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RESEARCH ARTICLE

Credit default swaps and firm risk

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Abstract
This study investigates how initiating a credit default swap (CDS) affects firm risk. Using the firm value volatility as a measure of firm risk, we document that firm risk decreases following the commencement of CDS trading. Further analysis indicates that the empty creditor channel, which arises when a debt holder with CDS protection has no interest in preserving the company it provides funds, is the primary way of influence. Our findings reveal a significant impact of financial innovation on a firm's behavior. We also document that market frictions affect the degree of such effect.

KEYWORDS
credit default swap, credit quality, empty creditor, financial constraint, firm value volatility

JEL CLASSIFICATION
G12, G14, G32

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 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 attracted considerable attention from financial researchers. 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 CDSs affect firm behavior. Not only does understanding the effect of CDSs on firm behavior help us address the critical question of whether financial innovation affects corporate finance, but it also can improve portfolio decision making. While there exists extensive literature investigating the impact of CDS inception on various firm behavior,[3] how these behaviors overall affect firm risk remains an underexplored question.

[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/).
[3]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 vs. 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.

CDS inception affects firm risk from both demand- and supply-side. The demand-side arguments propose the empty creditor and monitoring channels, while the supply-side arguments suggest the financing channel.[4] The empty creditor channel posits that a debt holder with CDS protection has no interest in preserving the company it provides funds and thus becomes exacting in debt renegotiation. To avoid this, borrowing firms tend to make more prudent decisions on investment and other corporate activities. Conversely, the monitoring channel implies that CDS trading serves as a hedge against default risk, consequently reducing creditors' incentive to monitor. This reduction in monitoring incentives allows firms to engage in riskier projects that could potentially benefit equity investors. In addition, the financing channel suggests that CDS inception reduces friction in credit supply, thereby increasing financial leverage and affecting firm risk.

The extant literature, drawing upon these channels, has proposed several different mechanisms through which CDS inception could influence the risks undertaken by firms. While the empty creditor and financing channels suggest a negative association between CDS inception and risk, the monitoring channel predicts an increase in firm risk following CDS inception. These effects generate varying predictions on firm risk, and it is essentially an open empirical question to study the aggregate effects of these channels.

Our study examines the effect of CDS inception on firm risk. Firm risk provides an overall assessment of 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.[5] Furthermore, firm value volatility plays a vital role in the valuation of capital structure and in the risk-return trade-offs independent of firm leverage (Choi & Richardson, 2016). A firm's level of risk also bears crucial implications for its hiring and investment behavior and other economic activities. For instance, 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. We follow prior studies by using firm value volatility—rather than volatility in the firm's equity or cash flow—to measure firm risk.[6]

We 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. We 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, we use both propensity score (PS) matching and an instrumental variable (IV) approach.

We document several interesting findings. First, we find that firm value volatility decreases after the introduction of CDS trading. When our 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 we use other matched samples. This negative effect amounts to 12.50% when assessed via an IV approach. These results suggest that firms become more conservative about their risk-taking behavior once CDS trading begins.

Second, we examine the channels driving the negative effects. To test the existence of the empty creditor channel, we employ institutional ownership as a proxy for shareholder bargaining power. We document that the negative effect of CDS inception on firm value volatility is more pronounced for firms with high shareholder bargaining power. This finding corroborates the empty creditor channel. To test the financing channel, we examine whether the effect of CDS inception on firm value volatility is a function of financial constraints. We use the index developed by Whited and Wu (2006) (hereafter WW index) and credit quality as proxies for financial constraints. We show that the decreased firm value volatility induced by CDS trading is more significant for less financially constrained firms. However, we do not find evidence to suggest that the financing channel drives the negative effect of CDS inception on firm risk.

Using the absolute value of a firm's CDS–bond basis to measure the price discrepancy between the corporate bond and the CDS market, we 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 firm behaviors, which supports the notion that policymakers should be aware of the effects of such frictions.

[4]Section 2 provides a detailed discussion of theoretical backgrounds and hypothesis development.
[5]In addition, Doshi et al. (2019) identify significant differences in the behavior of unlevered asset returns versus levered stock returns.
[6]In Appendix 2, we show that the relationship between firm value volatility and equity volatility is uncertain.

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

Subrahmanyam et al. (2014), Danis (2017), Narayanan and Uzmanoglu (2018b), and Colonnello et al. (2019) investigate the impact of CDS inception on default risk, yet our study differs in several respects. First, we 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 et al. (2018) document that firm risk has a significant effect on the likelihood of bankruptcy; in addition, those studies 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. Finally, 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 and increases firm leverage, it is possible to observe both decline in firm value volatility and increase in default risk. Our results thus do not challenge but supplement the findings of Subrahmanyam et al. (2014).

This study makes several contributions to the literature. First, our study extends the literature on the influence of CDS trading on firm behavior by providing empirical evidence on how overall it affects risk at the firm level. The literature has documented mixed findings on how CDS inception affects various decisions that influence firm risk. Some studies show that firms undertake more conservative or risk-averse activities after their CDS inception. For example, Subrahmanyam et al. (2017) show that firms increase their cash holdings following their CDS inception. Kim et al. (2018) establish that managers voluntarily disclose more information after CDS inception. Others, on the other hand, document that firms engage in riskier activities. For example, Saretto and Tookes (2013) find that firms involved with CDS trading exhibit higher leverage ratios. Martin and Roychowdhury (2015) find a decrease in borrowing firms' reporting conservatism following the initiation of CDS trading. Chang et al. (2019) document that the commencement of CDS trading encourages firms to take risks, resulting in increased innovation outputs. It is not clear how overall these different activities affect firm risk. Our study sheds light on this important question. Moreover, our research complements recent studies, such as those conducted by Danis and Gamba (2018) and Narayanan and Uzmanoglu (2018a), which investigate the aggregate effect of CDS initiation at the firm level.

Second, our study helps explain variations in levels of firm risk and identifies channels 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 & Mulani, 2009; Comin & Philippon, 2005), firm age (Davis et al., 2006), and firm size (Herskovic et al., 2018). We offer a novel perspective to explain firm risk—namely, by identifying a key link between the inception of CDS trading and firm value volatility.

Third, we contribute to the ongoing debate over the impact of financial innovation, especially the effect of CDSs. Zhao and Zhu (2020) study the externalities of CDS on stock return synchronicity. Da Fonseca and Gottschalk (2013), Pavlova and de Boyrie (2015), and Procasky and Yin (2022) study the interaction between CDS and options, foreign exchange (FX), and stock markets, respectively. We extend their studies to the firm risk and provide a reflection on how changes in derivative securities and markets influence research (Webb, 2022). We 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.

Finally, our study points to the importance of financial market friction in the transmission of a channel. Kim et al. (2017) show that the CDS-bond basis provides useful information for the pricing of corporate bonds. Li (2018) studies how credit market frictions affect the transmission of monetary policy. Christiano et al. (2014) and Arellano et al. (2019) point to financial market frictions as an additional channel through which volatility fluctuations can affect macroeconomic outcomes. We extend their studies to firm behavior.

The rest of this study proceeds as follows. In Section 2, we review the literature and develop our primary hypotheses. Section 3 details our empirical methodology. Section 4 describes the data, and Section 5 presents our empirical results. In Section 6, we conduct several robustness tests. We conclude in Section 7.

2 | THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Both demand- and supply-side theories explain how CDS inceptions could affect the risks taken by firms. Demand-side channels stem from the empty creditor channel and the monitoring channel. An empty creditor is a debt holder with no interest in preserving the company to which it provides funds. This problem arises when a creditor has overinsured its credit risk by purchasing CDSs yet still holds the firm's control rights. Theoretical studies (Bolton & Oehmke, 2011; Danis & Gamba, 2018) show that CDS trading provides creditors with more valuable outside options in renegotiation. As a result, creditors become more aggressive during renegotiation, and the likelihood of its success reduces. To avoid a renegotiation in which the creditors become exacting (Colonnello et al., 2019; Subrahmanyam et al., 2017), 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 (2011) findings. In other words, the empty creditor channel could drive the relationship between CDS inception and firm value volatility. This empty creditor channel reduces volatility in the focal firm's value following the inception of CDS trading on its debt.

On the other hand, by introducing a 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. 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 less 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 the monitoring channel, 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 increase the volatility of its value following the commencement of CDS trading.

On the supply side, CDS could also affect firm risk through a financing channel. CDS inception reduces friction on credit supply, which increases financial leverage. Such increased leverage, in turn, reduces firm value volatility. 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. Using the sample consisting of firms in the Standard & Poor's (S&P) 500 index from 2002 to 2010, they find that firms are more likely to increase their leverage ratio after the inception of CDS trading. Such a higher leverage ratio could be associated with a lower level of firm value volatility because Choi and Richardson (2016) show that "asset volatility decreases with leverage." Following Saretto and Tookes (2013), we expect that CDS inception increases leverage, thus reducing firm value volatility.

Theoretically, the aggregate effects of CDS inception on firm value volatility are ambiguous. While the empty creditor and financing channels suggest a negative relationship between CDS inception and firm value volatility, the monitoring channel predicts that CDS inception increases firm value volatility. Our first hypothesis is about the aggregate effects of CDS inception on firm value volatility from these three channels. In particular, we test the following hypothesis.

Hypothesis 1a. If the combined effect from empty creditor and financing channels dominates that of the monitoring channel, then firm value volatility will decrease after the inception of CDS trading.

Hypothesis 1b. If the effect of monitoring channel dominates the combined effect from empty creditor and financing channels, then firm value volatility will increase after the inception of CDS trading.

3 | EMPIRICAL SPECIFICATION

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, we 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:

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

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

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

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:

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

Equation (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, we only show the proof in Appendix 2. To estimate V and σ_V, we 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), we assume a debt maturity of 1 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):

$$DD = \frac{\ln\left(V/F\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \tag{4}$$

where μ is the expected return of V. According to this expression, σ_V is a major determinant of DD. Furthermore, Equation (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 Equations (1) and (3) to calibrate V and σ_V, respectively. In practice, however, market leverage is far too variable for Equation (3) to yield reliable results (Crosbie & Bohn, 2003). Following Vassalou and Xing (2004) and Bharath and Shumway (2008), we 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 Equation (1) 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.[7]
5. Use the last value obtained for σ_{V1} as the estimate of σ_V.

3.2 | Determinants of firm value volatility

We 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).[8] Following Ashcraft and Santos

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

[8]For one of our robust checks, we instead use Choi and Richardson's (2016) asset volatility measure.

(2009) and Subrahmanyam et al. (2014), we 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 1 year before time t (and set to 0 otherwise). We 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 our panel data, we control for both firm and time fixed-effects in years. To increase the robustness of our statistical results, we cluster standard errors at the firm level. Our regression model is written as follows:

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}, \tag{5}$$

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 1 year before time t. The vector $X_{i,t}$ represents our control variables; firm and year fixed-effects are included in the regression model. We 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, our study uses the following control variables.

- *Leverage*: The ratio of the book value of debt to the sum of that value and market equity, where "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.[10]
- *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 the 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 1 gives a detailed description of all variables used in the study.

3.3 | Endogeneity

3.3.1 | PS matching

Roberts and Whited (2013) show that, although PS matching may not solve endogeneity and self-selection problems in every context, it can mitigate some biases caused by these problems. We therefore calculate the PSs for all firms and then use those scores to match CDS firms with their non-CDS counterparts. In this procedure, we 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. We also employ several alternative methods for choosing matches, as described next, to assemble four different matched samples for analysis.

[9]Using the logarithm also makes it easier to interpret the economic significance of our 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.
[10]The results are similar if we define "book value of debt" as the sum of short-term debt and long-term debt.

- *"Closest one" sample*: For each CDS firm, we choose the single non-CDS firm whose PS is the closest.
- *"Closest two" sample*: For each CDS firm, we choose the two non-CDS firms whose PSs are closest to the focal firm's score.
- *"Closest one with PS difference less than 1%" sample*: For each CDS firm, we choose the single non-CDS firm whose PS 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, we choose the two non-CDS firms whose PSs 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 PS matching is to find an appropriate model to estimate the PS. 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), we use a probit model to estimate the probability of CDS inception:

$$\Pr(CDS\_traded_{i,t} = 1) = \Phi(\alpha + \beta \times X_{i,t}). \tag{6}$$

In this expression, *CDS_traded* is a dummy variable set equal to 1 for firms whose credit default swaps are traded during our 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. We use this probability of CDS trading to calculate the PSs when constructing the various matched samples.

3.3.2 | IV approach

We address the endogeneity problem not only by PS matching, as just described, but also by taking an IV approach. Following Saretto and Tookes (2013) and Subrahmanyam et al. (2014), we use *Lender_FX_hedging* as the IV. Minton et al. (2009) show that banks with a large amount of FX derivatives for hedging purposes are more likely to be net buyers of CDS. A bank's involvement with FX 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 our using an incorrect nonlinear model at the first stage, we follow Angrist and Pischke (2008) and apply a three-stage procedure to estimate the coefficients. In the first stage, we use the following probit model to estimate the predicted value of *CDS_trading* (i.e., *CDS_trading_IV*). Thus we regress *CDS_trading_IV* on control variables and the instrumental variable, *Lender_FX_hedging*:

$$CDS\_trading\_IV_{i,t} = \Phi(\alpha + \beta \times X_{i,t} + \gamma \times Z_{i,t}), \tag{7}$$

where Z is the instrumental variable (*Lender_FX_hedging*) and X is the vector of all control variables in Equation (5). We also control for industry-level and year fixed-effects in the regression model. In the next step, we use *CDS_trading_IV* as an instrument for *CDS_trading* in a conventional two-stage least-squares (2SLS) procedure.

4 | DATA

We 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. Our 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 we consider are those with stocks listed on the New York Stock Exchange, American Stock Exchange, or National Association of Securities Dealers Automated Quotations. We 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. We start by using the whole sample.[11]

Panel A of Table 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 our sample. The number of firms gradually decreases during this period: from 6669 firms in 2001 to 4227 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. Our final sample includes 762 firms for which CDS inception occurred within the 2001–2012 period.

Panel B of Table 1 gives summary statistics for variables capturing the firm characteristics of all firms, CDS firms, and non-CDS firms. We report results for $\ln(\sigma_V)$, σ_V, $\ln(Assets)$, *Leverage*, *Excess_return*, *Firm_age*, *R&D_ratio*, *MB_ratio*, and $\ln(Equity)$. For each variable, we report the number of observations (N), mean, standard deviation (SD), 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 we use in PS matching and also in our IV approach is *Lender_FX_hedging*, which measures the FX 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 5 years (Subrahmanyam et al., 2014). For each firm in our sample, we identify its main lenders and bond underwriters based on information from Dealscan and the Fixed Income Securities Database (FISD), respectively. For the lenders' information, we use Gvkey to match the Compustat and Dealscan data via the link provided by Chava and Roberts (2008). For the underwriters' information, we use six-digit CUSIP numbers to match the data between Compustat and the FISD. Finally, we 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.[12] Call report data, Dealscan, and FISD do not have a common identifier, so we manually match them by name, state, and other information of the relevant banks. We next turn to the 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 Equation (5). Table 2 reports the results. Our variable of interest is the coefficient for *CDS_trading*, which measures the impact of CDS inception on firm value volatility.

First, we use only the *CDS_trading* variable in the panel regression and control for firm and year fixed-effects; this is Model (1) in Table 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, we 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. These results suggest that CDS trading's reduction of firm value volatility is robust to controlling for other firm characteristics.[13] Our results support Hypothesis 1a about the aggregate effect of three channels on firm value volatility from the CDS inception.

[11]One of the robustness tests consists of comparing results when we remove financial firms from the sample.

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

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

TABLE 1 Summary statistics.

Panel A: CDS firms in the sample			
Year	**Number of CRSP–Compustat firms**	**New CDS firms**	**Cumulative number of CDS firms**
2001	6669	2	2
2002	5978	394	396
2003	5584	118	514
2004	5419	115	629
2005	5376	45	674
2006	5283	30	704
2007	5276	34	738
2008	4969	7	745
2009	4677	1	746
2010	4528	5	751
2011	4354	8	759
2012	4227	3	762

Panel B: Summary statistics								
	N	**Mean**	**SD**	**Skewness**	**Kurtosis**	**p25**	**p50**	**p75**
All firms								
$\ln(\sigma_V)$	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
CDS firms								
$\ln(\sigma_V)$	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
Non-CDS firms								
$\ln(\sigma_V)$	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

(Continues)

TABLE 1 (Continued)

Panel B: Summary statistics								
	N	Mean	SD	Skewness	Kurtosis	p25	p50	p75
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

Note: 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. We 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 our 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. We report results for $\ln(\sigma_V)$, σ_V, ln(*Assets*), *Leverage*, *Excess_return*, *Firm_age*, *R&D_ratio*, *MB_ratio*, and ln(*Equity*). For each variable, we report the number of observations (N), mean, standard deviation (SD), 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 1 for additional details.

Abbreviations: AMEX, American Stock Exchange; CDS, credit default swap; CRSP, Center for Research in Security Prices; CUSIP, Committee on Uniform Securities Identification Procedures; Nasdaq, National Association of Securities Dealers Automated Quotations; NYSE, New York Stock Exchange.

TABLE 2 CDS inception and firm value volatility: Whole sample.

Variable	(1)	(2)	(3)
CDS_trading	−0.046*** (0.013)	−0.066*** (0.013)	−0.073*** (0.013)
Leverage		0.090*** (0.023)	−0.253*** (0.026)
Firm_age		−0.104*** (0.012)	−0.147*** (0.014)
R&D_ratio		0.009*** (0.002)	0.007*** 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
Adjusted R^2	0.255	0.262	0.290
N	586,339	571,677	552,808

Note: This table presents the effect of credit default swap (CDS) inception on firm value volatility using the whole sample. We 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 1 gives a detailed description of the variables.

5.2 | Endogeneity

5.2.1 | PS matching

PS matched sample

We use Equation (6) to estimate the probability of CDS inception, which is then used as our PS for constructing the matched samples. First, we 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 our primary method of constructing the matched samples.

Panel A of Table 3 reports our PS 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 CDSs 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,

TABLE 3 Propensity score modeling.

Panel A: Propensity score modeling			Panel B: Difference in means before CDS inception		
Variable	**Coefficient**	**SE**	**Variable**	**β**	**SE**
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				

Note: This table presents the estimation results of propensity score matching. Panel A reports estimates of a probit model that regresses the probability of credit default swap (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. We employ the same set of independent variables as used by 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 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 our 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. We use the "Closest one" matched sample according to the propensity score derived from Subrahmanyam et al.'s (2014) model, and keep only the observations made before 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 1 for descriptions of the other variables. Robust standard errors (SE) are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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.

The coefficient for *Lender_FX_hedging* is 3.771 and significant at the 1% level when we control for other firm characteristics. This significantly positive coefficient establishes that CDSs are more likely to be traded on firms whose banks are relatively more involved in FX 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.

We next examine the effectiveness of our 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, we limit the comparison to our "Closest one" matched sample. We test the difference in means between the CDS and matched non-CDS firms by running the following regressions for each variable:

$$X_{i,t} = \alpha + \beta \times CDS\_traded_{i,t} + \varepsilon_{i,t}, \tag{8}$$

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 we 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 Equation (6), and $\Delta\sigma_V$ represents monthly changes in firm value volatility. For each variable, the regressions use only the data *before* CDS inception.

Panel B of Table 3 reports the results. before 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*, $\ln(Equity)$, or $\ln(Assets)$. 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 PSs with an insignificant mean difference. In other words, before any CDS trading, CDS firms and the matched non-CDS firms were similar in their respective likelihood of CDS trading. Hence we 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 our matching procedure is effective. We 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, we 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. We then calculate the mean changes in the logarithm of firm value volatility 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.

Figure 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. We observe similar patterns for the other event windows. The results indicate also that CDS inceptions' dampening of firm value volatility persists over years. We next formally test this effect by running the regression of Equation (5) with the PS matched sample.

Panel A of Table 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 we 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 we use the full sample data (See Table 2), which suggests that our result concerning the effect of CDS inception on firm value volatility is robust to whether we use full sample data or

[14]We 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.

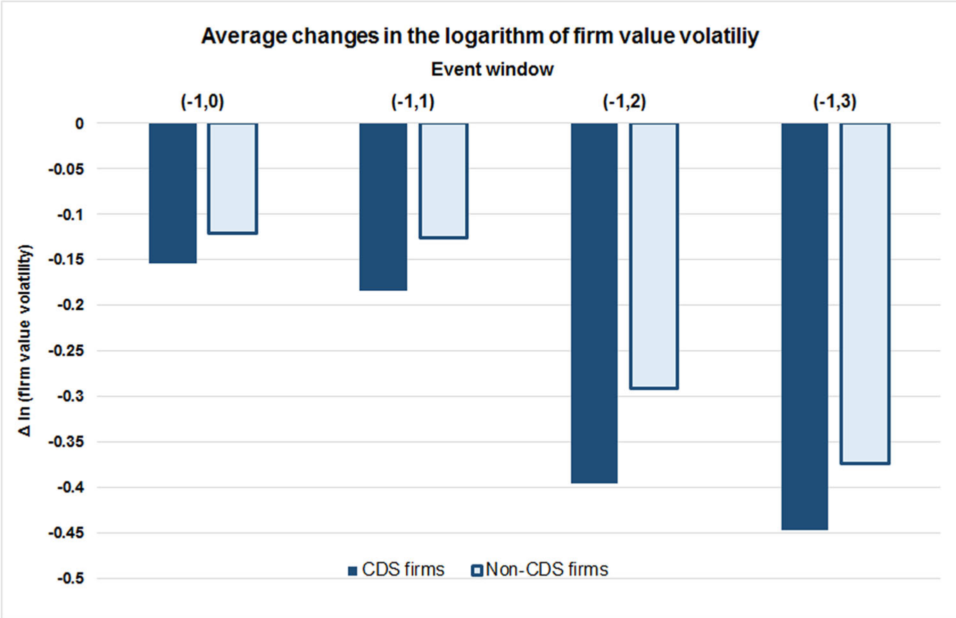

FIGURE 1 Changes in firm value volatility following credit default swap (CDS) inception. This figure plots cross-sectional average changes in $\ln(\sigma_V)$ for the CDS firms and their "Closest one" matched non-CDS firms before and after the inception of CDS trading. We calculate the changes in $\ln(\sigma_V)$ from 1 year before the CDS inception to 0, 1, 2, and 3 years thereafter. [Color figure can be viewed at wileyonlinelibrary.com]

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% × 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.

The coefficients for control variables are significant and have the expected signs. The coefficient for *Firm_age* is significantly negative; its value is −0.187 if we use the "Closest one" matched sample and include all control variables (column 3 of Panel A of Table 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 we use the "Closest one" matched sample and include all control variables. This result supports the findings of Chun et al. (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 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 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, our 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.

5.2.2 | IV approach

Next, we adopt an IV approach to mitigate the potential endogeneity problem of CDS trading. As mentioned in Section 3.3.1, we use *Lender_FX_hedging* as an instrumental variable (see Saretto & Tookes, 2013; Subrahmanyam et al., 2014). Our analysis follows Angrist and Pischke's (2008) three-stage procedure. We estimate the predicted value of *CDS_trading*, *CDS_trading_IV*, by (i) using the probit model that regresses *CDS_trading* on the instrumental variable

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

Variable	Panel A: "Closest one" and "Closest one, PS diff. < 1%" matched samples						Panel B: "Closest two" and "Closest two, PS diff. < 1%" matched samples					
	(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** (0.017)	−0.052*** (0.017)	−0.052*** (0.016)	−0.039*** (0.017)	−0.051*** (0.017)	−0.051*** (0.016)	−0.024 (0.016)	−0.039** (0.016)	−0.040*** (0.015)	−0.024 (0.016)	−0.039** (0.016)	−0.039** (0.015)
Leverage		0.100 (0.066)	0.123 (0.083)		0.129** (0.064)	0.120 (0.082)		0.089* (0.052)	0.092 (0.068)		0.138*** (0.052)	0.112 (0.069)
Firm_age		−0.171*** (0.034)	−0.187*** (0.036)		−0.177*** (0.034)	−0.190*** (0.036)		−0.217*** (0.027)	−0.240*** (0.029)		−0.210*** (0.028)	−0.233*** (0.030)
R&D_ratio		0.073*** (0.015)	0.071*** (0.014)		0.072*** (0.014)	0.068*** (0.014)		0.071*** (0.014)	0.068*** (0.014)		0.070*** (0.014)	0.066*** (0.013)
Excess_return			−0.114*** (0.010)			−0.112*** (0.010)			−0.107*** (0.008)			−0.105*** (0.008)
MB_ratio			0.042*** (0.008)			0.044*** (0.008)			0.028*** (0.007)			0.032*** (0.007)
ln(*Equity*)			0.025 (0.018)			0.015 (0.018)			0.026* (0.015)			0.016 (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
Adjusted 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

Note: This table presents the effect of credit default swap (CDS) inception on firm value volatility using the sample that includes CDS firms and also their matched non-CDS firms. We follow Subrahmanyam et al. (2014) in estimating each firm's propensity score, which is then used to match the CDS firms. We 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 our "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 1.

TABLE 5 CDS inception and firm value volatility: Instrumental variable approach.

Variable	First-stage *CDS_trading*	2SLS $\ln(\sigma_V)$
CDS_trading_IV		−0.125*** (0.024)
Leverage	2.468*** (0.280)	−0.182*** (0.032)
Firm_age	0.527*** (0.050)	−0.216*** (0.019)
R&D_ratio	−0.614 (0.388)	0.013** (0.005)
Excess_return	−0.140*** (0.037)	−0.072*** (0.005)
MB_ratio	−0.371*** (0.044)	0.061*** (0.004)
ln(*Equity*)	0.837*** (0.039)	−0.091*** (0.007)
Lender_FX_hedging	4.196*** (1.395)	
Industry fixed-effects	Yes	
Firm fixed-effects		Yes
Year fixed-effects	Yes	Yes
Fstatistic (excluded instrument)		2965
Pseudo-R^2	0.561	
Adjusted R^2		0.329
N	352,061	352,061

Note: This table presents the effect of credit default swap (CDS) inception on firm value volatility as estimated via an instrumental variable approach. We report results derived from the first-stage of a probit model and also from the two-stage least-squares (2SLS) regression in the three-stage procedure. Our 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 1 for a detailed description of the variables.

and all control variables in Equation (7) and then (ii) using *CDS_trading_IV* as an instrument for *CDS_trading* in a conventional 2SLS procedure.

Table 5 reports the results of this IV approach. The table's left and right columns report results from our first-stage probit model and the 2SLS regression, respectively. To test the IV's significance, we report the Fstatistic for the 2SLS regression's excluded instrument: $F = 2965$, suggesting that *Lender_FX_hedging* is a strong instrumental variable.[15]

In the 2SLS regression, the coefficient for *CDS_trading_IV* is negative and significant at the 1% level when we control for firm characteristics and for time and firm fixed-effects.[16] These results are consistent with those of the PS matched sample. The significantly negative coefficient implies an inverse relationship between CDS inception and firm value volatility. We therefore conclude that firm value volatility decreases after CDS inception and support Hypothesis 1a.

5.3 | Channel analyses

Our results of Hypothesis 1 show a negative effect of CDS inception on firm value volatility. The negative result can be driven by both the empty creditor and financing channels. We test these two channels separately.

[15]According to Stock et al. (2002) and Angrist and Pischke (2008), a significant IV is one for which $F > 10$.
[16]The results are similar if we 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*, we run the regressions without controlling for these variables and find the results are robust. They are available upon request.

5.3.1 | Empty creditor channel

We first study if the empty creditor is a channel that drives this outcome. Colonnello et al. (2019) document that shareholder bargaining power affects the severity of the empty creditor effect across firms. If the empty credit channel exists, the negative effect of CDS inception on firm value volatility is more pronounced for firms whose shareholders possess high bargaining power, which forms our second hypothesis.

Hypothesis 2. If the negative effect of CDS inception on firm value volatility is more pronounced for firms with high bargaining power, the empty creditor channel exists.

To test Hypothesis 2 about the empty creditor channel, we study the differential CDS effect on firm value volatility among firms with different levels of shareholder bargaining power. We follow Colonnello et al. (2019) and use institutional ownership as the proxy of shareholder bargaining power. A higher ownership by institutional investors implies stronger shareholder bargaining power. If we use the $INST5$ to proxy for shareholder bargaining power, then the following regression model applies,

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t} + \gamma \times X_{i,t} + \varkappa \times CDS\_trading_{i,t} \times INST5_{i,t} + \theta \times INST5_{i,t} + \varepsilon_{i,t}, \quad (9)$$

where $INST5$ is a dummy variable set equal to 1 if the firm has a fraction of shares outstanding held by the top five institutional investors above the cross-sectional median (and set to 0 otherwise). Following Chang et al. (2019), we use the information 1 year prior CDS inception to determine the $INST5$ and it is time invariant.[17] The interaction term $CDS\_trading \times INST5$ captures the difference in CDS effects between firms with high and low shareholder bargaining power. In addition, we replace $INST5$ with $INST10$ in Equation (9) for a robustness test. $INST10$ is a dummy variable set equal to 1 if the firm has a fraction of shares outstanding held by the top 10 institutional investors above the cross-sectional median (and set to 0 otherwise). In this case, the interaction term $CDS\_trading \times INST10$ captures the different CDS effects across firms with various shareholder bargaining power.

Table 6 presents the regression results. We compare the CDS firms with their "Closest one," "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, we include the same control variables as those used in column (3) of Panel A of Table 4. The left and right columns report results using $INST5$ and $INST10$, respectively.

In Table 6, the coefficients for the interaction terms involving $CDS\_trading \times INST5$ and $CDS\_trading \times INST10$ are smaller than −0.212 and significant at the 1% level for all PS matched samples. These negative coefficients indicate that firms with high ownership by top institutional investors exhibit a stronger negative CDS inception effect than other firms. In other words, the reduced firm value volatility induced by CDS inception is greater for firms with stronger shareholder bargaining power. Our findings support Hypothesis 2: the negative effect of CDS inception on firm value volatility is more pronounced for firms with high shareholder bargaining power, so there is evidence for the existence of the empty creditor channel.

5.3.2 | Financing channel

Another plausible channel for the aggregate negative influence of CDS inception on firm value volatility is the financing channel. We follow Chang et al. (2019) to test the financing channel. If a financing channel exists, we would expect the negative effect of CDS inception on firm value volatility to be more pronounced for firms with more financial constraints, as these firms benefit more from the reduction in friction on the supply side. These considerations lead to our third hypothesis.

Hypothesis 3. If the negative effect of CDS inception on firm value volatility is stronger for more financially constrained firms, the financing channel exists.

[17] It is common to have $INST5_{i,t}$ as one independent variable when we consider the interaction effect. In our regression, this time invariant variable is absorbed by the firm fixed-effects so its coefficient is omitted. The same rule applies for $INST10$, WW, and AA & AAA explained later.

TABLE 6 Hypothesis 2: Empty creditor channel.

Variable	Institutional ownership (top 5 investors) (1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%	Institutional ownership (top 10 investors) (1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%
CDS_trading	0.0492** (0.0203)	0.0519** (0.0204)	0.0557*** (0.0190)	0.0669*** (0.0197)	0.0471** (0.0203)	0.0474** (0.0204)	0.0567*** (0.0195)	0.0626*** (0.0197)
CDS_trading × *INST*5	−0.221*** (0.0258)	−0.225*** (0.0258)	−0.217*** (0.0258)	−0.227*** (0.0256)				
CDS_trading × *INST*10					−0.216*** (0.0259)	−0.218*** (0.0259)	−0.212*** (0.0258)	−0.220*** (0.0258)
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
Adjusted R^2	0.390	0.390	0.383	0.385	0.390	0.390	0.383	0.385
N	121,030	119,078	174,983	165,852	121,030	119,078	174,983	165,852

Note: This table reports the effect of credit default swap (CDS) inception on firm value volatility as a function of institutional ownership to test Hypothesis 2. We use the institutional ownership (top 5 or top 10 investors) as proxies for shareholder bargaining power. A higher ownership by top institutional investors means that shareholder bargaining power is stronger. We use the interaction terms *CDS_trading* × *INST*5 (Equation 9) and *CDS_trading* × *INST*10 to capture the difference in CDS effects between firms with high and low shareholder bargaining power; here *INST*5 (*INST*10) is dummy variable set equal to 1 if the firm has a fraction of shares outstanding held by the top 5 (10) institutional investors above the cross-sectional median (and 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. A detailed description of the variables is given in Appendix 1.

To test Hypothesis 3 pertaining to the financing channel, we use the financial constraints index developed by Whited and Wu (2006) (the WW index) as a proxy for financial constraints. A lower level of the WW index corresponds to less stringent financial constraint. To determine whether the effect of CDS inception varies with firms' financial constraints, we interact CDS trading with the financial constraint indicators. If we use the WW index to proxy for financial constraint, then the following regression model applies:

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t} + \gamma \times X_{i,t} + \varkappa \times CDS\_trading_{i,t} \times WW_{i,t} + \theta \times WW_{i,t} + \varepsilon_{i,t}, \tag{10}$$

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

Our second measure of financial constraints is credit quality. We use the credit rating assigned by S&P to measure a firm's overall quality and run the following regression model:

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t} + \gamma \times X_{i,t} + \varkappa \times CDS\_trading_{i,t} \times AA\&AAA_{i,t} + \theta \times AA\&AAA_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where $AA\&AAA_{i,t}$ is a dummy variable set equal to 1 if the focal firms have credit ratings of AA or AAA (set to 0 otherwise). A negative value of $\varkappa$ means the negative impact of CDS inception on firm value volatility is more pronounced for high credit quality firms that tend to be less financially constrained. We include both firm and year fixed-effects in these regressions.

Table 7 presents the regression results. We compare the CDS firms with their "Closest one," "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, we include the same control variables as those used in column (3) of Panel A of Table 4. The left and right columns report results using the WW index and the credit quality indicator, respectively.

In columns (1)–(4) of Table 7, the coefficients for the interaction terms involving $CDS\_trading \times WW$ are smaller than −0.122 and significant at the 1% level for all PS matched samples. These negative coefficients indicate that firms with a lower WW index exhibit a stronger negative CDS inception effect than firms with a higher WW index. These results suggest that the negative effect of CDS trading is stronger for firms that are viewed as less financially constrained. In other words, the results from the left panel of Table 7 show that firm value volatility, after introducing CDS, is reduced to a greater extent in less financially constrained firms.

The right panel of Table 7 shows that the coefficients for four interaction terms $CDS\_trading \times AA\&AAA$ are smaller than −0.103 and significant at the 1% or 5% level. These negative coefficients indicate that firms with a high credit quality exhibit a stronger negative CDS inception effect than do firms for which that credit quality is not high. The results are consistent with those in the left panel of Table 7. That is, the effects of CDS are stronger for firms that are less financially constrained. Overall, the results of Table 7 do not support Hypothesis 3: the negative effect of CDS inception on firm value volatility is less pronounced for more financially constrained firms. We do not find evidence to support the financing channel as one way of influence. The findings are also consistent with Chang et al. (2019) and imply that the documented effects are less likely to be explained by the financing channel.[18]

5.4 | CDS effect and CDS-bond basis

CDS and bond yield spreads both reflect a firm's credit risk premium. Any discrepancy in these two variables will be eliminated quickly by arbitrage if the market is frictionless. However, it has been shown that the arbitrage-free condition has often been violated in financial markets (Kapadia & Pu, 2012), and this violation is persistent (Lin et al., 2020). It is thus of interest to study how credit market friction affects the impact of CDS inception on firm value volatility.

[18]To test the robustness of our results in Tables 6 and 7, we also run the regressions to the two subsamples split by $INST5$, $INST10$, WW, or $AA\&AAA$, respectively. The results also show that the negative impact is stronger firms with high shareholder bargaining power or for less financially constrained firms. The results are available upon request.

TABLE 7 Hypothesis 3: Financing channel.

Variable	WW index (1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%	Credit quality index (1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%
CDS_trading	0.000764 (0.0199)	0.00186 (0.02)	0.0206 (0.019)	0.0168 (0.0193)	−0.0478*** (0.0166)	−0.0464*** (0.0166)	−0.0346** (0.0157)	−0.0333** (0.0157)
CDS_trading × *WW*	−0.123*** (0.0270)	−0.122*** (0.0270)	−0.148*** (0.0268)	−0.126*** (0.0270)				
CDS_trading × *AA&AAA*					−0.103** (0.0409)	−0.105** (0.0411)	−0.117*** (0.0413)	−0.117*** (0.0414)
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
Adjusted R^2	0.383	0.385	0.378	0.381	0.381	0.383	0.376	0.379
N	122,111	120,015	176,501	167,100	122,111	120,015	176,501	167,100

Note: This table reports the effect of credit default swap (CDS) inception on firm value volatility as a function of financial constraints to test Hypothesis 3. In the left panel, we use financial constraints index proposed by Whited and Wu (2006) (the WW index) as the proxy for financial constraints. A lower WW index means that financial constraints are looser. We use the interaction terms *CDS_trading* × *WW* (Equation 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 below the cross-sectional median (and set to 0 otherwise). In the right panel, we use the firm credit quality as the proxy of financial constraint. We use the interaction term *CDS_trading* × *AA&AAA* in the regressions to capture the difference in CDS effects between the firms with high and low credit rating, where *AA&AAA* is a dummy variable set equal to 1 if the focal firm has credit rating of AA or AAA (and 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. See Appendix 1 for a detailed description of the variables.

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 CDSs as a tool for transferring credit risk, in which case the CDS effect would be weaker. To assess how the effect of CDS inception on firm value volatility depends on the focal firm's CDS–bond basis, we augment Equation (5) with the interaction term $CDS\_trading \times ABS$:

$$\ln(\sigma_V)_{i,t} = \alpha + \beta \times CDS\_trading_{i,t} + \gamma \times X_{i,t} + \varkappa \times CDS\_trading_{i,t} \times ABS_{i,t} + \theta \times ABS_{i,t} + \varepsilon_{i,t}. \tag{12}$$

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) in month t; firm and year fixed-effects are included in the regression model. We use the average daily CDS-bond basis each month to determine ABS, so it is time variant. A positive value of $\varkappa$ 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. We only use the CDS firm and their matched non-CDS firm data since the CDS inception to run the panel regressions.

To estimate the CDS–bond basis, we use the par-equivalent CDS methodology developed by JP Morgan. Thus we 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:

$$|Basis_{i,t}| = |CDS_{i,t} - PECDS_{i,t}|, \tag{13}$$

where $CDS_{i,t}$ and $PECDS_{i,t}$ are, respectively, the quoted and par-equivalent CDS spreads at time t. We follow the procedure outlined in Nashikkar et al. (2011), Bai and Collin-Dufresne (2019), and Lin et al. (2020) to calculate the PECDS spread. Given price information on a firm's corporate bonds at time t, we 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 3 and 8 years. We then use the default intensity calibrated from bond prices to calculate the par-equivalent 5-year CDS spread.[19] 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%.

Table 8 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, we include the same control variables as those used in column (3) of Panel A of Table 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 ABS are insignificant. 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 firms with lower basis.

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 extends the studies of Christiano et al. (2014), Li (2018), and Arellano et al. (2019) to provide empirical evidence that market frictions influence the extent to which financial innovation affects firm behavior. This finding also supports the notion that policymakers should be willing to limit such frictions to improve channel transmission.

[19]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 FISD.

TABLE 8 CDS–bond basis and the effect of CDS inception.

Variable	(1) Closest one	(2) Closest one PS diff. < 1%	(3) Closest two	(4) Closest two PS diff. < 1%
CDS_trading	−0.074*** (0.028)	−0.076*** (0.028)	−0.084*** (0.027)	−0.081*** (0.027)
CDS_trading × *ABS*	0.024** (0.011)	0.026** (0.011)	0.021** (0.009)	0.019* (0.010)
ABS	−0.008 (0.009)	−0.010 (0.009)	−0.004 (0.006)	−0.002 (0.006)
Control variables	Yes	Yes	Yes	Yes
Firm fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.464	0.460	0.448	0.450
N	46,824	46,136	64,344	60,702

Note: This table reports the effect of credit default swap (CDS) inception on firm value volatility as a function of the absolute value of the CDS–bond basis. We use the interaction term *CDS_trading* × *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 1 for a detailed description of the variables.

6 | ROBUSTNESS TESTS

For our first robustness test, we check whether our results are robust to using the asset volatility measure of Choi and Richardson (2016). We then use a probit model with a set of covariates suggested by Martin and Roychowdhury (2015) to estimate each sample firm's PS, which is then used to select the matched non-CDS firm (or firms) for each CDS firm. The matching proceeds as described in Section 3.3.1. Third, we test the robustness of our results by excluding financial firms from the empirical analysis. Finally, we test for whether our results continue to hold when quarterly (rather than monthly) data are used in the panel regressions. For the sake of brevity, we have relegated the results of these robustness tests to the Supporting Information. Our conclusions remain robust under these different specifications.

7 | CONCLUSION

This study offers novel evidence that the inception of CDS trading leads to a decrease in firm risk. We use firm value volatility, which incorporates information on equity and corporate debt, as a proxy for firm risk. Our findings are robust to whether the potential endogeneity problems associated with CDS trading are addressed using PS matching or an IV approach.

We also document that the negative effect of CDS inception on firm value volatility is more pronounced for firms with significant shareholder bargaining power, supporting the empty creditor channel. This channel implies that the borrowing firms reduce firm risk to avoid a renegotiation in which the creditors become exacting due to CDS protection. Additionally, our study reveals that the CDS-induced decrease in firm value volatility is more pronounced for less financially constrained firms.

Using the CDS-bond basis as an indicator of price discrepancy, we document that the negative effect of CDS inception on firm value volatility is less pronounced for firms with a greater discrepancy between CDSs and corporate bonds. Our findings illuminate how market frictions can modify the degree to which financial innovation influences firm behavior, thus suggesting that policymakers should aim to manage these frictions.

Our empirical results demonstrate that CDS inception negatively affects firm risk in the US, mainly due to the empty creditor channel. However, different outcomes may occur under distinct legal or cultural environments. Therefore, examining the effect of CDS inception on firm value volatility using an international sample would be an intriguing area for future research, as this would enable an exploration of how legal systems or cultural variations across countries influence the CDS effects. These topics will be for future research.

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DATA AVAILABILITY STATEMENT

We 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 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 (CCM). The data used in this study were provided by the third parties specified in the article. Data could be obtained from those third parties.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX 1: DESCRIPTION OF VARIABLES

This appendix lists the variables used in our 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 1 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

Variable	Definition
Investment_grade	Dummy variable set to 1 if a firm has an 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
Leverage_market_value	The ratio of book value of debt to market 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
WW	Dummy variable set equal to 1 if the firm has a WW index above the cross-sectional median (and set to 0 otherwise)
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)
*INST*5	Dummy variable set equal to 1 if the firm has a fraction of shares outstanding held by the top five institutional investors above the cross-sectional median (and set to 0 otherwise)
*INST*10	Dummy variable set equal to 1 if the firm has a fraction of shares outstanding held by the top 10 institutional investors above the cross-sectional median (and set to 0 otherwise)

APPENDIX 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 Equation (3) we have

$$\frac{\partial \sigma_E}{\partial \sigma_V} = \frac{V}{E}\left(N(d_1) + \sigma_V N'(d_1)\frac{\partial d_1}{\partial \sigma_V}\right). \tag{A1}$$

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

$$\frac{\partial d_1}{\partial \sigma_V} = -\frac{\ln(V/F) + rT}{\sigma_V^2\sqrt{T}} + \frac{1}{2}\sqrt{T} \tag{A2}$$

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.