Credit Default Swaps and Firm Risk

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Friday 11th January, 2019

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Abstract

This paper investigates the impact of the inception of the credit default swap (CDS) on firm risk. Using firm value volatility as a measure of firm risk, we document that the volatility of reference firms' value decreases after the inception of CDS trading. The CDS effect on firm value volatility is less pronounced for the firms with more financial constraints or a higher CDS-bond price discrepancy. Our results show a significant impact of financial innovation on firm behaviour, supporting the empty creditor hypothesis developed by Bolton and Oehmke (2011). Our results also show the impact of market frictions on how significant financial innovations affect society.

JEL Classification: G12, G14, G32.

Keywords: Credit default swap; firm value volatility; empty creditor; financial constraint; price discrepancy.

1 Introduction

A credit default swap (CDS) is a credit insurance contract in which buyers make periodic payments (coupon, spread, or premium) over the life of the contract to insure against credit events on underlying reference 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, the CDS market has developed quickly over the last two decades.[2] The impact of this new but fast-growing credit derivative market has started to attract considerable attention from financial researchers. For example, Saretto and Tookes (2013), Subrahmanyam, Tang, and Wang (2014), Martin and Roychowdhury (2015) and Subrahmanyam, Tang, and Wang (2017), among others, provide evidence on the impact of CDS on firm behavior.[3] Understanding the impact of CDS on firm behavior is not only important to understand the critical question of whether financial innovation benefits society (see Zingales (2015) for an extensive review), it also helps improve portfolio decision making.

In this paper, we study the impact of CDS inception on firm risk. Firm risk is considered a reasonable representative of risk-taking behavior for a firm since it shows the net effect of all corporate risk-taking activities (Low, 2009). We use firm value volatility to measure firm risk instead of using equity volatility or cash flow volatility.[4] Low (2009) argues that it is problematic when using cash

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

[2] As of February 2018, the notional amount of CDS market is more than 10 trillion dollars. http://www.swapsinfo.org/charts/swaps/notional-outstanding.

[3] Saretto and Tookes (2013) find that firms with CDS trading have higher firm leverage and longer debt maturity. Subrahmanyam et al. (2014) show that probability of bankruptcy for reference firms increases after the inception of CDS trading. Martin and Roychowdhury (2015) document a decrease in borrowing firms' reporting conservatism (an 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 the inception of CDS trading on their debt.

[4] In Appendix 2, we show that the relationship between firm value volatility and equity volatility is uncertain.

flow volatility to measure firm risk, while Choi and Richardson (2016) demonstrate that firm value volatility is fundamentally different from equity volatility. Furthermore, firm value volatility plays a vital role in the valuation of capital structure and the trade-off between risk and return with the independence of financial leverage (Choi and Richardson, 2016).

We use a structural model to estimate firm value volatility. According to Merton (1974), equity can be viewed as a call option of firm value and priced by the Black-Scholes option formula. Thus, we could use equity information available on the market to estimate firm value and its volatility. We follow Vassalou and Xing (2004) and Bharath and Shumway (2008) to use an iterative procedure to estimate firm value volatility. Since this measure uses both equity and debt information, it is different from equity return volatility and could present the risks of a firm as a whole. To address the issue of endogeneity, we use both propensity score matching and an instrumental variable approach.

We document several interesting findings. First, we find that firm value volatility decreases after the introduction of CDS trading. When we use CDS firms with their closest one matched non-CDS firms in the regression, firm value volatility decreases by around 5.23% after the CDS inception. Results are similar when we use other matched samples. The negative impact is around 5.70% if we use the instrumental variable approach. These results suggest that firms become more conservative about their risk-taking behavior after the inception of CDS trading, which is consistent with the empty creditor hypothesis developed by Bolton and Oehmke (2011).

Second, applying the same analysis for different sub-samples, we find the impact of CDS inception is different for firms with different characteristics. Using the index developed by Whited and Wu (2006) (WW index) and dividend payer indicator as proxies for financial constraints, we find that the CDS effect on firm value volatility is less pronounced for more financially constrained firms. The empty creditor effect is thus weaker when a firm faces stricter financing conditions.

Using the absolute value of CDS-bond basis as the measure of price discrepancy between the corporate bond and CDS market, we find that the CDS inception has a weaker impact on firms with a higher level of price discrepancy. A higher level of price discrepancy suggests a higher level of limits-to-arbitrage and less integration between the CDS and the corporate bond market. As a result, the empty credit effect becomes weaker. This finding provides empirical evidence that market frictions have an impact on how significant financial innovations affect society, and thus gives support for policymakers to reduce them to improve social welfare.

Our difference from Subrahmanyam et al. (2014) lies in several ways. First, Subrahmanyam et al. (2014) investigate the impact of CDS inception on the default risk, while we study the impact of CDS inception on firm value volatility. Both bankruptcy risk and firm value volatility are two important dimensions of firm risk, and the research on them equally contributes to the literature. Second, following the structural model of Merton (1974), default risk depends on not only firm value volatility, but also leverage. Shumway (2001) and Correia, Kang, and Richardson (2018) document that firm risk have a significant impact on the probability of bankruptcy. They also find a positive relationship between leverage and the probability of bankruptcy. Besides, Saretto and Tookes (2013) and Subrahmanyam et al. (2017) provide evidence that the inception of CDS trading increases leverage. As a result, firm value volatility is largely different from default risk. Third, we document a different finding. Our results suggest that firms reduce their risk level after the inception of their CDS trading, which is different from the increase of default risk documented in Subrahmanyam et al. (2014).

Our study contributes to the literature in several ways. First, we contribute to an ongoing debate regarding the impact of financial innovation, particularly CDS on societal benefits. We find that CDS trading reduces firm risk measured by firm value volatility, showing evidence of the social impact of financial innovation. Our finding supports the view of academics that finance affects society; see, for example, Myers and Majluf (1984), Guiso, Sapienza, and Zingales (2004), Levine (2004) and Zingales (2015). Second, our study extends the existing literature on the impact of CDS trading on firm behaviors. Prior research shows the effects of CDS inception on firm behaviors including firm leverage, cash holding, and reporting conservatism. We provide empirical evidence about the reduction in firm value volatility after the advent of CDS trading. Third, our study uses information from the financial market and investigates its impact on firms' decisions, and thus contributes to the literature regarding the link between asset pricing and corporate finance.

The rest of the paper is organized as follows. In Section 2, we review the relevant literature and develop our hypotheses. Section 3 presents the empirical methodology. Section 4 describes the data and Section 5 presents our empirical results. In Section 6, we conduct several robustness tests. Finally, Section 7 summarizes our main findings and concludes the paper.

2 Literature review and hypotheses development

2.1 Empty creditor effect versus monitoring effect

The literature has documented two main mechanisms on how CDS inception affects firm behavior. One is the empty creditor effect, and the other is the monitoring effect.

Theoretically, Bolton and Oehmke (2011) show that the empty creditor effect could drive the relationship between CDS inception and firm value volatility. The empty creditor means that the debt holder has no desire to preserve a company to which they provide funds. This problem arises when a creditor has over-insured their credit risk by buying CDS but still holds the control rights in the firms. With the credit insurance obtained through the CDS market, the creditors have more bargaining power over borrowers in re-negotiations following a strategic default which occurs when it is more beneficial for the borrower to default. The increase in the bargaining power of the lender could lead to a decrease in the probability of strategic default. To avoid a re-negotiation in which the lenders have more bargaining power, the borrowers tend to make more prudent decisions on investment and other corporate finance activities. For example, Subrahmanyam et al. (2017) empirically show that firms increase their cash holdings after the inception of CDS trading on their debt, which is in line with the hypothesis. This empty creditor effect results in a decrease in firm value volatility after the inception of CDS trading on firms' debt.

On the other hand, the CDS market allows banks and bond investors to efficiently hedge their credit risk related to their investment in the borrowing firms. This credit risk transfer could reduce the monitoring incentive for lenders. It implies that the credit risk transfer resulting from CDS purchases leads to a weaker monitoring of borrowing firms, which is supported by Morrison (2005). In such case, the borrowing firms have more tolerance to risks and tend to engage in more-risky projects. Consistent with this hypothesis, Martin and Roychowdhury (2015) find a decrease in borrowing firms' reporting conservatism (an asymmetry in recognition of losses versus gains) after the initiation of CDS trading. Chang, Chen, Wang, Zhang, and Zhang (2017) document that the inception of CDS trading promotes firms' risk taking, resulting in an increase in innovation output. The risk-shifting behavior of the firm could lead to an increase in firm value volatility after the inception of CDS trading. We define this impact as the monitoring effect of CDS on firm value volatility.

In this paper, we study whether the empty creditor effect of CDS inception on firm value volatility dominates the monitoring effect. Our primary hypothesis is as follows:

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

2.2 CDS inception and financial constraint

There are two channels through which financial constraint could impact the effect of CDS inception on firm value volatility. First, in line with the view of the empty creditor effect, CDS inception could be considered as an exogenous shock which increases the threat of liquidation of the firms. Since more financially constrained firms have fewer options for external financing, they tend to be mindful of the danger of going bankrupt. As a result, these firms are more likely to be prudent in decision making and to increase management efficiency to mitigate the bankruptcy threat. The firms' more preparedness for the events of financial distress may make them less affected by the exogenous shock of CDS inception. In other words, the empty creditor effect of CDS on firm value volatility may be weaker for more financially constrained firms.

Second, Eisdorfer (2008) finds that risk-shifting incentives are stronger for more financially constrained firms than for less financially constrained firms. In such case, the risk-shifting incentives that result from the less creditor monitoring incentive may be stronger for more financially distressed firms. Parlour and Winton (2013) show that credit risk transfer via loan sales or CDS purchases tends to increase the monitoring incentive for riskier credits but reduces the monitoring incentive for safer credits. They demonstrate that the bank is more likely to use CDS as a means for transferring the credit risk of safer credits while using loan sales to transfer the risk of riskier credits. However, since it tends to be more difficult for the bank to sell the loan of riskier credit, the bank might expand the use of CDSs for riskier credits which results in a low level of monitoring. In other words, the monitoring effect of CDS inception on firm value volatility is stronger for more financially constrained firms. In sum, if the empty creditor effect is weaker or (and) the monitoring effect is stronger for more financially constrained firms, we expect the negative impact of CDS inception on firm value volatility is weaker for more financially constrained firms.

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

2.3 CDS inception and CDS-bond pricing discrepancy

The absolute value of 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 price discrepancy could imply the existence of limits-to-arbitrage. Limits-to-arbitrage might occur when the transaction cost and risk of a security are high. A higher absolute value of CDS-bond basis thus could indicate a higher transaction cost and risk of CDS trading. Moreover, a higher level of price discrepancy also suggests that a firm's CDS and corporate bond market are less integrated, which makes the CDS spread less informative. These conditions might reduce the creditor's incentives for using CDS as a credit risk transfer tool, thus making the empty creditor effect weaker. We propose the following hypothesis to study the relationship between the price discrepancy of the credit market and the effect of CDS inception on firm value volatility:

Hypothesis 3: The empty creditor effect of CDS inception on firm value volatility is less pronounced for firms with a higher absolute value of CDS-bond basis.

3 Empirical specification

3.1 Firm value volatility

Firm value is not directly observable, which imposes a constraint on estimating firm value volatility. Merton (1974) proposes a structure model and shows that equity and debt are both options of firm value. Equity could be identified as a call option of firm value and priced by the Black-Scholes option pricing formula. Since equity price is observable from the market, we could use equity information with the Black-Scholes option pricing formula to estimate the firm's value and its volatility.

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

$$E = VN(d_1) - e^{-rT} FN(d_2), \tag{1}$$

where 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 rate, T is the debt maturity, $N(.)$ is the cumulative distribution function of standard normal distribution, d_1 is given by

$$d_1 = \frac{ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{2}$$

and $d_2 = d_1 - \sigma_V \sqrt{T}$. σ_V is the firm value volatility.

Under Merton's (1974) assumptions, the link between firm value volatility σ_V and equity value volatility σ_E is expressed by following equation:

$$\sigma_E = (V/E)N(d_1)\sigma_V. \tag{3}$$

Besides equity information, we also need debt face value and maturity information to estimate V and σ_V. Following Vassalou and Xing (2004) and Bharath and Shumway (2008), we assume the debt maturity is one year and the face value equals short-term debt plus one-half of long-term debt.

Under the structure model, default risk could be measured by distance to default (DD):

$$DD = \frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{4}$$

where μ is the expected return of V. According to Eq. (4), σ_V is an important determinant of DD. Meanwhile, leverage and asset expected return also affect the default risk.

Theoretically, we could use Eq. (1) and (3) to calibrate V and σ_V. However, in practice, the market leverage moves around far too much for Eq. (3) to provide reasonable results (Crosbie and Bohn, 2003). Following Vassalou and Xing (2004) and Bharath and Shumway (2008), we use an iterative procedure to estimate firm value volatility in each month using the information over the past year. The process is as follows:

1. Estimate the volatility from a time series of equity price over the past year, and use it as the first step estimate of firm value volatility, σ_{V0}.
2. Put σ_{V0} into Eq. (1) to calculate the time series of V.
3. Estimate the volatility from the time series of V, and use it as the second step estimate of firm value volatility, σ_{V1}.
4. Replace σ_{V0} with σ_{V1}, and repeat step 2 to 4 until a convergence criterion is met.[5]
5. Use the last σ_{V1} as the estimate of σ_V.

[5]The absolute difference between σ_{V0} and σ_{V1} is less than 0.001.

3.2 The determinants of firm value volatility

We use a regression model to examine the effect of the inception of CDS trading on firm value volatility. The dependent variable is firm value volatility, which is estimated using the structured model. Following Ashcraft and Santos (2009) and Subrahmanyam et al. (2014), we use an indicator variable of CDS trading to estimate the impact of CDS trading on firm value volatility. CDS trading is a dummy variable which equals one if the firm has CDS traded on its debt one year before and zero otherwise. We regress firm value volatility on CDS trading and other control variables which are used as the determinants of firm value volatility in the literature. We also take into consideration firm and time effects. An unobserved firm effect occurs for a given firm when the residuals of the firm may be correlated across years. Meanwhile, 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 which are fixed in our panel data, we control for both firm and time fixed effects. We also cluster standard errors at the firm level to provide more robust statistical results. Our regression model is written as follows,[6]

$$Ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\ Trading_{i,t} + \gamma \times X_{i,t} + \theta_1 \times Firm_i + \theta_2 \times Year_t + \varepsilon_{i,t}, \tag{5}$$

where $CDS\ Trading$ is the key independent variable which equals one if the firm has CDS traded on its debt one year before and zero otherwise, $X_{i,t}$ is the vector of the control variable, and $Firm_i$ and

[6]The ordinary least squares regression for a typical difference-in-difference approach follows the equation: $Ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\ Traded_{i,t} \times Post_{i,t} + \beta_1 \times Post_{i,t} + \beta_2 \times CDS\ Traded_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}$, where $CDS\ Traded$ is a dummy variable taking the value of one if a firm has CDS traded on its debt any time during our sample period and zero otherwise and indicator variable *Post* equals one for observations after the inception of CDS and zero otherwise. However, since we include time and firm fixed effects in the model, both indicator variables, $CDS\ Traded$ and *Post*, are not necessary. Eq. (5) is equivalent to a typical difference-in-difference model with $CDS\ Trading$ standing for the interaction term $CDS\ Traded \times Post$.

$Year_t$ are firm and time fixed effect variables, respectively. We use the logarithm transformation to reduce the skewness of firm value volatility.[7] β captures the impact of the inception of CDS trading on firm value volatility.

The literature has documented that many variables can affect firm value volatility. For example, Black (1976) shows the effect of leverage on firm-level volatility as the change in leverage drives the change in firm value volatility. Comin and Mulani (2009) use total R&D expenses over total sales as a proxy for R&D innovation and investigate the role of R&D innovation in the increase in firm value volatility. Their findings show that an increase in R&D intensity leads to an increase in firm value volatility since it causes "turnover in the market leader". This evidence is consistent with the findings of Comin and Philippon (2005). Davis, Haltiwanger, Jarmin, and Miranda (2006) investigate the impact of firm age on firm value volatility. They find that firm volatility declines with firm age. Following these studies, we use the following variables as control variables in our study.

- *Leverage*. Leverage is 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 market equity is the number of common shares outstanding multiplied by the stock price.
- *Firm age*. Firm age is defined as the natural logarithm of the number of years from the first time the firm appears in the Compustat database.
- *R&D_ratio*. R&D_ratio is the ratio of research and development (R&D) expenses over total sales.
- *Excess return*. Excess return is the firm's return in excess of market over the past year.

[7] Using the logarithm also provides a better economic significance intepretation. The change of logarithm measures the impact on volatility in percentage, while the change of the variable itself measures the impact in level.

- *MB_ratio*. MB_ratio is the ratio of market value of assets over the 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 credit (txditcq).
- $\ln(equity)$. $\ln(equity)$ is the natural logarithm of the firm's equity market value, which is used as a proxy for firm size.

Panel A of Appendix 1 provides a detailed description of variables used in the regression model (5).

3.3 Endogeneity

There is a potential endogeneity problem for CDS trading which causes the spurious effect of the inception of CDS trading on firm value volatility. This might be the case when there is an unknown factor that affects both the inception of CDS trading and firm value volatility at the same time. Following Subrahmanyam et al. (2014) and Martin and Roychowdhury (2015), we use propensity score matching and an instrumental variable (IV) approach to mitigate the endogeneity problem.

3.3.1 Propensity score matching

First, we use the propensity score matched sample to reduce the impact of the endogeneity problem on our results. Roberts and Whited (2013) show that, although matching might not solve the endogeneity and self-selection problems in every context, this approach can mitigate some biases caused by these problems. We first calculate the propensity scores for all firms, and then use the scores to match CDS firms and their non-CDS firms. We follow Roberts and Whited (2013) to conduct the matching with replacement. This means that each non-CDS firm may be used more than once for the matching purpose. Moreover, we use several alternatives for choosing matches. Specifically, we use the following four matched samples in our analysis:

- "*Closest one*" sample. For each CDS firm, we choose one non-CDS firm that has the closest propensity score to it.
- "*Closest two*" sample. For each CDS firm, we choose two non-CDS firms that have the closest propensity scores to it.
- "*Closest one with a propensity score difference less than 1%*" (Closest one PS diff $< 1\%$) sample. For each CDS firm, we choose one non-CDS firm that has the closest propensity score to it with the condition that the difference in scores between those firms is less than 1%.
- "*Closest two with a propensity score difference less than 1%*" (Closest two PS diff $< 1\%$) sample. For each CDS firm, we choose two non-CDS firms that have the closest propensity scores to it with the condition that the difference in scores between those firms is less than 1%.

One of the challenges of the propensity score matching method is to find an appropriate model to estimate the propensity score. In the literature, Ashcraft and Santos (2009) suggest a model for estimating the propensity score to address the endogeneity problem of CDS trading. Saretto and Tookes (2013), Subrahmanyam et al. (2014), and Martin and Roychowdhury (2015) develop the model of Ashcraft and Santos (2009) in their studies. These models are different in terms of using covariates and defining the dependent variable. However, the key common covariate among these studies is *Lender_FX_hegding*, which measures the lenders' and underwriters' foreign exchange hedging activities.[8] Following Subrahmanyam et al. (2014) and Martin and Roychowdhury (2015), we use a probit model to estimate the probability of CDS trading on firms' debt,

$$Prob.(CDS\ Traded_{i,t} = 1) = \Phi(\alpha + \beta \times X_{i,t} + \gamma_1 \times Industry_i + \gamma_2 \times Year_t), \tag{6}$$

where $CDS\ Traded$ is a dummy variable which equals one for the firms with CDS traded during the period of our sample and zero otherwise. X is the vector of the set of covariates that are considered the determinants of the probability of CDS trading. $Industry_i$ is the industry fixed effect variable, while $Year_t$ is the time fixed effect variable. Panel B of Appendix 1 shows the information about the covariates used in the probit model (6). Then we use the probability of CDS trading as the propensity scores to construct the matched sample.

3.3.2 Instrumental variable approach

In addition to propensity score matching, we use an instrumental variable approach to mitigate the impact of the endogeneity problem. Following Saretto and Tookes (2013) and Subrahmanyam et al. (2014), we use $Lender\_FX\_hegding$ as the instrumental variable. Minton, Stulz, and Williamson (2009) show that banks with a large amount of foreign exchange derivatives for hedging purpose are more likely to be net buyers of CDSs. This could imply that banks tend to hedge more than one component of their portfolios. Foreign exchange derivatives activities of banks are not likely to have a direct relationship with their borrower's volatility. In particular, the independence between the bank's foreign exchange derivatives activities and their borrower's volatility is more likely to happen when the borrower and bank are in the same country.

Since the endogenous variabe, $CDS\ Trading$, is a dummy variable, the conditional expectation

[8] Please refer to Appendix 1 for a detailed description on how to construct this measure.

function (CEF) associated with the first stage is probably nonlinear. In order to avoid problem due to an incorrect nonlinear model at the first stage, we follow Angrist and Pischke (2009) and apply a there-stage procedure to estimate the coefficients. In the first stage, we estimate the predicted value of *CDS Trading* (*CDS Trading_IV*) using the following probit model that regresses *CDS Trading* on control variables and the instrumental variable, *Lender_FX_hegding*,

$$CDS\ Trading\_IV_{i,t} = \Phi(\alpha + \beta \times X_{i,t} + \gamma \times Z_{i,t} + \theta_1 \times Industry_i + \theta_2 \times Year_t), \quad (7)$$

where Z is the instrumental variable, *Lender_FX_hegding*. X is the vector of all control variables in Eq. (5). In the next step, we use *CDS Trading_IV* as an instrument for *CDS Trading* in a conventional two-stage least square (2SLS) procedure.

4 Data

We use data from Markit to identify the inception of CDS trading. We use the date when a CDS spread quote first appears in Markit as the inception date for a firm. Our CDS inception data cover the period from 2001 to 2012. The dependent variable is firm value volatility, which is estimated using the structured model proposed by Bharath and Shumway (2008). The stock price and other financial information used to calculate firm value volatility and other variables are from the Compustat and Center for Research in Security Prices (CRSP) data sets (CRSP-Compustat merged quarterly database). We only consider firms with stocks listed on NYSE, AMEX, or Nasdaq. We match CDS data from Markit with the information from the CRSP-Compustat merged database using the first six digits of CUSIP. Following Subrahmanyam et al. (2017), we first use the whole sample for this study.[9]

Panel A of Table 1 presents the whole sample by year between 2001 and 2012. The second column shows the total number of U.S. companies included in our sample. The number of firms gradually decreases during the sample period, from 6672 firms in 2001 to 4228 firms in 2012. The third column reports the number of firms for which CDS trading was initiated during that year. Consistent with Subrahmanyam et al. (2017), CDS inception happens more frequently before 2005. For example, there are 680 ($4+396+120+115+45$) firms that have CDS inceptions before 2005, while there are only 88 firms ($30+34+7+1+5+8+3$) after 2005. In total, there are 768 firms in our sample that have CDS inception during the sample period of 2001 to 2012.

Panel B of Table 1 provides summary statistics of firm characteristics variables for all firms, CDS firms, and non-CDS firms. We report the results of $\ln(\sigma_V)$, σ_V, $ln(asset)$, $Leverage$, $Excess\ return$, $Firm\ age$, $R\&D\_ratio$, MB_ratio_equity, and $\ln(equity)$. For each variable, we report the number of observations (N), mean, standard deviation (std), skewness, and the 25^{th}, 50^{th}, and 75^{th} percentile value. We winsorize all variables at the 1^{st} and 99^{th} percentiles to mitigate the impact of outliers. We could observe a higher level of firm value volatility for the non-CDS firms. The mean σ_V of CDS firms is 0.511, while it is 0.827 for the non-CDS firms. Similarly, the mean $ln(\sigma_V)$ of CDS firms is -0.823, while it is -0.459 for the non-CDS firms. The CDS firms tend to have a lower level of firm value volatility compared with non-CDS firms.

[Insert Table 1 here]

$Lender\_FX\_hegding$ is one main variable we use in our propensity score matching model and instrumental variable approach analysis. The $Lender\_FX\_hegding$ measures the foreign exchange hedging activities by banks and underwriters. Specifically, it is the average of the ratio of the

[9] In the robustness test, we check our results by excluding financial firms.

notional volume of foreign exchange derivatives used for hedging (not trading) purposes to 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 our sample, we identify its main lenders and bond underwriters, respectively, using information from Dealscan and the Fixed Income Securities Database (FISD). For the lenders' information, we match the data between Compustat and Dealscan by Gvkey using the link provided by Chava and Roberts (2008). For the underwrites' information, we use CUSIP six digits to match the data between Compustat and FISD. Finally, we collect banks' information including total assets, credit derivative, foreign exchange (FX) hedging activities, and Tier 1 capital ratio from the Federal Reserve call report.[10] Since there is no common identifier between Dealscan, FISD, and call report data, we manually match them by name, state, and other information of the relevant banks.We next turn to empirical analysis.

5 Empirical results

5.1 CDS inception and firm value volatility: whole sample

We start our empirical analysis using the whole sample to run the regression of Eq. (5). Table 2 reports the regression results. Our variable of interest is the coefficient of $CDS\ Trading$, which measures the impact of the CDS inception on firm value volatility.

First, we only use the variable of $CDS\ Trading$ in the panel regression and control for firm and year fixed effects (Model (1) in Table 2). The coefficient of $CDS\ Trading$ is -0.0464 and significant at the 1% level. A negative value of the coefficient means firm value volatility declines after the

[10] Since Compustat and Federal Reserve call report are updated quarterly, we calculate the variables that use information from them in each quarter and expand those variables to monthly frequency. All other variables are calculated in each month.

inception of CDS trading. In particular, firm value volatility decreases by -4.64% after the CDS on its debt starts trading.

Next, we introduce other control variables into the regression (Models (2) and (3) in Table 2). The coefficients of *CDS Trading* continue to be significantly negative. The coefficient of *CDS Trading* is -0.0659 under Model (2) and -0.0731 under Model (3). Both of them are significant at the 1% level. These results suggest that the negative impact of CDS inception on firm value volatility is robust to the control of other firm characteristics variables. These findings support the *Hypothesis 1*.[11]

[Insert Table 2 here]

5.2 Endogeneity issue

5.2.1 Propensity score matching

5.2.1.1 Propensity score matched sample

We use Eq. (6) to estimate the probability of CDS inception, which is then used as propensity scores to construct the matched samples. First, we follow Subrahmanyam et al. (2014) and use the covariates, including $\ln(asset)$, *Leverage*, *ROA*, *Excess return*, *Equity volatility*, *Tangibility*, $Sale\_ratio$, $EBIT\_ratio$, $WCAP\_ratio$, RE_ratio, $Cash\_ratio$, $CAPX\_ratio$, SP_rating, $Unsecured\_debt$, $Lender\_FX\_hegding$, $Lender\_Tier1\_capital$, $Lender\_credit\_derivative$, and $Lender\_size$.[12] We use this model as our primary method to construct the matched samples.

[11] The number of observations under different model specification is different due to the missing value of some variables. We also tried to use the observations that do not have missing values and the results do not change.

[12] Panel B of Appendix 1 explains how to construct these variables.

Panel A of Table 3 report the regression results. Most of the explanatory variables have a significant impact on the probability of CDS trading. For example, the coefficient of $\ln(asset)$, which is a proxy for firm size, is significantly positive with the value of 0.762 (the p-value is less than 0.01), suggesting that CDS trading is more likely to occur for large firms. The firms with a higher excess stock return have a higher probability of CDS traded on their debts. In addition, CDS is more likely to be initiated on the firms that have a higher tangible asset ratio, sale-to-asset ratio, and profitability. The probability of CDS initiation is also higher for the rated firms and the firms with a higher ratio of unsecured debts over total assets.

The coefficient of *Lender_FX_hegding* is 3.771 with a p-value less than 0.001 after controlling for other firm characteristics. This significantly positive coefficient indicates CDS is more likely to be traded on the firms that have their banks involved in more foreign exchange hedging activities. This result is consistent with the findings of Saretto and Tookes (2013) and Subrahmanyam et al. (2014). Overall, the pseudo-R^2 of this regression is 0.587, which indicates these variables could explain the probability of CDS trading to a reasonable extent.

[Insert Table 3 here]

We next examine the effectiveness of our matching procedure by testing the mean difference in the characteristics between the CDS firms and their matched non-CDS firms before the inception of CDS. For simplicity, we only choose the "*Closest one*" matched sample in our comparison. We test the difference in means between the CDS and matched non-CDS firms by running the following regressions for each variable,

$$X_{i,t} = \alpha + \beta \times CDS\ Traded_{i,t} + \theta_1 \times Firm_i + \theta_2 \times Year_t + \varepsilon_{i,t}, \tag{8}$$

where $CDS\ Traded$ is dummy variable that equals one if a firm has CDS traded on its debt any time during our sample period and zero otherwise, $X_{i,t}$ is the firm characteristic variable, and $Firm_i$ and $Year_t$ are firm and time fixed effect variables respectively. β captures the difference in means of each variable between the CDS firms and their matched non-CDS firms. The firm characteristics variables we consider include $\ln(\sigma_V)$, $Leverage$, $Firm\ age$, $R\&D\_ratio$, $Excess\ return$, MB_ratio_equity, $\ln(equity)$, $\ln(asset)$, $Propensity\ score$, and $\Delta\sigma_V$. $Propensity\ score$ is the probability of CDS inception using Eq. (6) following the model of Subrahmanyam et al. (2014), while $\Delta\sigma_V$ is the monthly changes in firm value volatility. For each variable, we only use the data before the CDS inception in the regression.

Panel B of Table 3 reports the results. The results show that prior to the CDS inception, there is no statistical difference between the CDS firms and their matched non-CDS firms in terms of $\ln(\sigma_V)$, $R\&D\_ratio$, MB_ratio_equity, $\ln(equity)$, and $\ln(asset)$. Although the CDS firms and their matched non-CDS firms are statistically different in $Leverage$, $Excess\ return$, and $Firm\ age$, they are close to each other in the propensity scores with an insignificant t-statistic of 0.163. In other words, before the inception of CDS, the CDS firms and their matched non-CDS firms are similar in the probability of CDS trading. These results indicate that most firm characteristics, including the probability of CDS trading, are not likely to drive the difference in firm value volatility after the CDS inception, suggesting our matching procedure is effective. Also, we test the mean difference between the changes in firm value volatility ($\Delta\sigma_V$) of the CDS firms and their matched non-CDS firms before the CDS inception. The result shows that mean changes in firm value volatility are not statistically significant (t-statistic = 0.503) before the inception of CDS. Thus, according to Roberts and Whited (2013), the matched sample satisfies the assumption of parallel trends.

5.2.1.2 Results

To provide a visual analysis of the impact of CDS inception on firm value volatility, we compare the changes in the firm value volatility for the CDS firms and their *"Closest one"* matched non-CDS firms before and after the inception of CDS trading. We define the date of CDS inception as date 0. We then calculate the average changes in the logarithm of firm value volatility for the CDS firms and the matched non-CDS firms from one year before the CDS inception to zero (-1,0), one (-1,1), two (-1,2) and three (-1,3) years after the CDS inception.

Figure 1 plots the results. Overall, the CDS and matched non-CDS firms exhibit a decreasing trend in firm value volatility. However, there is a more significant decrease in firm value volatility for the CDS firms than that for the matched non-CDS firms. For example, from year -1 to year 1, the logarithm of firm value volatility of the CDS firms decreases by 0.19 on average, while the decrease for the matched non-CDS firms is only 0.13. Since the mean firm value volatility is around 0.53, this gap of 0.06 means a difference of firm value volatility change of about 3.20%. We observe the same pattern for the other event windows. The results also indicate that the adverse effect of CDS inception on firm value volatility is persistent over years. We next formally test the impact by running the regression of Eq. (5) using the propensity score matched sample.

[Insert Figure 1 here]

Panel A of Table 4 reports the results for the matched samples using "*Closest one*" and "*Closest one with a propensity score difference less than 1%*" (Closest one PS diff$<$1%) as selecting criteria. When we use the "*Closest one*" matched sample and do not control for other variables, the coefficient of $CDS\ Trading$ is -0.0403 and is significant at the 5% level. This result is close to that using the full sample data reported in Table 2. This suggests that our result about the impact of CDS inception on firm value volatility is robust to whether we use full sample data or matched sample data. After we include other firm characteristics variables, the coefficient of *CDS Trading* changes to -0.0523 and is still significant at the 1% level. This means that on average the inception of CDS trading decreases approximately 5.23% of the mean firm value volatility. Given that the mean firm value volatility is around 0.53, the level of firm value volatility decreases approximately by 2.76% ($0.53 \times 5.23\%$) after the inception of CDS trading. Similarly, the results of "*Closest one with a propensity score difference less than 1%*" sample show that CDS inception has a negative impact on firm value volatility as well.

The coefficients of the control variables are significant and have signs as expected. The coefficient for *Leverage* is positive, predicting that an increase in financial leverage leads to an increase in firm value volatility. This result is consistent with previous findings in the literature. The coefficient for *Firm age* is significantly negative with the value of -0.187 (*p*-value is less than 1%) if we use the "*Closest one*" matched sample and include all control variables (column (3)). This result is consistent with the findings of Davis et al. (2006), and suggests that firm value volatility is lower for old firms compared with young firms. Furthermore, the coefficient of *R&D_ratio* is 0.0705 and significant at the 1% level if we 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 a rise in R&D intensity increases firm value volatility. The coefficients for *Excess return* and *MB_ratio* are -0.114 and 0.042, respectively, in column (3), with both *p*-values being less than 1%. These results suggest the statistically significant effect of historical stock return and market-to-book ratio on firm value volatility.

Panel B of Table 4 reports the results for the alternative matched samples using "*Closest two*" and "*Closest two with a propensity score difference less than 1%*" (Closest two PS diff<1%) as selecting criteria. The results show that the effect of CDS inception on firm value volatility is robust. The coefficients of *CDS Trading* in all models are negative. For example, the coefficients of *CDS Trading* in columns (3) and (6) are -0.0399 and -0.0386, respectively. The corresponding p-values for these two coefficients are less than 1% and less than 5%, respectively. Overall, our results suggest that the negative relationship between CDS trading and firm value volatility is robust for the choice of the sample used in the empirical analysis.

[Insert Table 4 here]

5.2.2 Instrumental variable approach

Next, we use an instrumental variable approach to mitigate the potential endogeneity problem of CDS trading. As mentioned in Section 3.3.1, we use *Lender_FX_hegding* as an instrumental variable for this approach. This instrumental variable has been used in previous studies, including Saretto and Tookes (2013) and Subrahmanyam et al. (2014). Following Angrist and Pischke (2009), we apply the three-stage procedure to run the analysis. We estimate the predicted value of CDS trading, *CDS Trading_IV*, using the probit model that regresses CDS trading on the instrumental variable and all control variables in Eq. (5), then use *CDS Trading_IV* as an instrument of *CDS Trading* in a conventional 2SLS procedure.

Table 5 reports the results of the instrumental variable approach. The left and right columns report the results of first-stage probit model and the 2SLS regression respectively. To test the significance of the instrumental variable, we report the F-statistic on the excluded instrument in the 2SLS regression. The F-statistic is 2066.12, suggesting that it is a strong instrumental variable.[13]

[13] According to Stock, Yogo, and Wright (2002) and Angrist and Pischke (2009), the F-statistic should be greater than 10 to be an significant instrumental variable.

The coefficients of *CDS Trading_IV* is negative and significant at the 5% level in the 2SLS regression. These results are consistent with those of the propensity score matched sample. The coefficient of *CDS Trading_IV* in Table 5 is -0.057 with a *p*-value less than 5% after we control for firm characteristics variables and the time and firm fixed effect. The significantly negative coefficient implies a negative relationship between the CDS trading inception and firm value volatility. This indicates that after the inception of CDS trading, firm value volatility decreases, supporting *Hypothesis 1* that the empty creditor effect dominates the monitoring incentives effect.

[Insert Table 5 here]

5.3 CDS inception and financial constraints

In this section, we study whether the impact of CDS inception on firm value volatility is different among firms with varying levels of financial constraint. The literature shows that firms with CDS inception tend to hold more cash (Subrahmanyam et al., 2017) or increase corporate innovations (Chang et al., 2017). However, the relationship between the CDS impact and financial constraint is not conclusive. Subrahmanyam et al. (2017) document that the positive effect of CDS on cash holding is stronger for the firms with more financial constraints, while Chang et al. (2017) show that the positive impact of CDS on firm innovation is stronger for less financially constrained firms.

We use the financial constraints index (WW index) developed by Whited and Wu (2006) and the dividend payer indicator as proxies for financial constraints. A higher level of the WW index means higher financial constraints, while the firms that do not pay a dividend tend to be more financially constrained than the firms that do pay a dividend. To test whether the impact of CDS inception is different between more and less financially constrained firms, we introduce the interaction terms of

CDS trading indicator and financial constraint indicator. If we use the WW index as the proxy of financial constraint, we run the following regression model,

$$
\begin{aligned}
Ln(\sigma_V)_{i,t} = \alpha \,+\, \beta \times CDS\ Trading_{i,t} \,+ \gamma \times X_{i,t} \\
+\, \theta_1 \times Firm_i \,+\, \theta_2 \times Year_t \,+\, \kappa \times CDS\ Trading_{i,t} \times WW_{i,t} + \varepsilon_{i,t}, \quad (9)
\end{aligned}
$$

where $WW_{i,t}$ is a dummy variable which equals one if the WW index is above the cross-sectional median and zero otherwise. A positive value of κ means the negative impact of CDS inception on firm value volatility is less pronounced for more financially constrained firms. Similarly, if we use the dividend payer as the proxy of financial constraint, we run the following regression,

$$
\begin{aligned}
Ln(\sigma_V)_{i,t} = \alpha \,+\, \beta \times CDS\ Trading_{i,t} \,+ \gamma \times X_{i,t} \\
+\, \theta_1 \times Firm_i \,+\, \theta_2 \times Year_t \,+\, \kappa \times CDS\ Trading_{i,t} \times DV_{i,t} + \varepsilon_{i,t}, \quad (10)
\end{aligned}
$$

where $DV_{i,t}$ is a dummy variable taking the value of -1 if the firm pays dividends and zero otherwise.[14] A positive value of κ indicates the negative impact of CDS inception on firm value volatility is less pronounced for more financially constrained firms.

Table 6 reports the regression results. We consider the CDS firms with their "*Closest one*", "*Closest one with a propensity score difference less than 1%*" (Closest one PS diff. <1%), "*Closest two*", or "*Closest two with a propensity score difference less than 1%*" (Closest two PS diff. <1%) matched non-CDS firms. For all regressions, we include the same control variables as those used in column (3) in Table 4. The left and right columns report the results using the WW index and dividend payment indicator, respectively.

[14] We set the values of -1 and 0 for the dummy variable $DV_{i,t}$ to make the null hypothesis of κ being positive.

The coefficients of *CDS Trading* are negative for all model specifications, suggesting the inception of CDS trading reduces firm value volatility. The coefficients of the interaction terms $CDS\ Trading \times WW$ are more than 0.126 and significant at the 1% level for the propensity score matched samples. These positive coefficients indicate that the firms with a higher WW index have a weaker CDS inception effect than the firms with a lower WW index. In other words, the negative impact of CDS inception on firm value volatility is weaker for the more financially constrained firms.

Similarly, the coefficients of $CDS\ Trading\ \times DV$ are both 0.131 for "*Closest one*" and "*Closest one with a propensity score difference less than 1%*" matched samples, and 0.137 and 0.135 for the "*Closest two*" and "*Closest two with a propensity score difference less than 1%*", respectively. All of them are significant at the 5% level or above. The significantly positive coefficient suggests that the negative impact of CDS inception is more significant for the firms that pay a dividend and are considered as being less financially constrained. Overall, the results from Table 6 support our *Hypothesis 2* that the negative impact of CDS inception on firm value volatility is less pronounced for more financially constrained firms.

[Insert Table 6 here]

5.4 CDS inception and CDS-bond basis

In this subsection, we investigate whether the price discrepancy between CDSs and corporate bonds affects the impact of CDS inception on firm value volatility. Following the literature, we use the absolute value of the CDS-bond basis to proxy for price discrepancy. A higher level of absolute value means there exists a more severe price discrepancy between the CDS and the corporate bond market. To estimate the CDS-bond basis, we use the par equivalent CDS methodology developed by

JP Morgan. We calculate the absolute value of CDS-bond basis by the absolute difference between the quoted CDS spread and the par-equivalent CDS (PECDS) spread on the same reference entity,

$$|basis_{i,t}| = |CDS_{i,t} - PECDS_{i,t}|, \tag{11}$$

where $CDS_{i,t}$ and $PECDS_{i,t}$ are the quoted CDS spread for the five-year contract and the par-equivalent CDS spreads at time t, respectively. We follow the procedure in Nashikkar, Subrahmanyam, and Mahanti (2011), Bai and Collin-Dufresne (2018) and Lin, Man, Wang, and Wu (2018) to calculate the PECDS spread. Given the price information of corporate bonds for a firm at time t, we calibrate the constant default intensity for this firm by minimizing the pricing errors of the corporate bonds. We use the bonds for each firm with a maturity between three and eight years in the calibration. We then use the default intensity calibrated from bond prices to calculate the par-equivalent five-year CDS spread.[15] The par-equivalent CDS spread is set equal to the coupon rate that equates the expected value of the premium leg to that of the contingent leg. The recovery rate is set at 40%.

To examine the different impact of CDS inception on firm value volatility between the firms with a higher or lower absolute value of the CDS-bond basis, we include the interaction term $CDS\ Trading \times ABS$ in Eq. (5),

$$\begin{aligned} Ln(\sigma_V)_{i,t} = \alpha \ + \ \beta \times CDS\ Trading_{i,t} \ + \gamma \times X_{i,t} \\ + \ \theta_1 \times Firm_i \ + \ \theta_2 \times Year_t \ + \ \kappa \times CDS\ Trading_{i,t} \times ABS_{it} + \varepsilon_{i,t}, \end{aligned} \tag{12}$$

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

where *ABS* is a dummy variable which equals one if the CDS firm has an absolute value of CDS-bond basis above the cross-sectional median and zero otherwise. A positive value of κ indicates the negative impact of CDS inception on firm value volatility is less pronounced for the CDS firms with a higher absolute value of the CDS-bond basis.

Table 7 presents the results of regression for the "*Closest one*", "*Closest one with a propensity score difference less than 1%*" (Closest one PS diff. $<1\%$), "*Closest two*", or "*Closest two with a propensity score difference less than 1%*" (Closest two PS diff. $<1\%$) matched samples. For all regressions, we include the same control variables as those used in column (3) in Table 4. The coefficients of $CDS\ Trading$ are negative for all model specifications, suggesting the inception of CDS trading reduces firm value volatility. The coefficients of the interaction terms $CDS\ Trading \times ABS$ are more than 0.02 and significant at the 1% level for the propensity score matched samples. These positive coefficients indicate that the firms with a higher absolute CDS-bond basis have a weaker negative CDS inception effect than the firms with a lower absolute CDS-bond basis. These results support our *Hypothesis 3* that the negative impact of CDS inception on firm value volatility is less pronounced for the CDS firms with a higher absolute value of CDS-bond basis, which is the proxy for the price discrepancy between CDSs and corporate bonds.

[Insert Table 7 here]

6 Robustness test

In this section, we run three robustness tests. First, we conduct a robustness test by using a probit model with a set of covariates suggested by Martin and Roychowdhury (2015) to estimate the propensity score for each firm. We select the matched non-CDS firm (firms) for each CDS firm using this score. The matching procedure is carried out consistently with the method described in Section 3.3.1. Second, we test the robustness of our results by excluding financial firms from the empirical analysis. Third, we test whether our results continue to hold if we use quarterly data in the panel regressions.

6.1 A different propensity score matching model

Table 8 presents the estimates of the impact of CDS inception on firm value volatility using the CDS firms and their non-CDS firms matched by the propensity scores of the Martin and Roychowdhury (2015) model.

Panel A of Table 8 reports the results of propensity score modeling. The variables include the lagged values of $\ln(equity)$, $Investment\_grade$, SP_rating, $Leverage\_book\_value$, Net_income_ratio, $Equity\_volatility\_year$, and MB_ratio_equity.[16] The results are similar to those of Subrahmanyam et al. (2014). CDS is more likely to be traded on larger firms or (and) the firms with a higher credit rating, higher leverage, higher profitability, and lower market-to-book ratio. Overall, the pseudo-R^2 of this regression is 0.625 and slightly higher than that of the model of Subrahmanyam et al. (2014).

Panel B of Table 8 reports the panel regression results. The results are close to those of using the firms matched by the propensity scores of the Subrahmanyam et al. (2014) model reported in Table 4. The CDS inception continues to show a significantly negative impact on firm value volatility. After controlling for firm characteristics, the estimated coefficients of *CDS Trading* are negative and significant at the 10% level. The coefficients of *CDS Trading* in columns (1) to (4) in Table 8 are -0.0261, -0.0252, -0.0244 and -0.0245, respectively. The corresponding p-values for these coefficients are less than 10%. These results indicate that firm value volatility decreases after the

[16]Please refer to Panel B of Appendix 1 about how to construct these variables.

inception of CDS trading. Hence, the effect of CDS trading on firm value volatility is robust when we use a different model to estimate the propensity score.

[Insert Table 8 here]

6.2 Excluding financial firms

We have used the sample including financial firms for the main analysis. This analysis is consistent with the study conducted by Subrahmanyam et al. (2017). To test whether our results are robust to the choice of sample firms, we also follow Ashcraft and Santos (2009), Saretto and Tookes (2013), and Martin and Roychowdhury (2015) to use the sample consisting of only non-financial firms. We exclude financial firms from our analysis and re-run the regression of Eq. (5).

Table 9 reports the regression results. The coefficients of $CDS\ Trading$ continue to be significantly negative when we include control variables in the regression. For example, the coefficients of $CDS\ Trading$ in in columns (1) to (4) in Table 9 are -0.0438, -0.0462, -0.0374 and -0.0404, respectively. They are significant at least at the 5% level. The result of instrumental variable approach is -0.0799 and also significant at the 1% level. These estimation results are also close to those using all firms reported in Table 4. The sign and the significance of other control variables' coefficients are consistent with those in the main analysis. These results provide empirical evidence that our findings of the negative relationship between CDS trading and firm value volatility is robust for the sample excluding financial firms.

[Insert Table 9 here]

6.3 Quarterly regression results

Most of our explanatory variables in our empirical analysis are updated at the quarterly frequency. We expand them to match the monthly asset volatility. To check whether this data expansion affects our results, we run the panel regressions using quarterly data.

Table 10 reports the regression results. We report the results of both propensity score matching and the instrumental variable approach. Results continue to be significant. All the *CDS_Trading* coefficients are negative and significant at the 1% level for the four different propensity score matching samples. The *CDS_Trading_IV* is negative and significant at the 10% level for the instrumental variable approach. Results show that the negative impact of CDS inception on asset volatility is robust when we use quarterly data.

[Insert Table 10 here]

7 Conclusion

In this paper, we provide empirical evidence that the inception of CDS trading leads to a decrease in firm value volatility. We use asset volatility, which includes the information on equity and corporate debt, as a proxy for firm value volatility. This finding is robust after we address the endogeneity problem of CDS trading by using propensity score matching and an instrumental variable approach.

In addition, we find that the negative impact of CDS inception on firm value volatility is less pronounced for more financially constrained firms. This finding indicates that the empty creditor effect is weaker or (and) the monitoring effect is stronger for more financially constrained firms. Further, we show that the negative impact of CDS inception on firm value volatility is less pronounced for the firms with a higher level of price discrepancy between CDS and the corporate bond market. Our results show that market frictions have the impact on how financial innovation affects society, and provide support for policymakers to control them.

Our findings support the hypothesis that the empty creditor effect of CDS trading dominates the monitoring incentives effect on firm value volatility. It contributes to the ongoing literature relating to the impact of the CDS market on firm behavior. One question of interest is the channels through which the CDS inception affects firm behavior to reduce firm value volatility. For example, Subrahmanyam et al. (2017) show that firms increase cash holdings after the inception of CDS trading. This is for future research.

Appendix 1: Variables Description

Panel A: Variables in the main analysis – firm value volatility regression	
Variable	**Definition**
CDS Trading	Dummy variable that takes the value of one if the firm has CDS traded on its debt one year before time *t* and zero otherwise
$\ln(\sigma_V)$	The natural logarithm of firm value volatility, which is estimated using the model proposed in Bharath and Shumway (2008) based on the KMV model
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 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 over total sales
Excess return	The firm's return in excess of market over the past year
MB_ratio	The ratio of market value of assets over the 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 credit (txditcq)
$\ln(equity)$	The natural logarithm of the firm's equity market value

Panel B: Variables in propensity score matching models	
Variable	**Definition**
CDS Traded	Dummy variable that takes the value of one if the firm has CDS traded on its debt during the sample period and zero otherwise
$\ln(asset)$	The natural logarithm of the firm's total assets
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 market equity is the measure of the number of common shares outstanding multiplied by the stock price.
ROA	The firm's return on assets

(continued)

Variables	**Definition**
Excess return	The firm's return in excess of 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
Sale_ratio	The ratio of sales to total assets
EBIT_ratio	The ratio of earnings before interest and tax 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 expenditure to total assets
SP_rating	Dummy variable that takes the value of one if the firm is rated and zero otherwise
Unsecured_debt	The ratio of unsecured debt to total debt
Lender_FX_hegding	The lenders' and underwriters' ratio of total amount of the foreign exchange hedging activities to total assets over the previous five years
Lender_Tier1_capital	The Tier One capital ratio of the lenders over the previous five years
Lender_credit_derivative	The lenders' and underwriters' ratio of total amount of the credit derivative activities to total assets over the previous five years
Lender_size	The size of the lending banks and underwriters measured by the logarithm of total assets of those banks and underwriters over the previous five years
$\ln(equity)$	The natural logarithm of the firm's equity
Investment_grade	Dummy variable that takes the value of one if a firm has a S&P credit rating above BB+ and zero otherwise
SP_rating	Dummy variable that takes the value of one if the firm is rated and zero 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

Appendix 2: Firm value volatility and equity volatility

Besides firm value volatility, equity volatility is another popular risk measure. Since equity is a call option of the firm value, equity volatility measures the risk of the call option with firm value as the underlying asset.

Theoretically speaking, the relationship between equity volatility and firm value volatility is non-linear. It is not clear whether a decrease in firm value volatility also means a decline in equity volatility. There are two reasons for this. First, following Eq. (3), we have

$$\frac{\partial \sigma_E}{\partial \sigma_V} = \frac{V}{E}(N(d_1) + \sigma_V N'(d_1)\frac{\partial d_1}{\partial \sigma_V}). \tag{13}$$

The sign of $\frac{\partial \sigma_E}{\partial \sigma_V}$ is uncertain since

$$\frac{\partial d_1}{\partial \sigma_V} = -\frac{ln(V/F) + rT}{\sigma_V^2 \sqrt{T}} + 0.5\sqrt{T} \tag{14}$$

could be positive or negative. Second, the relationship between σ_E and σ_V is also affected by V/E, a measure of leverage. Choi and Richardson (2016) find a strong positive relationship between firm leverage and equity volatility. 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.

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Table 1: Summary statistics

This table presents summary statistics for firms in whole sample. Panel A reports the number of sample firms and CDS trading inceptions by year, between 2001 and 2012. The whole sample from the CRSP-Compustat Merged database includes all firms traded on the NYSE, AMEX, and Nasdaq during the sample period 2001–2012. We merge the CDS data from Markit with the CRSP-Compustat merged data using the first six digits of CUSIP. There are 768 firms in the sample that have CDS traded at some point during the sample period. The second column shows the total number of companies included in our analysis. The third column reports the number of firms for which CDS trading was initiated during that year (firms with a CDS spread quote first appearing in the database). The fourth column shows the number of firms with active CDS trading during each year. Panel B provides summary statistics of firm characteristics variables for all firms, CDS firms, and non-CDS firms. We report the results of $\ln(\sigma_V)$, σ_V, $ln(asset)$, *Leverage*, *Excess return*, *Firm age*, *R&D_ratio*, *MB_ratio_equity*, and $\ln(equity)$. For each variable, we report the number of observations (N), mean, standard deviation (std), skewness, and the 25^{th}, 50^{th} and 75^{th} percentile value. We winsorize all variables at the 1^{st} and 99^{th} percentiles to mitigate the impact of outliers. The detailed variables description is provided in Appendix 1.

Panel A: CDS firms in the sample

Year	**Number of CRSP-Compustat firms**	**New CDS firms**	**Active CDS firms**
2001	6672	4	4
2002	5981	396	392
2003	5587	120	505
2004	5422	115	608
2005	5379	45	642
2006	5286	30	647
2007	5278	34	650
2008	4971	7	618
2009	4678	1	590
2010	4529	5	578
2011	4355	8	575
2012	4228	3	560

(*Continued*)

Table 1: Continued

Panel B: Summary statistics

ALL FIRMS	(1) N	(2) mean	(3) std	(4) skewness	(5) kurtosis	(6) p25	(7) p50	(8) 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
$\ln(asset)$	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	55.53	0	0	0.060
MB_ratio_equity	697,320	1.474	1.503	2.644	11.46	0.596	1.008	1.750
$\ln(equity)$	700,139	5.683	2.071	0.198	2.616	4.171	5.611	7.085

CDS FIRMS	(9) N	(10) mean	(11) std	(12) skewness	(13) kurtosis	(14) p25	(15) p50	(16) 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	15.50	0.310	0.427	0.597
$\ln(asset)$	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	43.05	2,478	0	0	0.003
MB_ratio_equity	92,703	1.238	0.982	3.202	18.96	0.685	0.980	1.477
$\ln(equity)$	92,762	8.520	1.413	-0.390	3.136	7.610	8.523	9.566

NON-CDS FIRMS	(9) N	(10) mean	(11) std	(12) skewness	(13) kurtosis	(14) p25	(15) p50	(16) 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
$\ln(asset)$	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	47.94	0	0	0.075
MB_ratio_equity	604,617	1.510	1.565	2.541	10.63	0.574	1.013	1.809
$\ln(equity)$	607,377	5.249	1.794	0.066	2.682	3.963	5.262	6.516

Table 2: CDS inception and firm value volatility: The whole sample

This table presents the estimates of the effect of CDS inception on firm value volatility using the whole sample. We run the panel regressions of the logarithm firm value volatility on *CDS Trading* and other control variables, including *Leverage*, *Firm age*, *R&D_ratio*, *Excess return*, *MB_ratio*, and $\ln(equity)$. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Dep. Var.	$\ln(\sigma_V)$		
	(1)	(2)	(3)
CDS Trading	-0.0464***	-0.0659***	-0.0731***
	(0.0132)	(0.0133)	(0.0130)
Leverage		0.0901***	-0.253***
		(0.0226)	(0.0255)
Firm age		-0.104***	-0.147***
		(0.0117)	(0.0138)
R&D_ratio		0.00860***	0.00728***
		(0.00239)	(0.00242)
Excess return			-0.0610***
			(0.00382)
MB_ratio			0.0600***
			(0.00297)
$\ln(equity)$			-0.107***
			(0.00556)
Firm Fixed Effect	YES	YES	YES
Year Fixed Effect	YES	YES	YES
Clustered Standard Error	YES	YES	YES
$Adj.\ R^2$	0.255	0.262	0.290
N	586,339	571,677	552,808

Table 3: Propensity score modeling

This table presents the estimation results of the probability of CDS trading and the difference in means of firm characteristics between the CDS and matched non-CDS firms. Panel A provides the estimation results of the probability of CDS trading on its determinants using a probit model. The dependent variable, *CDS Traded*, equals one if there is a CDS traded on the firm's debt during the sample period and zero otherwise. We use the set of independent variables following Subrahmanyam et al. (2014). The sample period is 2001–2012. In panel B, we examine the difference in means of firm characteristics between the CDS and matched non-CDS firms by running the following regressions,

$$X_{i,t} = \alpha + \beta \times CDS\,Traded_{i,t} + \theta_1 \times Firm_i + \theta_2 \times Year_t + \varepsilon_{i,t},$$

where *CDS Traded* is a dummy variable that equals one if a firm has a CDS traded on its debt any time during our sample period, and zero otherwise, $X_{i,t}$ is the variable of interest, and $Firm_i$ and $Year_t$ are firm and time fixed effect variables, respectively. β captures the difference in the means of each variable between the CDS firms and their matched non-CDS firms. We use the "*Closest one*" matched sample using the propensity score of Subrahmanyam et al. (2014) model, and only keep the observations before the CDS inception. *Propensity score* is the probability of CDS inception. $\Delta\sigma_V$ is the monthly changes in firm value volatility. The other variables description is provided in Appendix 1. Robust standard errors are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Propensity score modeling			Panel B: Difference in means before inception		
Variables	Coefficient	Std Error	Variables	β	t-stats
$\ln(asset)$	0.762***	(0.00515)	$ln(\sigma_V)$	-0.037	(-1.323)
Leverage	0.0364	(0.0304)	*Leverage*	-0.026*	(-1.868)
ROA	0.0569	(0.161)	*Excess return*	0.043**	(2.500)
Excess return	0.0421***	(0.0104)	*Firm age*	0.204***	(3.130)
Equity volatility	-0.0910***	(0.00923)	*R&D_ratio*	0.019	(1.637)
Tangibility	0.339***	(0.0305)	*MB_ratio_equity*	0.042	(0.503)
Sale_ratio	0.464***	(0.0325)	$ln(equity)$	0.030	(0.274)
EBIT_ratio	1.557***	(0.180)	$ln(asset)$	-0.072	(-1.036)
WCAP_ratio	-0.435***	(0.0409)	*Propensity score*	0.007	(0.163)
RE_ratio	-0.0634***	(0.00896)	$\Delta\sigma_V$	0.0004	(0.503)
Cash_ratio	0.579***	(0.0494)			
CAPX_ratio	-0.916***	(0.136)			
SP_rating	1.332***	(0.0130)			
Unsecured_debt	0.679***	(0.0156)			
Lender_FX_hegding	3.771***	(0.359)			
Lender_Tier1_capital	-0.0177	(0.470)			
Lender_credit_derivative	-0.0265***	(0.00659)			
Lender_size	0.0352***	(0.00633)			
Industry Fixed Effect	YES				
Year Fixed Effect	YES				
Robust standard error	YES				
Pseudo R^2	0.587				
N	262,910				

Table 3: Continued

Panel B: Firm characteristics of the CDS firms and their matched non-CDS firms before the inception

	CDS firms			Matched non-CDS firms				
Variables	Mean	Std	Median	Mean	Std	Median	Diff	t-stats
$\ln(\sigma_V)$	-0.628	0.482	-0.677	-0.591	0.547	-0.634	-0.037	(-1.323)
Leverage	0.240	0.192	0.192	0.266	0.235	0.194	-0.026*	(-1.868)
Excess return	0.0679	0.481	0.109	0.0245	0.497	0.0571	0.043**	(2.500)
Firm age	2.840	0.894	2.944	2.636	0.972	2.639	0.204***	(3.130)
R&D_ratio	0.0390	0.325	0	0.0198	0.0503	0	0.019	(1.637)
MB_ratio_equity	1.453	1.231	1.092	1.411	1.114	1.033	0.042	(0.503)
$\ln(equity)$	7.742	1.389	7.709	7.712	1.499	7.598	0.030	(0.274)
$\ln(asset)$	8.059	1.093	7.877	8.131	1.202	7.949	-0.072	(-1.036)
Propensity score	0.613	0.262	0.646	0.606	0.277	0.652	0.007	(0.163)
$\Delta\sigma_V$	-0.00572	0.0793	-0.00354	-0.00612	0.0866	-0.00289	0.0004	(0.503)

Table 4: CDS inception and firm value volatility: Propensity score matched sample

This table reports the estimates of the effect of CDS inception on firm value volatility in the sample including the CDS firms and their propensity score matched non-CDS firms. We follow Subrahmanyam et al. (2014) to estimate the propensity score of each firm, which is then used to match the CDS firms. We run the panel regressions of the logarithm firm value volatility on *CDS Trading* and other control variables. We also control for firm and time fixed effects and cluster standard errors at the firm level. Panel A reports the results of "*Closest one*" and "*Closest one with a propensity score difference less than 1%*" (Closest one PS diff. $< 1\%$) matched samples, while Panel B reports the results of "*Closest two*" and "*Closest two with a propensity score difference less than 1%*" (Closest two PS diff. $< 1\%$) matched samples. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Panel A: Closest one and Closest one PS diff. $< 1\%$ matched samples

Dep. Var.	$\ln(\sigma_V)$					
	(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. $< 1\%$
CDS Trading	-0.0403**	-0.0519***	-0.0523***	-0.0386**	-0.0513***	-0.0510***
	(0.0170)	(0.0169)	(0.0163)	(0.0170)	(0.0169)	(0.0163)
Leverage		0.0997	0.123		0.129**	0.120
		(0.0658)	(0.0829)		(0.0641)	(0.0824)
Firm age		-0.171***	-0.187***		-0.177***	-0.190***
		(0.0336)	(0.0355)		(0.0335)	(0.0356)
R&D_ratio		0.0729***	0.0705***		0.0720***	0.0683***
		(0.0145)	(0.0137)		(0.0143)	(0.0135)
Excess return			-0.114***			-0.112***
			(0.0103)			(0.0104)
MB_ratio			0.0420***			0.0441***
			(0.00778)			(0.00771)
ln(*equity*)			0.0250			0.0152
			(0.0179)			(0.0176)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES	YES	YES
$Adj.\ R^2$	0.358	0.365	0.380	0.359	0.367	0.382
N	123,983	122,925	122,111	121,887	120,829	120,015

(*Continued*)

Table 4: Continued

Panel B: Closest two and Closest two PS diff. $<$ 1% matched samples

Dep. Var.	$\ln(\sigma_V)$					
	(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	-0.0235	-0.0388**	-0.0399***	-0.0238	-0.0392**	-0.0386**
	(0.0161)	(0.0160)	(0.0154)	(0.0161)	(0.0160)	(0.0154)
Leverage		0.0890*	0.0917		0.138***	0.112
		(0.0521)	(0.0680)		(0.0519)	(0.0690)
Firm age		-0.217***	-0.240***		-0.210***	-0.233***
		(0.0272)	(0.0289)		(0.0279)	(0.0298)
R&D_ratio		0.0707***	0.0684***		0.0699***	0.0663***
		(0.0143)	(0.0135)		(0.0139)	(0.0131)
Excess return			-0.107***			-0.105***
			(0.00811)			(0.00845)
MB_ratio			0.0283***			0.0322***
			(0.00672)			(0.00687)
$\ln(equity)$			0.0258*			0.0158
			(0.0150)			(0.0150)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES	YES	YES
$Adj.\ R^2$	0.353	0.363	0.376	0.356	0.366	0.379
N	180,248	177,879	176,501	170,771	168,409	167,100

Table 5: CDS inception and firm value volatility: An instrumental variable approach

This table reports the estimates of the effect of CDS inception on firm value volatility using an instrumental variable approach. We report the results of the first-stage probit model and 2SLS regression in the three-stage procedure. The main instrumental variable is *Lender_FX_hegding* that measures the foreign exchange hedging activities of the firm's banks and underwriters. We control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

	First-stage	2SLS
Dep. Var.	*CDS Trading*	$\ln(\sigma_V)$
CDS Trading_IV		-0.0570**
		(0.0279)
Leverage	2.468***	-0.174***
	(0.280)	(0.0344)
Firm age	0.527***	-0.190***
	(0.0500)	(0.0198)
R&D_ratio	-0.614	0.0125*
	(0.388)	(0.00695)
Excess return	-0.140***	-0.0638***
	(0.0372)	(0.00523)
MB_ratio	-0.371***	0.0639***
	(0.0441)	(0.00470)
$\ln(equity)$	0.837***	-0.0972***
	(0.0390)	(0.00810)
Lender_FX_hegding	4.196***	
	(1.395)	
Industry Fixed Effect	YES	
Firm Fixed Effect		YES
Year Fixed Effect	YES	YES
Clustered Standard Error	YES	YES
F-statistic (excluded intrument)		2066.12
Pseudo R^2	0.254	
Adj. R^2		0.333
N		316,400

Table 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. We use the financial constraints index (WW index) proposed by Whited and Wu (2006) and dividend payer indicator as proxies for financial constraints. A higher WW index means higher financial constraints, while the firms that do not pay a dividend tend to be more financially constrained. We use the interaction terms $CDS\ Trading \times WW$ (Eq. (9)) or $CDS\ Trading \times DV$ (Eq. (10)) to capture the difference in the CDS effects between more and less financially constrained firms. WW is a dummy variable which equals one if the firm has a WW index above the cross-sectional median at the inception of CDS and zero otherwise. DV is a dummy variable which takes the value of -1 if the firm pays non-zero dividends at the inception of CDS and zero otherwise. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Dep. Var.	$\ln(\sigma_V)$							
	WW index				Dividend payer indicator			
	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	-0.132***	-0.125***	-0.115***	-0.118***	-0.0419**	-0.0406**	-0.0288*	-0.0278*
	(0.0209)	(0.0213)	(0.0211)	(0.0205)	(0.0167)	(0.0167)	(0.0158)	(0.0158)
$CDS\ Trading \times WW$	0.139***	0.132***	0.126***	0.139***				
	(0.0263)	(0.0266)	(0.0267)	(0.0265)				
$CDS\ Trading \times DV$					0.131**	0.131**	0.137***	0.135***
					(0.0512)	(0.0514)	(0.0515)	(0.0516)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	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 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 absolute value of CDS-bond basis. We use the interaction term $CDS\ Trading \times ABS$ in the regressions to captures the difference in the CDS effects between the CDS firms with high and low absolute value of CDS-bond basis. *ABS* is a dummy variable which equals one if the CDS firm has an absolute value of CDS-bond basis above the cross-sectional median and zero otherwise. The CDS-bond basis is the difference between the quoted CDS spread and the par-equivalent CDS (PECDS) spread on the same reference entity. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Dep. Var.	$\ln(\sigma_V)$			
	Closest one	Closest one PS diff. $< 1\%$	Closest two	Closest two PS diff. $< 1\%$
$CDS\ Trading$	-0.146***	-0.145***	-0.141***	-0.139***
	(0.0268)	(0.0267)	(0.0263)	(0.0262)
$CDS\ Trading \times ABS$	0.0212***	0.0204***	0.0215***	0.0205***
	(0.00762)	(0.00760)	(0.00767)	(0.00764)
Control variables	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES
$Adj.\ R^2$	0.390	0.393	0.380	0.385
N	83,720	81,624	138,110	128,709

Table 8: CDS inception and firm value volatility: Propensity score matching model of Martin and Roychowdhury (2015)

This table reports the estimates of the effect of CDS inception on firm value volatility in the sample including the CDS firms and their propensity score matched non-CDS firms. We follow Martin and Roychowdhury (2015) to estimate the propensity score and select the propensity score matched non-CDS firms. Panel A reports the results of propensity score modeling, while Panel B reports the panel regression results. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Panel A: Propensity score modeling

Probability (CDS Traded)		
Variables	Coefficient	Std Error
$\ln(equity)$	0.610***	(0.00360)
Investment_grade	0.401***	(0.00963)
SP_rating	1.276***	(0.00999)
Leverage_book_value	1.439***	(0.0249)
Net_income_ratio	0.0192***	(0.00341)
Equity_volatility_year	0.132***	(0.00769)
MB_ratio_equity	-0.0669***	(0.00148)
Industry Fixed Effect	YES	
Year Fixed Effect	YES	
Robust standard error	YES	
Pseudo R^2	0.625	
N	612,305	

Table 8: Continued

Panel B: Regression result

Dep. Var.	$\ln(\sigma_V)$			
	(1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%
CDS Trading	-0.0261*	-0.0252*	-0.0244*	-0.0245*
	(0.0139)	(0.0140)	(0.0133)	(0.0134)
Leverage	-0.108	-0.103	-0.114*	-0.0963
	(0.0678)	(0.0682)	(0.0581)	(0.0587)
Firm age	-0.156***	-0.153***	-0.162***	-0.168***
	(0.0314)	(0.0314)	(0.0258)	(0.0261)
R&D_ratio	0.0239	0.0240	0.0515**	0.0511**
	(0.0195)	(0.0195)	(0.0255)	(0.0255)
Excess return	-0.129***	-0.130***	-0.125***	-0.127***
	(0.00921)	(0.00920)	(0.00764)	(0.00774)
MB_ratio	0.0800***	0.0796***	0.0764***	0.0762***
	(0.00743)	(0.00742)	(0.00684)	(0.00685)
$\ln(equity)$	-0.0965***	-0.0942***	-0.0832***	-0.0834***
	(0.0143)	(0.0144)	(0.0124)	(0.0125)
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES
$Adj.\ R^2$	0.400	0.399	0.396	0.394
N	154,544	152,959	222,420	213,645

Table 9: CDS inception and firm value volatility: Excluding financial firms

This table reports the estimates of the effect of CDS inception on firm value volatility using the sample excluding financial firms. Column (1), (2), (3) and (4) present the results for the sample including the CDS firms and their propensity score matched non-CDS firms. Column (5) presents the results of the estimation using an instrumental variable approach. We run the panel regressions of the logarithm firm value volatility on *CDS Trading* and other control variables. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Dep. Var.	$\ln(\sigma_V)$				
	(1) Closest one	(2) Closest one PS diff. $< 1\%$	(3) Closest two	(4) Closest two PS diff. $< 1\%$	(5) IV approach
CDS Trading	-0.0438***	-0.0462***	-0.0374**	-0.0404***	
	(0.0168)	(0.0168)	(0.0154)	(0.0155)	
CDS Trading_IV					-0.0799***
					(0.0293)
Leverage	0.273***	0.265***	0.232***	0.238***	-0.176***
	(0.0771)	(0.0774)	(0.0658)	(0.0669)	(0.0351)
Firm age	-0.234***	-0.233***	-0.240***	-0.238***	-0.201***
	(0.0370)	(0.0373)	(0.0301)	(0.0310)	(0.0209)
R&D_ratio	0.0466***	0.0459***	0.00798	0.00796	0.00964*
	(0.0128)	(0.0127)	(0.0198)	(0.0193)	(0.00535)
Excess return	-0.104***	-0.103***	-0.0908***	-0.0897***	-0.0592***
	(0.00948)	(0.00961)	(0.00794)	(0.00826)	(0.00528)
MB_ratio	0.0293***	0.0307***	0.0312***	0.0330***	0.0563***
	(0.00824)	(0.00825)	(0.00666)	(0.00689)	(0.00463)
ln(*equity*)	0.0546***	0.0481***	0.0370**	0.0304**	-0.0870***
	(0.0173)	(0.0172)	(0.0149)	(0.0152)	(0.00815)
Firm Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES	YES
$Adj.\ R^2$	0.372	0.372	0.373	0.375	0.325
N	120,292	118,237	173,276	164,749	291,603

Table 10: CDS inception and firm value volatility: Quarterly frequency

This table reports the estimates of the effect of CDS inception on firm value volatility using firm-quarter observations. Columns (1) to (4) present the results for the sample including the CDS firms and their propensity score matched non-CDS firms. Column (5) presents the results of the estimation using an instrumental variable approach. We run the panel regressions of the logarithm firm value volatility on *CDS Trading* and other control variables. We also control for firm and time fixed effects and cluster standard errors at the firm level. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the firm level are reported in brackets. The detailed variables description is provided in Appendix 1.

Dep. Var.	$\ln(\sigma_V)$				
	(1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%	(5) IV approach
CDS Trading	-0.0452***	-0.0516***	-0.0308**	-0.0397***	
	(0.0163)	(0.0163)	(0.0148)	(0.0150)	
CDS Trading_IV					-0.0531*
					(0.0279)
Leverage	0.235***	0.231***	0.231***	0.208***	-0.166***
	(0.0849)	(0.0850)	(0.0691)	(0.0706)	(0.0348)
Firm age	-0.194***	-0.206***	-0.229***	-0.234***	-0.192***
	(0.0310)	(0.0317)	(0.0243)	(0.0254)	(0.0194)
R&D_ratio	0.0461	0.0459	0.0288	0.0288	0.0117
	(0.0290)	(0.0289)	(0.0253)	(0.0254)	(0.00721)
Excess return	-0.114***	-0.112***	-0.114***	-0.114***	-0.0631***
	(0.0101)	(0.0102)	(0.00779)	(0.00801)	(0.00531)
MB_ratio	0.0254***	0.0260***	0.0174***	0.0192***	0.0625***
	(0.00788)	(0.00798)	(0.00646)	(0.00690)	(0.00498)
ln(*equity*)	0.0531***	0.0484***	0.0705***	0.0630***	-0.0964***
	(0.0172)	(0.0173)	(0.0141)	(0.0145)	(0.00819)
Firm Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
Clustered Standard Error	YES	YES	YES	YES	YES
$Adj.\ R^2$	0.387	0.385	0.393	0.390	0.335
N	44,331	43,319	64,286	60,703	105,133

Figure 1: Changes in firm value volatility around the inception of CDS. 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. We calculate the changes in $ln(\sigma_V)$ from one year before the CDS inception to zero, one, two, and three years after the CDS inception. For each CDS firm, we select a matched firm from the non-CDS firm sample based on the propensity scores by the model of Subrahmanyam et al. (2014).