Hypothesis 2.

[INSERT Table 5.10 about Here]

5.7 Conclusion

This paper examines the effect of CDS inception on an important aspect of debt structure, debt specialization. I consider both demand-side and supply-side channels that can explain the impact of CDS inception on debt specialization. On the demand-side, firms are more likely to choose a higher degree of debt specialization after the inception of CDSs. With the reduced probability of a strategic default due to the CDS inception, firms tend to specialize, using fewer debt types to reduce the probability of inefficient liquidation. On the supply side, CDS inception reduces the frictions of the credit supply, allowing firms to have a lower degree of debt specialization.

Using two measures of debt specialization, I find that firms tend to increase their level of debt specialization after the introduction of CDS trading. The results remain robust after addressing the endogeneity of CDS trading. I also provide evidence that the positive impact of CDS inception on debt specialization is more pronounced for firms facing a higher bankruptcy risk or a higher liquidation cost. This finding suggests that the expected bankruptcy cost is one channel through which CDS inception affects focal firms' debt specialization.

5.8 Appendices, tables, and figures

Appendix 5.1: Description of variables

This appendix lists the variables used in my analysis and explains how they are constructed.

Variable	Definition
CDS_trading	A dummy variable set to 1 if the firm has credit default swaps traded on its debt 1 year before time t (and set to 0 otherwise)
DS	The Herfindahl index of debt type usage (see 5.3.1)
ODT90	A dummy variable set equal to 1 if the focal firms have at least 90% of their debt from one type of debt (set to 0 otherwise) (see 5.3.1)
MB_ratio	The ratio of the market value of assets to total assets, where market value of assets is the sum of debt in the current liabilities, long-term debt, preferred stock, and market value of equity minus the balance sheet deferred taxes and investment tax credit
$\ln(Assets)$	The natural logarithm of the firm's total assets
Firm_age	The number of years from the first time the firm appeared in the Compustat database
Leverage	The ratio of the book value of debt to the sum of the book value of debt and market equity, where book value of debt is the sum of short-term debt and a half of long-term debt and where market equity is the number of common shares outstanding multiplied by the stock price
Profitability	The ratio of operating income before depreciation to total assets
Tangibility	The ratio of property, plant, and equipment to total assets
CFV	The standard deviation of quarterly operating income over the previous 12 quarters scaled by the total assets
DMAT	The firms' mean debt maturities weighted by amounts
CDS_Firm	A dummy variable set equal to 1 if the firm has CDSs traded on its debt during the sample period (and set to 0 otherwise)
ROA	The firm's return on assets
Excess_return	The firm's return in excess of the market over the past year
Equity_volatility	The natural logarithm of the firm's annualized equity volatility
Tangibility	The ratio of property, plant, and equipment to total assets
Sales_ratio	The ratio of sales to total assets
EBIT_ratio	The ratio of earnings before interest and taxes to total assets
WCAP_ratio	The ratio of working capital to total assets
RE_ratio	The ratio of retained earnings to total assets
Cash_ratio	The ratio of cash to total assets
CAPX_ratio	The ratio of capital expenditures to total assets

(*continued*)

Variable	Definition
SP_rating	A dummy variable set to 1 if the firm is rated (and set to 0 otherwise)
Unsecured_debt	The ratio of unsecured debt to total debt
Lender_FX_hedging	The lenders' and underwriters' ratio of the total amount of foreign exchange hedging activities to total assets over the previous 5 years
Lender_Tier1_capital	The Tier-1 capital ratio of the firm's lenders over the previous 5 years
Lender_credit_derivative	The lenders' and underwriters' ratio of the total amount of credit derivative activities to the total assets over the previous 5 years
Lender_size	The size of the focal firm's lending banks and underwriters as measured by the logarithm of total assets of those banks and underwriters over the previous 5 years

Table 5.1: Summary statistics

This table presents the summary statistics of the firm characteristic variables for all firms, CDS firms, and non-CDS firms. I report the results for *DS*, *ODT90*, ln(*Assets*), *Profitability*, *Div_payer*, *Tangibility*, *CFV*, *R&D_ratio*, *Rated*, and *MB_ratio*. For each variable, I report the number of observations (*N*), mean, standard deviation (S.D.), skewness, and kurtosis, and the 25th, 50th, and 75th percentile values. All the variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. See Appendix 5.1 for additional details.

ALL FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DS	23,688	0.736	0.264	−0.408	1.701	0.477	0.806	1.000
ODT90	23,688	0.514	0.500	−0.054	1.003	0.000	1.000	1.000
ln(*Assets*)	22,683	6.459	1.996	0.128	2.704	5.027	6.458	7.786
Profitability	22,642	0.086	0.178	−3.087	17.548	0.062	0.115	0.166
Div_payer	22,683	0.362	0.481	0.575	1.331	0.000	0.000	1.000
Tangibility	22,683	0.287	0.241	0.983	2.941	0.097	0.206	0.424
CFV	21,856	0.019	0.024	4.288	27.629	0.007	0.012	0.021
R&D_ratio	22,683	0.044	0.098	3.884	21.027	0.000	0.000	0.041
Tangibility	21,290	0.368	0.482	0.547	1.299	0.000	0.000	1.000
Rated	22,683	1.535	1.233	2.930	14.761	0.811	1.162	1.798
CDS FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DS	4,880	0.678	0.252	−0.173	1.741	0.448	0.692	0.923
ODT90	4,880	0.408	0.492	0.373	1.139	0.000	0.000	1.000
ln(*Assets*)	4,832	8.775	1.229	0.410	2.990	7.876	8.660	9.583
Profitability	4,824	0.138	0.078	−0.413	8.741	0.094	0.134	0.178
Div_payer	4,832	0.657	0.475	−0.663	1.439	0.000	1.000	1.000
Tangibility	4,832	0.322	0.234	0.719	2.489	0.130	0.258	0.487
CFV	4,761	0.011	0.013	5.681	54.138	0.005	0.008	0.013
R&D_ratio	4,832	0.018	0.037	5.001	52.013	0.000	0.000	0.020
Tangibility	4,719	0.958	0.201	−4.569	21.877	1.000	1.000	1.000
Rated	4,832	1.362	0.945	3.137	18.270	0.801	1.097	1.594
NON-CDS FIRMS	***N***	**Mean**	**S.D.**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
DS	18,808	0.750	0.265	−0.483	1.731	0.486	0.851	1.000
ODT90	18,808	0.541	0.498	−0.164	1.027	0.000	1.000	1.000
ln(*Assets*)	17,851	5.832	1.675	0.087	3.052	4.649	5.908	6.943
Profitability	17,818	0.071	0.194	−2.840	14.841	0.048	0.109	0.163
Div_payer	17,851	0.282	0.450	0.970	1.941	0.000	0.000	1.000
Tangibility	17,851	0.277	0.241	1.066	3.113	0.088	0.193	0.402
CFV	17,095	0.021	0.026	3.992	23.981	0.007	0.013	0.024
R&D_ratio	17,851	0.051	0.108	3.496	17.234	0.000	0.000	0.053
Tangibility	16,571	0.200	0.400	1.499	3.246	0.000	0.000	0.000
Rated	17,851	1.582	1.296	2.826	13.709	0.814	1.183	1.862

Table 5.2: CDS inception and debt specialization: Baseline model

This table presents the effect of CDS inception on debt specialization using the whole sample. In column (1) and (2), I use the tobit model to regress *DS* on *CDS_trading*,*CDS_Firm* and other control variables lagged by one year, including ln(*Assets*), *MB_ratio*, *Profitability*, *Div_payer*, *Tangibility*, *CFV*, *R&D_ratio*, *Rated*. In column (3), I use OLS regression with firm and time fixed effect. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Appendix 5.1 provides a detailed description of the variables.

Variable	**(1)**	**(2)**	**(3)**
CDS_trading	0.049***	0.052***	0.0229**
	(0.014)	(0.014)	(0.0105)
CDS_Firm	−0.016	−0.010	
	(0.017)	(0.016)	
ln(*Assets*)	−0.013***	−0.019***	−0.0440***
	(0.004)	(0.004)	(0.0066)
Profitability	0.168***	0.150***	0.0432**
	(0.031)	(0.031)	(0.0211)
Div_payer	0.006	0.026**	−0.0032
	(0.010)	(0.010)	(0.0093)
Tangibility	−0.142***	−0.174***	−0.1827***
	(0.019)	(0.027)	(0.0352)
CFV	1.208***	0.840***	0.4619***
	(0.193)	(0.191)	(0.1423)
R&D_ratio	0.540***	0.450***	−0.0862
	(0.060)	(0.066)	(0.0551)
Rated	−0.092***	−0.084***	−0.0165
	(0.012)	(0.013)	(0.0115)
MB_ratio	0.024***	0.023***	0.0053**
	(0.004)	(0.004)	(0.0025)
Industry Fixed Effect	No	Yes	No
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	No	No	Yes
Clustered standard errors	Yes	Yes	Yes
Adj. R^2	0.128	0.158	0.517
N	20,593	20,442	20,593

Table 5.3: Propensity score modeling

This table presents the estimation results of the propensity score matching. Panel A reports the estimates of a probit model that regresses the probability of CDS trading on its determinants. The dependent variable, *CDS_Firm*, is set to 1 if there is a CDS traded on the firm's debt during the sample period and is otherwise set to 0. I employ the same set of independent variables as used by Subrahmanyam et al. (2014). The sample period is 2001–2012. Financial and utility firms are excluded. In Panel B, I examine the difference in means of firm characteristics—between the CDS and the matched non-CDS firms before CDS inception—by running the following regressions:

$$X_{i,t} = \alpha + \beta \times CDS\_Firm_{i,t} + \varepsilon_{i,t}.$$

Here the vector $X_{i,t}$ is my variable of interest; industry-level and time fixed effects are also included; and β captures the difference in means of each variable between the CDS firms and the matched non-CDS firms. I use the "Closest one" matched sample according to the propensity score derived using Subrahmanyam et al.'s (2014) model, and keep only the observations made prior to CDS inception. As before, *Propensity_score* is the probability of CDS inception and ΔDS represents yearly changes in debt specialization. See Appendix 5.1 for descriptions of the other variables. Robust standard errors (S.E.) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Propensity score modeling			Panel B: Difference in means before CDS inception		
Variable	**Coefficient**	**S.E.**	**Variable**	β	**S.E.**
ln(*Assets*)	0.762***	(0.006)	ln(*Assets*)	0.074	(0.148)
Leverage	0.228***	(0.035)	*MB_ratio*	0.105	(0.119)
ROA	−0.170	(0.189)	*Profitability*	0.003	(0.010)
Excess_return	0.003	(0.012)	*Div_payer*	0.053	(0.064)
Equity_volatility	−0.087***	(0.011)	*Tangibility*	0.011	(0.023)
Tangibility	0.406***	(0.036)	*CFV*	−0.001	(0.002)
Sales_ratio	0.396***	(0.036)	*R&D_ratio*	0.003	(0.004)
EBIT_ratio	1.184***	(0.202)	*Rated*	0.007	(0.056)
WCAP_ratio	−0.563***	(0.046)	*Propensity_score*	−0.013	(0.043)
RE_ratio	−0.080***	(0.009)	ΔDS	0.000	(0.020)
Cash_ratio	0.546***	(0.056)	*DS*	−0.025	(0.035)
CAPX_ratio	−0.712***	(0.150)			
SP_rating	1.420***	(0.014)			
Unsecured_debt	0.721***	(0.017)			
Lender_FX_hedging	2.747***	(0.406)			
Lender_Tier1_capital	2.276***	(0.538)			
Lender_credit_derivative	−0.014*	(0.007)			
Lender_size	0.018**	(0.007)			
Industry fixed effects	Yes				
Year fixed effects	Yes				
Pseudo-R^2	0.598				
N	209,07				

Table 5.4: CDS inception and debt specialization: Propensity score matched sample

This table presents the effect of CDS inception on debt specialization using the sample that includes CDS firms and their matched non-CDS firms. I follow Subrahmanyam et al. (2014) in estimating each firm's propensity score, which is then used to match the CDS firms. I run Tobit regressions of *DS* on *CDS_trading*, and on the other control variables lagged by one year, while accounting for firm and time fixed effects. Panel A reports the results for my "Closest one" and "Closest one with PS difference less than 1%" matched samples; Panel B contains results for the "Closest two" and "Closest two with PS difference less than 1%" matched samples. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. Detailed descriptions of the variables are provided in Appendix 5.1.

	Panel A: "Closest one" and "Closest one, PS diff. < 1%" matched samples						Panel B: "Closest two" and "Closest two, PS diff. < 1%" matched samples					
Variable	**(1) Closest one**	**(2) Closest one**	**(3) Closest one**	**(4) Closest one PS diff. < 1%**	**(5) Closest one PS diff. < 1%**	**(6) Closest one PS diff. < 1%**	**(7) Closest two**	**(8) Closest two**	**(9) Closest two**	**(10) Closest two PS diff. < 1%**	**(11) Closest two PS diff. < 1%**	**(12) Closest two PS diff. < 1%**
CDS_trading	0.073***	0.077***	0.099***	0.068***	0.072***	0.094***	0.072***	0.077***	0.106***	0.068***	0.072***	0.100***
	(0.016)	(0.016)	(0.015)	(0.017)	(0.016)	(0.015)	(0.015)	(0.015)	(0.013)	(0.016)	(0.015)	(0.013)
CDS_Firm	0.032*	0.027		0.032*	0.026		0.038**	0.032**		0.037**	0.032**	
	(0.019)	(0.018)		(0.019)	(0.018)		(0.016)	(0.016)		(0.016)	(0.016)	
ln(*Assets*)	−0.039***	−0.036***	−0.037***	−0.037***	−0.034***	−0.034***	−0.046***	−0.041***	−0.041***	−0.043***	−0.037***	−0.037***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Profitability		−0.153	−0.152		−0.129	−0.128		−0.159*	−0.159*		−0.109	−0.110
		(0.095)	(0.095)		(0.095)	(0.095)		(0.085)	(0.085)		(0.087)	(0.087)
Div_payer		0.030**	0.031**		0.029**	0.030**		0.014	0.014		0.014	0.014
		(0.015)	(0.015)		(0.015)	(0.015)		(0.012)	(0.012)		(0.013)	(0.013)
Tangibility		0.072	0.074		0.067	0.069		0.118***	0.119***		0.103**	0.105**
		(0.049)	(0.049)		(0.049)	(0.050)		(0.040)	(0.040)		(0.042)	(0.042)
CFV		0.921**	0.924**		1.182**	1.185**		0.933**	0.944**		1.343***	1.356***
		(0.449)	(0.452)		(0.487)	(0.491)		(0.427)	(0.430)		(0.473)	(0.476)
R&D_ratio		1.200***	1.200***		1.193***	1.192***		1.236***	1.237***		1.262***	1.262***
		(0.263)	(0.261)		(0.262)	(0.261)		(0.236)	(0.235)		(0.241)	(0.239)
Rated		−0.071***	−0.071***		−0.071***	−0.071***		−0.058***	−0.059***		−0.059***	−0.059***
		(0.022)	(0.022)		(0.022)	(0.022)		(0.019)	(0.019)		(0.019)	(0.019)
MB_ratio		0.013*	0.013*		0.012	0.012		0.019***	0.019***		0.017**	0.016**
		(0.008)	(0.008)		(0.008)	(0.008)		(0.007)	(0.007)		(0.007)	(0.007)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.322	0.362	0.360	0.312	0.352	0.350	0.401	0.443	0.441	0.381	0.425	0.422
N	6,852	6,755	6,755	6,715	6,619	6,619	10,157	9,989	9,989	9,418	9,269	9,269

Table 5.5: CDS inception and debt specialization: Instrumental variable approach

This table presents the effect of CDS inception on debt specialization as estimated via an instrumental variable approach. I report the results derived from the regresions using the full-information maximum likelihood (FIML) estimation. My instrumental variable is *Lender_FX_hedging*, which measures the foreign exchange hedging activities of the firms' banks and underwriters. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. See Appendix 5.1 for a detailed description of the variables.

	First-stage	**Second-stage**
Variable	*CDS_trading*	*DS*
CDS_trading		0.052**
		(0.022)
CDS_Firm		0.006
		(0.016)
ln(*Assets*)	0.783***	−0.006
	(0.057)	(0.004)
Profitability	−0.040	0.048
	(0.464)	(0.037)
Div_payer	0.326***	0.032***
	(0.081)	(0.010)
Tangibility	0.602**	−0.092***
	(0.281)	(0.027)
CFV	−3.042	0.647***
	(2.773)	(0.214)
R&D_ratio	2.240	0.204***
	(1.497)	(0.079)
Rated	1.648***	−0.025*
	(0.146)	(0.013)
MB_ratio	0.006	0.017***
	(0.058)	(0.004)
Lender_FX_hedging	4.904**	
	(1.956)	
Industry Fixed Effect	Yes	Yes
Year fixed effects	Yes	Yes
Clustered standard errors	Yes	Yes
N	11,807	11,807

Table 5.6: Bankruptcy risk and the effect of CDS inception

This table reports the effect of CDS inception on debt specialization as a function of bankruptcy risk. I use $Distance-to-default$ proposed by Vassalou and Xing (2004), and $Altman's\ Z-score$ (**Altman, 1968**), as proxies for bankruptcy risk. A lower level of either $Distance-to-default$ or $Altman's\ Z-score$ indicates a higher bankruptcy risk. I use the interaction terms $CDS\_trading \times DD$ (Eq. (5.5)) and $CDS\_trading \times ZS$ (Eq. (5.6)) to capture the difference in CDS effects between firms facing higher and firms facing lower bankruptcy risk; here DD is an indicator set equal to 1 if the firm has a $Distance-to-default$ below the cross-sectional median upon the inception of CDS (and set to 0 otherwise), and ZS is an indicator set equal to 1 if the firm has a $Altman's\ Z-score$ less than 3 (and set to 0 otherwise). All the regressions control for industry and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is provided in Appendix 5.1..

	$Distance-to-default$				$Altman's\ Z-score$			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
$CDS\_trading$	0.032*	0.026	0.028	0.023	0.017	0.006	0.010	−0.000
	(0.019)	(0.019)	(0.018)	(0.018)	(0.023)	(0.023)	(0.022)	(0.022)
CDS_Firm	0.017	0.016	0.025	0.025	0.031*	0.030	0.036**	0.034**
	(0.018)	(0.018)	(0.015)	(0.015)	(0.018)	(0.018)	(0.016)	(0.016)
$CDS\_trading \times DD$	0.112***	0.114***	0.119***	0.119***				
	(0.025)	(0.026)	(0.024)	(0.024)				
DD	−0.078***	−0.079***	−0.092***	−0.090***				
	(0.019)	(0.019)	(0.014)	(0.015)				
$CDS\_trading \times ZS$					0.097***	0.105***	0.106***	0.116***
					(0.026)	(0.026)	(0.025)	(0.025)
ZS					−0.090***	−0.098***	−0.113***	−0.122***
					(0.020)	(0.021)	(0.016)	(0.017)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.389	0.379	0.484	0.463	0.396	0.389	0.494	0.481
N	6,739	6,603	9,953	9,233	6,694	6,563	9,901	9,191

Table 5.7: Liquidation cost and the effect of CDS inception

This table reports the effect of CDS inception on debt specialization as a function of bankruptcy risk. I follow Garlappi and Yan (2011) in using *Intangibles* as a proxy for the liquidation cost . A higher level of *Intangibles* indicates a higher liquidation cost. I use the interaction terms *CDS_trading* × *INTA* (Eq. (5.7)) to capture the difference in CDS effects between firms facing higher or lower liquidation cost; here *INTA* is an indicator set equal to 1 if the firm has an *Intangibles* score above the cross-sectional median upon the inception of CDS (and set to 0 otherwise). All the regressions control for industry and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is presented in Appendix 5.1..

	Intangibles			
Variable	**Closest one**	**Closest one PS diff. < 1%**	**Closest two**	**Closest two PS diff. < 1%**
CDS_trading	−0.000	−0.005	0.013	−0.000
	(0.022)	(0.022)	(0.021)	(0.021)
CDS_traded	0.052***	0.050***	0.050***	0.052***
	(0.017)	(0.018)	(0.015)	(0.015)
CDS_trading × *INTA*	0.124***	0.125***	0.099***	0.113***
	(0.026)	(0.026)	(0.025)	(0.025)
INTA	−0.152***	−0.152***	−0.139***	−0.154***
	(0.021)	(0.021)	(0.017)	(0.017)
Control variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes
Pseudo-R^2	0.443	0.431	0.521	0.515
N	6,651	6,520	9,858	9,148

Table 5.8: CDS inception and debt specialization: Alternative measure of debt specialization

This table reports the effect of CDS inception on debt specialization measured by *ODT*90, which is a dummy variable set equal 1 if the focal firms have at least 90% of their debt from one type of debt (set to 0 otherwise). Columns (1)–(4) present the results for a sample that includes CDS firms and their propensity score matched non-CDS firms; column (5) contains the results when an instrumental variable approach is adopted. I use probit model to run regressions of *ODT*90 on *CDS_trading*, and on the other control variables lagged by one year, while accounting for firm and time fixed effects. I apply (FIML) estimation to the regression with the instrumental variable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A more detailed description of the variables is provided in Appendix 5.1.

Variable	**(1) Closest one**	**(2) Closest one PS diff. $< 1\%$**	**(3) Closest two**	**(4) Closest two PS diff. $< 1\%$**	**(5) IV approach**
CDS_trading	0.351***	0.326***	0.358***	0.332***	0.274**
	(0.081)	(0.081)	(0.078)	(0.078)	(0.124)
CDS_Firm	0.076	0.075	0.100	0.095	−0.044
	(0.086)	(0.087)	(0.078)	(0.078)	(0.084)
ln(*Assets*)	−0.137***	−0.128***	−0.155***	−0.139***	−0.081***
	(0.033)	(0.034)	(0.029)	(0.029)	(0.022)
Profitability	−0.542	−0.490	−0.536	−0.372	0.378*
	(0.418)	(0.418)	(0.373)	(0.379)	(0.203)
Div_payer	0.197***	0.193***	0.122**	0.119**	0.133***
	(0.067)	(0.067)	(0.056)	(0.058)	(0.051)
Tangibility	−0.061	−0.078	0.126	0.066	−0.631***
	(0.211)	(0.213)	(0.179)	(0.183)	(0.133)
CFV	3.433*	4.192**	3.531**	4.958***	5.099***
	(1.902)	(2.017)	(1.795)	(1.919)	(1.227)
R&D_ratio	6.392***	6.347***	6.483***	6.530***	1.857***
	(1.318)	(1.316)	(1.179)	(1.189)	(0.491)
Rated	−0.103	−0.098	−0.065	−0.065	−0.204***
	(0.111)	(0.111)	(0.093)	(0.094)	(0.065)
MB_ratio	0.062*	0.058*	0.072**	0.068**	0.102***
	(0.035)	(0.035)	(0.029)	(0.030)	(0.023)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.100	0.0986	0.124	0.118	
N	6,755	6,619	9,989	9,269	11,807

Table 5.9: Bankruptcy risk and the effect of CDS inception: Alternative measure of debt specialization

This table reports the effect of CDS inception on debt specialization as a function of bankruptcy risk. Here, I measure debt specification using $ODT90$. I use $Distance-to-default$ proposed by Vassalou and Xing (2004), and $Altman's\ Z-score$ (**Altman, 1968**), as proxies for bankruptcy risk. A lower level of either $Distance-to-default$ or $Altman's\ Z-score$ indicates a higher bankruptcy risk. I use the interaction terms $CDS\_trading \times DD$ (Eq. (5.5)) and $CDS\_trading \times ZS$ (Eq. (5.6)) to capture the difference in CDS effects between firms facing higher and firms facing lower bankruptcy risk; here DD is an indicator set equal to 1 if the firm has a $Distance-to-default$ below the cross-sectional median upon the inception of a CDS (and set to 0 otherwise), and ZS is an indicator set equal to 1 if the firm has a $Altman's\ Z-score$ less than 3 (and set to 0 otherwise). All the regressions control for industry and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is provided in Appendix 5.1..

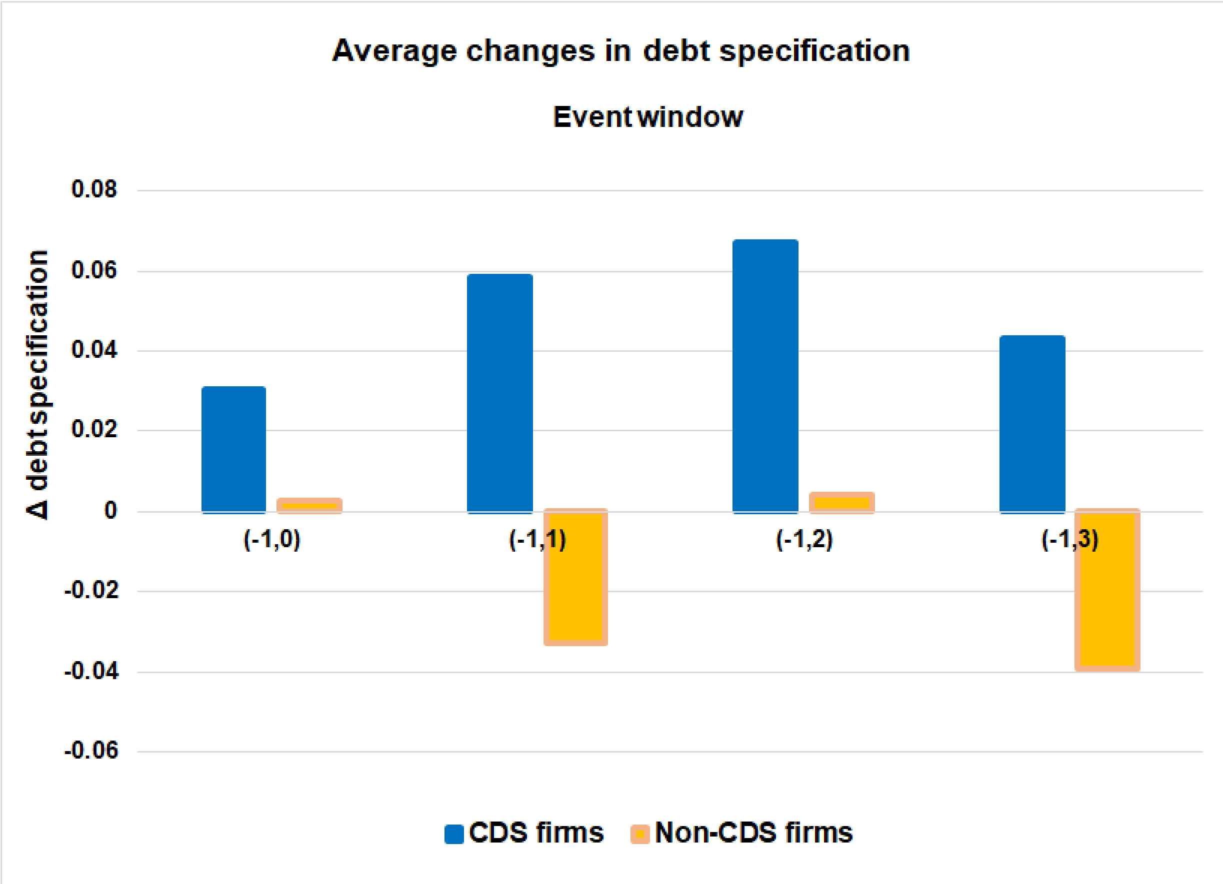
	$Distance-to-default$				$Altman's\ Z-score$			
Variable	**Closest one**	**Closest one PS diff. $<1\%$**	**Closest two**	**Closest two PS diff. $<1\%$**	**Closest one**	**Closest one PS diff. $<1\%$**	**Closest two**	**Closest two PS diff. $<1\%$**
CDS_trading	0.122	0.102	0.124	0.111	0.080	0.041	0.062	0.028
	(0.093)	(0.093)	(0.090)	(0.089)	(0.110)	(0.110)	(0.105)	(0.105)
CDS_Firm	0.033	0.031	0.073	0.073	0.102	0.097	0.125	0.112
	(0.087)	(0.087)	(0.078)	(0.078)	(0.089)	(0.089)	(0.080)	(0.081)
$CDS\_trading \times DD$	0.596***	0.584***	0.606***	0.567***				
	(0.120)	(0.120)	(0.112)	(0.112)				
DD	−0.393***	−0.384***	−0.433***	−0.389***				
	(0.088)	(0.089)	(0.068)	(0.070)				
$CDS\_trading \times ZS$					0.441***	0.464***	0.484***	0.499***
					(0.120)	(0.121)	(0.114)	(0.115)
ZS					−0.381***	−0.405***	−0.480***	−0.492***
					(0.091)	(0.093)	(0.073)	(0.076)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.110	0.108	0.136	0.128	0.107	0.107	0.136	0.130
N	6,739	6,603	9,953	9,233	6,694	6,563	9,901	9,191

Table 5.10: Liquidation cost and the effect of CDS inception: Alternative measure of debt specialization

This table reports the effect of CDS inception on debt specialization as a function of bankruptcy risk. Here, I measure debt specification using $ODT90$. I follow Garlappi and Yan (2011) and use $Intangibles$ as a proxy for liquidation cost . A higher level of $Intangibles$ indicates a higher liquidation cost. I use the interaction terms $CDS\_trading \times INTA$ (Eq. (5.7)) to capture the difference in CDS effects between firms facing a higher and firms facing a lower liquidation cost; here $INTA$ is an indicator set equal to 1 if the firm has a $Intangibles$ score above the cross-sectional median upon the inception of a CDS (and set to 0 otherwise). All the regressions control for industry and time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors (in parentheses) are clustered at the firm level. A detailed description of the variables is provided in Appendix 5.1.

	Intangibles			
Variable	**Closest one**	**Closest one PS diff. $< 1\%$**	**Closest two**	**Closest two PS diff. $< 1\%$**
$CDS\_trading$	−0.019	−0.036	0.011	−0.046
	(0.107)	(0.107)	(0.103)	(0.103)
CDS_traded	0.193**	0.183**	0.195**	0.200**
	(0.086)	(0.087)	(0.078)	(0.078)
$CDS\_trading \times INTA$	0.605***	0.601***	0.561***	0.614***
	(0.121)	(0.121)	(0.117)	(0.117)
$INTA$	−0.648***	−0.639***	−0.678***	−0.737***
	(0.095)	(0.095)	(0.075)	(0.077)
Control variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes
Pseudo-R^2	0.118	0.116	0.147	0.144
N	6,651	6,520	9,858	9,148

Figure 5.1: Changes in debt specialization following CDS inception.
This figure plots the cross-sectional average changes in *DS* for the CDS firms and their "Closest one" matched non-CDS firms before and after the inception of CDS trading. I calculate the changes in *DS* from 1 year before the CDS inception to 0, 1, 2, and 3 years thereafter. For each CDS firm, I select a matched firm from the non-CDS firm sample based on the propensity scores calculated as described in the model of Subrahmanyam et al. (2014).



Chapter 6

Conclusion

The three essays in my thesis provide empirical evidence on how CDS inception affects firm risk and on two new aspects of debt structure, the debt maturity profile and debt specialization. I thoroughly consider both demand-side and supply-side effects of CDS inception. I also discuss and provide evidence on the channels for CDS inception through which the impacts on those outcomes occur. In this chapter, I present a summary of the findings of the three essays presented in Chapter 2, Chapter 3 and Chapter 4.

6.1 Credit default swaps and firm risk

This chapter offers empirical evidence that the inception of CDS trading leads to a decrease in firm risk. I use firm value volatility, which incorporates information on equity and corporate debt, as a proxy for firm risk. My findings support the hypothesis that, with regard to firm value volatility, the empty creditor effect of CDS trading dominates the monitoring effect. The results are robust to the potential endogeneity problems associated with CDS trading due to the use of propensity score matching or, instead, an instrumental variable approach. I also find that the CDS-induced decrease in firm value volatility is less pronounced for more financially constrained firms. This finding indicates that the monitoring effect is stronger for firms that are more financially constrained. In addition, I document that the negative effect of CDS inception on firm value volatility is less pronounced for firms characterized by a greater price discrepancy between the credit default swaps and the corporate bonds. My results reveal that market frictions influence the extent to which financial innovation affects society, from which it follows that policymakers should seek to control those frictions.

This study contributes to the literature examining the effect of CDS markets on firm behavior. One question of interest involves the particular *channels* through which CDS inception could affect firm behavior in ways that reduce firm value volatility. I find that the firms' expenditure levels on hiring and investment decrease after the inception of CDS trading, but that their operating leverages do not change significantly. The results suggest that the decrease in firm value volatility after CDS inception could be partially attributed to the reduced hiring input or/and investment rates, but not to operating leverage. Another question concerns the two possible ways to attain my results. One way is that both the empty creditor effect and the monitoring effect exist, but that the empty creditor effect is stronger. The alternative way is that only the empty creditor effect exists. My results are more likely to support the first possibility as I find that the monitoring effect is stronger—for firms that are more financially constrained.

6.2 Credit default swaps and debt maturity profile

This chapter provides empirical evidence that the inception of CDS trading leads to an increase in the dispersion of corporate debt maturity profiles. I employ the two measures of maturity dispersion proposed by Choi et al. (2018). My finding is robust when addressing the potential endogeneity problems associated with CDS trading by using propensity score matching or instead via an instrumental variable approach. I also find that the positive relationship between CDS inception and debt maturity dispersion is stronger during periods of increased tightening of the credit market condition. This finding indicates that the effect of CDS inception on debt maturity dispersion could be established through the credit supply channel. Furthermore, I document that the positive effect of CDS inception on debt maturity dispersion is more pronounced for higher quality firms. These results support the idea that higher quality firms are more likely to use debt maturity dispersion as a risk management tool to cope with the threat from an empty creditor problem caused by CDS inception.

My findings support the hypothesis that, concerning debt maturity dispersion, the combined effect from the *tougher creditor effect* and the *cost reduction effect* dominates the *commitment effect*. One possible channel is through the shock in credit supply due to the CDS inception. This chapter contributes to the literature addressing the influence of the CDS market on firms' financing decision and risk management and provides interesting implications regarding the way in which financial market innovations interact with corporate behaviors.

6.3 Credit default swaps and debt specialization

This chapter examines the effect of CDS inception on an important aspect of debt structure, debt specialization. I consider both the demand-side and the supply-side channels that can explain the impact of CDS inception on debt specialization. On the demand-side, firms are more likely to choose a higher degree of debt specialization after the inception of CDSs. With the reduced probability of a strategic default due to the CDS inception, firms tend to specialize in fewer debt types to reduce the probability of inefficient liquidation. On the supply side, CDS inception reduces the frictions of the credit supply, which allows firms to have a lower degree of debt specialization. Using two measures of debt specialization, I find that firms tend to increase the level of debt specialization after the introduction of CDS trading. The results remain robust after addressing the endogeneity of CDS trading. I also provide evidence that the positive impact of CDS inception on debt specialization is more pronounced for firms facing a higher bankruptcy risk or a higher liquidation cost. This finding suggests that the expected bankruptcy cost is one channel through which CDS inception affects focal firms' debt specialization.

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