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Withholding Bad News in the Face of Credit Default Swap Trading: Evidence from Stock Price Crash Risk

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Abstract

Credit default swaps (CDSs) are a major financial innovation related to debt contracting. Because CDS markets facilitate bad news being incorporated into equity prices via cross-market information spillover, CDS availability may curb firms' information hoarding. We find that CDS trading on a firm's debt reduces the future stock price crash risk. This effect is stronger in active CDS markets, when the main lenders are CDS market dealers with securities trading subsidiaries, or when managers have more motivation to hoard information. Our findings suggest that debt market financial innovations curtail the negative equity market effects of firms withholding bad news.

I. Introduction

A credit default swap (CDS) is similar to an insurance contract in that a buyer pays periodic insurance premiums to a seller to cover losses from a reference entity's adverse credit events, such as bankruptcy. During the 2008 financial crisis, many regulators, practitioners, and academics questioned the value of CDS trading (e.g., Stulz (2010)) and blamed it for the excessive risk-taking and stock price crashes at many firms, including Lehman Brothers. George Soros, a prominent

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hedge fund manager, reportedly called for an outright ban on such trades.[1] However, despite the public controversy, little is known about the impact of CDS trading on stock prices. This study examines how CDS trading affects the firm's stock price crash risk, and its findings are useful to understanding how financial innovations in the debt market affect equity market stability.

CDS trading can play an important informational role (Lee, Naranjo, and Velioglu (2018)). Studies show that managers often withhold information, especially negative news (Kothari, Shu, and Wysocki (2009)), for reasons such as career concerns or compensation incentives (e.g., Jensen and Meckling (1976), Jensen and Murphy (1990), Bolton, Scheinkman, and Xiong (2006), and Jiang, Petroni, and Wang (2010)). Withholding negative news can result in a large stock price drop (a crash) when the hoarded information is eventually and cumulatively revealed (Jin and Myers (2006), Hutton, Marcus, and Tehranian (2009)). Stulz ((2010), p. 73) notes that one of CDS trading's useful functions is that it reveals information about the reference firms. Indeed, Batta, Qiu, and Yu (2016) show that after CDS trading, analyst forecasts become more accurate. Moreover, due to the asymmetric payoffs between debt and equity, CDS traders are concerned more about negative information about the reference firm, especially firm-specific negative information, than they are about positive information (Acharya and Johnson (2007), Boehmer, Chava, and Tookes (2015), Han, Subrahmanyam, and Zhou (2017), and Lee, Naranjo, and Sirmans (2021a)). Hence, one may expect a negative relationship between CDS trading and stock price crash risk.[2]

To identify the relationship between the inception of CDS trading and stock price crashes, we use a comprehensive panel data set that spans an extended period of time and covers a wide cross section. The data set includes transactions and quotes drawn from multiple leading CDS data sources, which are also used by Subrahmanyam, Tang, and Wang (2014), (2017) and Li and Tang (2016). We construct three standard measures of stock price crash risk: negative skewness, down-to-up volatility, and an indicator of the realized extreme stock price decline (e.g., Jin and Myers (2006), Hutton et al. (2009), and Kim, Li, and Zhang (2011a), (2011b)). Our first key finding is that after controlling for various known determinants of stock price crash risk, the inception of CDS trading significantly reduces

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[1]"Ban CDS as 'instruments of destruction'—Soros," June 12, 2009, *Reuters*, https://www.reuters.com/article/soros-swaps/update-1-ban-cds-as-instruments-of-destruction-soros-idUSPEK34367320090612.

[2]We acknowledge some tension in this hypothesis. A CDS might increase the bankruptcy risk for the reference firm (e.g., Subrahmanyam et al. (2014)). If riskier firms have a greater crash risk (e.g., Kim, Wang, and Zhang (2016), An, Chen, Li, and Xing (2018)), then the inception of CDS trading may lead to a higher stock price crash risk. Oehmke and Zawadowski (2017) analyze position and trading data and find that traders use CDS contracts for both hedging and speculation. See Section II for further discussion.

the occurrence of future stock price crashes. This decrease in stock price crash risk is both statistically significant and economically meaningful for all three stock price crash risk measures. The CDS effect is also robust to additional control variables, such as short interest, default risk, and managerial incentives, and it is significant across different time horizons.

The inception of CDS trading for firms may not be randomly determined, leading to endogeneity concerns about the causal inference of our baseline finding. We employ multiple approaches to address these concerns. For example, we examine the robustness of the results to a large array of additional control variables, propensity score matching, placebo testing, and an instrumental variable estimation. Following prior studies, we construct the instrumental variables by relying on a firm's lenders' use of foreign exchange (FX) derivatives for hedging purposes and the percentage of CDS-referenced borrowers for a firm's lenders (e.g., Saretto and Tookes (2013), Batta et al. (2016), and Batta and Yu (2019)). Using these instrumental variables, we employ the three-stage "pseudo-instrumental variable (IV)" approach of Adams, Almeida, and Ferreira (2009) for the IV estimation; we find that the negative effect of CDS trading on stock price crash risk remains significant.

We further show that price discovery is the channel through which the robust negative link between CDS trading and stock price crash risk develops. First, we provide some evidence that bad news signals from the CDS market are indeed incorporated into equity prices in a timely manner. For firms with CDS trading, we show that negative stock returns have a lower volatility before an announcement of negative earnings news or of a credit rating watch, suggesting that such trading can help reduce the uncertainty associated with bad news. We also document negative stock returns soon after an increase in the CDS spread, suggesting the timely incorporation of negative news into stock prices. Similarly, we examine the impact of CDS trading on the monthly volatility of negative equity returns before and after the announcement of negative credit rating watches; we find that CDS trading facilitates the flow of negative information to equity markets.

We conduct a series of cross-sectional tests to strengthen support for CDS trading impacting crash risk via the price discovery channel. We focus on three key elements of the CDS-market-driven price discovery that relate to bad news: CDS market activity, whether the main lenders are CDS market dealers, and the likelihood of hiding the news. We find that the negative association between CDS trading and stock price crash risk is stronger when there are more CDS quotes or spikes in the CDS spread, which is also consistent with CDS market activity's importance in price discovery. Next, we consider the role of CDS market dealers in price discovery. We find that CDS trading is more negatively associated with stock price crash risk when a firm's main lender is a CDS market dealer with securities trading subsidiaries, which is consistent with such dealers facilitating price discovery.

We conjecture that the negative effect of hoarding bad news about price discovery is stronger when there is more negative news to be hoarded. We indeed find, when we measure opacity using Hutton et al.'s (2009) accrual-based proxy for hiding bad news, that the CDS effect is more pronounced when financial reporting is more opaque. The effect is also more salient when managerial incentives to hide bad news are greater; we measure such incentives using managerial earnings guidance optimism and CEO overconfidence. This evidence supports the price discovery of hidden bad news as a channel through which CDS trading affects stock price crash risk.

Our finding that CDS trading reduces the likelihood of stock price crashes contributes to the literature on the interaction between CDS markets and their related financial markets (e.g., Acharya and Johnson (2007), Kapadia and Pu (2012), Parlour and Winton (2013), and Lee et al. (2021a)).[3] Our article extends this literature by showing that information revelation in the CDS market can have positive spillover effects in the equity market. Consequently, our study also advances the literature on the determinants of stock price crash risk. That is, we show that credit derivative trading can mitigate stock price crash risk over and above factors identified in previous studies. To the best of our knowledge, our article is the first to show how developments in the credit market can help stabilize the equity market.

At first glance, CDS may seem like a side bet on a firm's underlying assets that has no impact on firm fundamentals. However, recent studies document that CDS trading has significant effects on financial markets, corporate policies, and the real economy.[4] Our study helps to elucidate how the CDS market affects firms' information environments. This literature generally examines how firms' initiation of CDS trading affects disclosure practices, analysts' forecasts, and managerial behaviors. The evidence is mixed. Martin and Roychowdhury (2015) find a reduction in accounting conservatism after CDS initiation due to weaker monitoring by creditors, and Kim and Zhang (2016) find that reduced accounting conservatism is associated with a higher stock price crash risk. In contrast, in other studies on the effects of CDS initiation, Batta et al. (2016) find improved information intermediation and Kim, Shroff, Vyas, and Wittenberg-Moerman (2018) document more voluntary disclosure, conditions that could lower stock price crash risk. By relying on the theory that bad news hoarding leads to a higher stock price crash risk, the new findings we document here offer direct evidence on how CDS trading per se affects the withholding of bad news. One novel insight from our findings is that CDS trading can act as a cross-market price discovery mechanism that mitigates the problem of firms withholding bad news from the public.

The rest of this article is organized as follows: Section II develops testable hypotheses on how CDS trading affects a firm's stock price crash risk. Section III describes the statistics of our sample data. Section IV presents our main empirical findings with regard to the effect of CDS trading on stock price crash risk and addresses endogeneity concerns. Section V provides a comprehensive analysis of the channels through which information is revealed. Section VI concludes the article.

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[3]Another strand of the literature shows that other derivative markets, such as equity options, also affect price discovery in the underlying market (see, e.g., Conrad (1989), Hu (2014), and Ni, Pearson, Poteshman, and White (2021)).

[4]See Augustin, Subrahmanyam, Tang, and Wang (2014), (2016) for a description of the CDS market's development and a review of the literature. Bartram, Conrad, Lee, and Subrahmanyam (2022) study the effects of CDS around the world.

II. Hypothesis Development

CDS trading is relevant to stocks, as the two are linked through common firm fundamentals. According to structural models of corporate finance, concurrent equity and CDS prices are decided within the same framework. However, due to the CDS market's concentrated structure (Atkeson, Eisfeldt, and Weill (2013)),[5] insider information could flow into other markets through CDS trading, especially when a firm experiences negative credit news and has a greater number of bank relationships (Acharya and Johnson (2007)).[6] Moreover, Blanco, Brennan, and Marsh (2005) and Qiu and Yu (2012) document that the CDS market facilitates the price discovery of other related securities. Batta et al. (2016) show that CDS spreads contain information that is useful to both equity and credit rating analysts. They find that after the inception of CDS trading, the dispersion of and errors in analysts' earnings per share (EPS) forecasts decrease and downgrades by both stock and bond analysts become more frequent and timely before large negative earnings surprises. Lee et al. (2021a) also provide evidence that information flows from CDS to equity markets. Hence, by facilitating the incorporation of bad news into equity prices, CDS trading reduces a firm's ability to hoard negative information, decreasing the likelihood of a stock price crash. Based on the above discussions, our first hypothesis, stated in alternative form, is as follows:

Hypothesis 1. A firm's stock price crash risk is lower after the inception of CDS trading on its debts.

This hypothesis is refutable because CDS trading can also facilitate firms' risk-taking, which in turn may increase their stock price crash risk (e.g., Kim et al. (2016), An et al. (2018)).[7] Because a CDS contract provides coverage for a lender's losses upon default, lenders are more willing to lend to a firm when CDS trading is available (Bolton and Oehmke (2011), Saretto and Tookes (2013)). The lender is also more likely to allow reference firms to take on more risk and less likely to be concerned about the losses that arise from agency problems. Ashcraft and Santos (2009) find that for risky firms, the cost of debt increases after the onset of CDS trading. Chang, Chen, Wang, Zhang, and Zhang (2019) find that when CDS trading is available, firms pursue riskier innovations. Subrahmanyam et al. (2014) show that the initiation of CDS trading increases both the lender base and the bankruptcy risk due to a higher empty creditor problem and the increased probability of coordination failure in conditions of financial distress. Martin and Roychowdhury

[5]Atkeson et al. ((2013), Figure 2) show that as of the end of 2011, only 12 of the largest bank holding companies with derivative positions that included CDS had trading assets above $5 billion.

[6]The use of CDS to lay off credit risk might affect information production and dissemination through the creditor monitoring channel (Parlour and Winton (2013)).

[7]Prior literature documents mixed evidence on the relationship between corporate risk-taking and stock price crash risk. For example, Hong and Stein ((2003), Table 2) find a negative association between lagged volatility and crash risk, whereas Kim et al. ((2016), Table 3) document a positive association between these variables. Moreover, Hilscher, Pollet, and Wilson (2015) argue that the CDS market is a sideshow.

(2015) argue that CDS trading reduces lenders' incentives to continue monitoring borrowers.[8]

We examine the price discovery channel by focusing on two key underlying factors: CDS trading activity and bad news hoarding. The price discovery channel relies on the premise that the CDS market serves as a source of information for equity market participants. The basic idea is that the default-risk nature of CDS requires CDS traders to search for information, particularly bad news. Subsequent trading based on this information thus provides a useful signal for equity market participants. Hence, we predict that CDS trading's price discovery role will be more prominent when CDS market activity is high, as such activity reflects intense information searching by CDS traders and can signal the discovery of bad news. Stated differently, we expect stronger CDS-to-equity market information spillover and equity market price discovery when the CDS market is more active. For example, Qiu and Yu (2012) find that the high endogenous liquidity of CDS contracts is associated with a greater information flow from the CDS market to the equity market ahead of major credit events.[9] Hence, our second hypothesis, stated in alternative form, is as follows:

Hypothesis 2. The negative association between CDS trading and the firm's stock price crash risk is stronger when the CDS market is more active.

An entity that contributes to price discovery in the market must have access to and be able to trade on nonpublic information. Moreover, unlike managers' unwillingness to reveal negative information to the public, the entity has its own incentives to reveal such information through CDS trading. CDS market dealers are arguably well positioned to detect bad news inside a corporation and impound it into CDS prices. Several studies document that CDS price discovery works more effectively when the reference firms are linked to financial institutions, such as banks, through lending relationships (e.g., Acharya and Johnson (2007), Subrahmanyam et al. (2014), (2017)). As the firms' lead lenders, these financial institutions have access to the issuers' private information. They also have strong incentives to trade CDS to hedge their credit risk exposure on the reference companies. Hence, our third hypothesis, stated in alternative form, is as follows:

Hypothesis 3. The negative association between CDS trading and stock price crash risk is stronger when the firm's main lender is a CDS market dealer with securities trading subsidiaries.

We can also directly link the CDS effect on stock price crash risk to bad news hoarding. Before CDS traders can play a role in uncovering the bad news a firm is withholding, corporate managers must first withhold it. Accordingly, to the extent

[8]To focus on the price discovery effect of CDS trading, we follow prior literature and control for risk-taking in our stock price risk regressions. For example, in their study on CEO overconfidence and stock price crash risk, Kim et al. (2016) note that controlling for return volatility should help to rule out an alternative explanation of risk-taking. Our empirical results are not affected by controlling for risk-taking.

[9]Qiu and Yu (2012) measure the contracts' endogenous liquidity using the total number of distinct dealers that provide quotes for single-name CDS contracts.

that bad news hoarding drives stock price crashes, CDS-to-equity market information spillover and equity market price discovery are expected to be more pronounced for firms that are more likely to withhold bad news. The prior literature on stock price crash risk considers ex ante incentives (e.g., equity market pressure and managerial incentives) to hoard bad news. It also identifies indicators of bad news hoarding (e.g., abnormal accruals and short interest). In our next hypothesis, we rely on this literature to investigate whether CDS trading's price discovery role is stronger when firms are expected to engage in bad news hoarding or when they actually do so.

In their seminal paper, Hutton et al. (2009) develop an accrual-based measure of financial reporting opacity and find that stock price crash risk increases with such opacity. The intuition behind using an accrual-based measure is that managers have discretion over the accounting of the accrual component of earnings. Kim and Zhang (2016) also find a positive association between financial reporting opacity and the expected stock price crash risk. We expect the reduced crash risk from CDS trading to be more pronounced when firms actually use opacity in their financial reporting to hoard bad news.

Managers have various incentives to withhold and delay the disclosure of bad news (e.g., Bergstresser and Philippon (2006), Kothari et al. (2009)), such as career concerns and compensation contracts, which may reflect managerial optimism or overconfidence. For example, Andreou, Louca, and Petrou (2017) find that CEOs have financial incentives to hide bad news early in their careers. Kim et al. (2011b) show that CFOs' equity compensation incentives are positively associated with their firm's stock price crash risk. Kim et al. (2016) argue that firms with overconfident CEOs are more likely to withhold bad news, as they tend to overestimate the returns on a negative net present value project and to ignore privately observed negative feedback. If the onset of CDS trading facilitates the incorporation of hoarded bad news into the equity price, we predict that this effect will be strengthened when managers' incentives induce them to hide or delay the release of bad news, either via mandated or voluntary disclosure. Hence, our fourth and final hypothesis, stated in alternative form, is as follows:

Hypothesis 4. The negative association between CDS trading and the firm's stock price crash risk is stronger when financial reporting is more opaque and when managers have more incentives to hide bad news.

III. Data, Measures, and Descriptive Statistics

In this section, we first introduce the CDS and stock data sets. Next, we explain how we measure CDS trading and stock price crash risk. We then provide the summary statistics for our sample.

A. CDS Trading Data

To compile a comprehensive data set for identifying CDS trading, we employ both CDS transaction data from CreditTrade and the GFI Group and CDS quotes

TABLE 1

Sample Summary by Year

Table 1 reports the distribution of firms from 1996 to 2014. Columns 1 and 2 report the distribution of firms with credit default swap (CDS) contracts during the sample period. *No. of New CDSs* in column 1 is the total number of CDS inceptions in a year. *No. of Firms* in column 2 reports the total number of firms in the subsample of firms with CDS trading in a year. *No. of Firms* in column 3 reports the total number of firms in the subsample of firms without CDS trading in a year. *No. of Firms* in column 4 reports the total number of firms in a year, including firms with and without CDS contracts.

	Firms with CDSs		Firms Without CDSs	All Firms
Year	No. of New CDSs	No. of Firms	No. of Firms	No. of Firms
	1	2	3	4
1996	4	4	3,939	3,943
1997	38	42	4,031	4,073
1998	28	72	4,303	4,375
1999	52	125	4,083	4,208
2000	126	241	3,640	3,881
2001	169	402	3,324	3,724
2002	92	494	3,157	3,650
2003	98	595	3,086	3,678
2004	70	668	2,964	3,632
2005	35	693	2,906	3,598
2006	39	707	2,862	3,567
2007	23	708	2,751	3,457
2008	9	678	2,641	3,319
2009	4	671	2,624	3,295
2010	7	682	2,614	3,294
2011	13	686	2,590	3,278
2012	6	677	2,530	3,206
2013	6	666	2,549	3,217
2014	1	564	2,236	2,806
Total	820	9,375	58,830	68,201

from the Markit Group.[10] The actual CDS transactions reflect the CDS price, which is agreed upon between counterparties, whereas CDS quotes show the binding prices from committed buyers and sellers. Tang and Yan (2017) provide a comprehensive analysis of CDS transactions. Due to the limited number of transactions in the CDS market, CDS quotes are used to provide complementary information about the focal firms. Hence, the transactions and quotes combined provide a full picture of CDS activities and reveal information about the focal firms.

We focus on single-name CDS contracts in the United States. Specifically, CreditTrade covers the period from June 1996 to Mar. 2006, the GFI Group covers the period from Jan. 2002 to Apr. 2009, and Markit covers the period from Aug. 2001 to Dec. 2014. After merging these three data sets, our composite data set covers CDS activities from 1996 to 2014. The overlapping time periods allow us to validate the data quality for each source. In our baseline analysis, we use information about the inception of CDS trading or CDS quotes to assess changes in the stock price crash risk with the onset of CDS contracts. Table 1 reports the distribution of firms across years. Most CDS contracts were initiated in 2000 and 2001.

B. Stock Price Crash Risk Measures

We use the negative conditional firm-specific skewness of the weekly returns (NCSKEW) as the primary proxy for firm-specific crash risk (e.g., Hutton et al.

[10]Similar data are used by Subrahmanyam et al. (2014), (2017), Li and Tang (2016), Shan, Tang, and Winton (2019), and Shan, Tang, Yan, and Zhou (2021).

(2009), Kim et al. (2011a), (2011b), and Kim, Li, and Li (2014)). To determine the robustness of our results, we adopt down-to-up volatility (DUVOL) and an indicator of actual stock price crashes (CRASH) as alternative measures.

We construct the stock crash risk proxies using stock returns from CRSP. To avoid look-ahead bias and ensure that our analysis of stock price crash risk considers only the financial data available to investors, we follow Kim et al. (2011a), (2011b) in using the weekly returns for the 12-month period that ends 3 months after the firm's fiscal year-end. Then, for all firms, we regress the weekly stock returns for a year on the value-weighted market return in the current week, 2 weeks forward, and 2 weeks back, as follows:

$$(1) \qquad R_{i,t} = \alpha_i + \beta_{1,i} R_{m,t} + \beta_{2,i} R_{m,t-1} + \beta_{3,i} R_{m,t-2} + \beta_{4,i} R_{m,t+1} + \beta_{5,i} R_{m,t+2} + \varepsilon_{i,t}.$$

In equation (1), $R_{i,t}$ is the stock return for firm i in week t, $R_{m,t}$ is the return of CRSP's value-weighted market index in week t, and $\varepsilon_{i,t}$ is an error term. We use equation (1) to decompose the total return into its systematic and firm-specific components after introducing the lead and lag returns to account for nonsynchronous trading. The natural logarithm of 1 plus the residual in equation (1), $\log(1+\varepsilon_{i,t})$, proxies for the firm-specific weekly return for firm i in week t ($W_{i,t}$).

We calculate NCSKEW by taking the negative of the third moment of the firm-specific weekly returns, $W_{i,t}$, for each sample year and dividing it by the standard deviation of the firm-specific weekly returns raised to the third power. Specifically, we calculate NCSKEW for each firm i in year t as follows:

$$(2) \qquad \text{NCSKEW}_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^3\right] / \left[(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{3/2}\right],$$

where $W_{i,t}$ is as previously defined and n is the number of weekly return observations in year t. A higher negatively skewed return distribution (i.e., a higher value for NCSKEW) indicates a higher crash risk.

The first alternative stock price crash proxy, DUVOL, is calculated as the natural logarithm of the standard deviation of the weekly stock returns during the weeks in which $W_{i,t}$ is lower than its annual mean (down weeks) over the standard deviation of the weekly stock returns during the weeks in which $W_{i,t}$ is higher than its annual mean (up weeks). Specifically, for each firm i in year t, DUVOL is calculated as follows:

$$(3) \qquad \text{DUVOL}_{i,t} = \log\left\{\left[(n_u-1)\sum\nolimits_{\text{DOWN}} W_{i,t}^2\right] / \left[(n_d-1)\sum\nolimits_{\text{UP}} W_{i,t}^2\right]\right\},$$

where n_u is the number of up weeks and n_d is the number of down weeks. A higher value for DUVOL indicates a higher crash risk.

The second alternative proxy for stock price crashes, CRASH, is an indicator that equals 1 if a firm experiences at least one stock price crash in a year, and 0 otherwise. A stock price crash is defined as an extremely negative weekly stock return that falls below the mean of the firm-specific weekly returns in a fiscal year by a standard deviation of 3.09. This standard deviation indicates approximately 0.1% in a normal distribution.

C. Descriptive Statistics

We extract equity information from CRSP, firms' fundamental information from Compustat, analysts' forecast data from IBES, loan data from DealScan, corporate bond data from Mergent FISD, and institutional holding data from Thomson Reuters' 13F data set. After merging these data sets, we have 761 CDS-referenced firms with complete financial and accounting data during the 1996–2014 period.

Table 2 reports the descriptive statistics for the key dependent and independent variables. We find that in contrast to non-CDS-referenced firms, CDS-referenced firms on average are larger in size and have higher leverage, higher profitability, and higher weekly stock returns with a lower standard deviation. The means of NCSKEW and DUVOL for the CDS-referenced firms are higher than those for the whole sample. To isolate the effect of other known determinants of firm-specific crash risk (Jin and Myers (2006), Hutton et al. (2009), Kim et al. (2011a), (2011b), and Kim and Zhang (2016)), we control for the opaqueness of accounting reports, firm-specific standard deviations and returns, the change-of-equity-turnover ratio, size, the market-to-book ratio, financial leverage, profitability, the tangible-asset

TABLE 2

Descriptive Statistics

Table 2 reports the descriptive statistics for the main variables of our regressions. The sample period is from 1996 to 2014. Panel A reports the descriptive statistics for the variables for all firms. Panel B reports the descriptive statistics for the variables for credit default swap (CDS)-referenced firms only. *No. of obs.* denotes the total number of observations in each sample. The detailed definitions of all other variables are reported in the Appendix.

	Mean	Std. Dev.	25%	Median	75%
Panel A. All Firms (no. of obs. = 55,447)					
$CDS\_ACTIVE_{i,t-1}$	0.145	0.352	0.000	0.000	0.000
$CDS\_FIRM_{i,t-1}$	0.185	0.388	0.000	0.000	0.000
$NCSKEW_{i,t-1}$	0.024	0.823	−0.421	−0.018	0.399
$DUVOL_{i,t-1}$	0.013	0.513	−0.321	−0.007	0.323
$CRASH_{i,t-1}$	0.203	0.402	0.000	0.000	0.000
$DTURN_{i,t-1}$	0.024	0.814	−0.228	0.006	0.252
$SIGMA_{i,t-1}$	0.058	0.032	0.035	0.050	0.073
$RET_{i,t-1}$	−0.216	0.281	−0.265	−0.125	−0.059
$SIZE_{i,t-1}$	6.237	2.116	4.687	6.125	7.657
$MB_{i,t-1}$	3.663	4.268	1.232	2.098	4.124
$LEV_{i,t-1}$	0.172	0.180	0.002	0.124	0.287
$ROA_{i,t-1}$	0.011	0.127	−0.003	0.034	0.072
$OPAQUE_{i,t-1}$	0.250	0.205	0.111	0.190	0.321
$PPE_{i,t-1}$	0.266	0.248	0.067	0.180	0.407
$SALE_{i,t-1}$	1.000	0.865	0.436	0.826	1.326
$LEND_{i,t-1}$	0.578	0.494	0.000	1.000	1.000
Panel B. CDS-Referenced Firms (no. of obs. = 10,232)					
$NCSKEW_{i,t-1}$	0.089	0.769	−0.331	0.041	0.447
$DUVOL_{i,t-1}$	0.050	0.489	−0.268	0.039	0.354
$CRASH_{i,t-1}$	0.206	0.404	0.000	0.000	0.000
$DTURN_{i,t-1}$	0.087	0.663	−0.143	0.056	0.297
$SIGMA_{i,t-1}$	0.039	0.022	0.024	0.034	0.048
$RET_{i,t-1}$	−0.100	0.146	−0.114	−0.057	−0.029
$SIZE_{i,t-1}$	8.713	1.376	7.765	8.623	9.592
$MB_{i,t-1}$	4.477	4.794	1.531	2.603	5.365
$LEV_{i,t-1}$	0.267	0.163	0.147	0.253	0.369
$ROA_{i,t-1}$	0.040	0.065	0.016	0.039	0.070
$OPAQUE_{i,t-1}$	0.168	0.138	0.078	0.130	0.210
$PPE_{i,t-1}$	0.323	0.259	0.102	0.266	0.528
$SALE_{i,t-1}$	0.869	0.718	0.366	0.707	1.135
$LEND_{i,t-1}$	0.960	0.195	1.000	1.000	1.000

ratio, sales, and a lending relationship. The Appendix provides detailed descriptions of the variables.

IV. CDS Trading and Stock Price Crash Risk

This section discusses our model specification and reports our empirical findings on the effect of CDS trading on individual firms' stock price crash risk. After elaborating on the regression model, we present our baseline regression results, followed by robustness tests for our baseline results. We then address endogeneity concerns related to the selection of CDS trading and to possible omitted variables.

A. Model Specification

To examine the effect of CDS trading on stock price crash risk, we create a multivariate regression model that links our crash risk measures in year t to the indicator of CDS trading in year $t-1$ and to a set of control variables in year $t-1$:[11]

$$\text{(4)}\quad \text{CRASH\_PROXIES}_{i,t} = \alpha_0 + \alpha_1 \text{CDS\_ACTIVE}_{i,t-1} + \beta_1 \text{CDS\_FIRM}_{i,t-1} + \sum_{j=1}^{m} \gamma_j \text{CONTROL\_VARIABLE}_{i,t-1} + \varepsilon_{i,t}.$$

$\text{CRASH\_PROXIES}_{i,t}$ is the set of stock price crash risk measures adopted in our analysis. Specifically, we use the negative skewness of the firm-specific weekly return (NCSKEW) as the primary measure and the down-to-up volatility (DUVOL) and the indicator of actual stock price crashes in a firm-year (CRASH) as alternative measures of the firm-specific stock price crash risk. $\text{CDS\_ACTIVE}_{i,t-1}$ is an indicator variable that equals 1 for any year after the inception of CDS trading in firm i, and 0 otherwise. We define the inception of CDS trading as the first time either a CDS transaction or a quote is observed in our combined data set.[12] $\text{CDS\_FIRM}_{i,t-1}$ is an indicator variable that equals 1 for all firm i observations if a CDS transaction or a quote on firm i is documented during our sample period, and 0 otherwise. Equation (4) is estimated using an OLS approach for $\text{NCSKEW}_{i,t}$ and $\text{DUVOL}_{i,t}$ and a probit regression for $\text{CRASH}_{i,t}$. Standard errors are robust and clustered at the firm level.

The set of control variables includes $\text{OPAQUE}_{i,t-1}$, $\text{DTURN}_{i,t-1}$, $\text{SIGMA}_{i,t-1}$, $\text{RET}_{i,t-1}$, $\text{SIZE}_{i,t-1}$, $\text{MB}_{i,t-1}$, $\text{LEV}_{i,t-1}$, $\text{PPE}_{i,t-1}$, $\text{ROA}_{i,t-1}$, $\text{SALE}_{i,t-1}$, $\text{LEND}_{i,t-1}$, and year and industry fixed effects. We use these variables to isolate the effect of the well-documented determinants of stock price crash risk (e.g., Chen, Hong, and Stein (2001), Hutton et al. (2009), and Kim et al. (2011a), (2011b)). $\text{OPAQUE}_{i,t-1}$

[11]Following the prior literature on stock price crash risk, we measure our determinants with a lag. Our control variables are measured in year $t-1$ to be consistent with our measurement of CDS trading at year $t-1$ and to better deal with an omitted variable bias arising from factors correlated with CDS trading at year $t-1$.

[12]All quotes in our data are binding quotes that can be readily traded. We treat the first observation of either quote or trade as an indicator of the inception of CDS trading. Both trade and quote reflect market participants' interest and information. Tang and Yan (2007) find that the quote-to-trade ratio is 14:1 and, for their 1997–2006 sample period, that one contract is traded per month on average. They also show that making the next trade can take from less than 1 day to more than a month of quotes. Tang and Yan (2010) examine determinants of CDS spreads.

reflects the opaqueness of the firm's financial report. Hutton et al. (2009) find that financial reporting opacity is significantly positively related to stock price crash risk. Thus, we expect a positive coefficient on $\text{OPAQUE}_{i,t-1}$.

$\text{DTURN}_{i,t-1}$ is the average monthly share turnover of firm i in year t minus the turnover in year $t-1$ and a proxy for differences of opinion between investors. We expect the coefficient on $\text{DTURN}_{i,t-1}$ to be positive because Chen et al. (2001) show that heterogeneous opinion is positively related to the probability of experiencing extremely negative stock returns in the future. $\text{SIGMA}_{i,t-1}$ and $\text{RET}_{i,t-1}$ are, respectively, the standard deviation and arithmetic mean of the firm-specific weekly returns of firm i in year $t-1$. Chen et al. (2001) find that stocks with a lower past volatility are more likely to experience a price crash, whereas Kim et al. (2011a), (2011b) document a positive relationship between past volatility and future stock price crash risk. As our sample period has a significant overlap with that of Kim et al. (2011a), (2011b), we expect $\text{SIGMA}_{i,t-1}$ to have a positive coefficient. Additionally, because prior literature shows that higher past returns are associated with a higher likelihood of future stock price crashes (Chen et al. (2001), Kim et al. (2011a), (2011b)), we expect $\text{RET}_{i,t-1}$ to have a positive coefficient.

$\text{SIZE}_{i,t-1}$ is the logarithm of a firm's total assets, and $\text{MB}_{i,t-1}$ is the ratio of the market value of equity to the book value of equity. Because the stocks of large firms and firms with a high market-to-book ratio are more likely to experience a future stock price crash (e.g., Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a), (2011b)), we expect positive coefficients on $\text{SIZE}_{i,t-1}$ and $\text{MB}_{i,t-1}$. $\text{LEV}_{i,t-1}$ is the total long-term debt divided by total assets. Hutton et al. (2009), Kim et al. (2011a), (2011b), and Callen and Fang (2013) show that financial leverage is negatively related to stock price crash risk. We further control for the tangibility of a firm's assets, $\text{PPE}_{i,t-1}$, which is plant, property, and equipment scaled by total assets. One might expect firms with more tangible assets to have greater transparency and stability in their asset values and thus be less prone to stock price crash risk. $\text{ROA}_{i,t-1}$ is the ratio of income before extraordinary items divided by total assets. The effect of ROA on stock price crash risk is inconclusive: Hutton et al. (2009) and Kim et al. (2011a), (2011b) find a negative association, whereas Callen and Fang (2013) and Kim et al. (2014) find a positive one. To further control for the effect of firm performance, we include asset turnover, $\text{SALE}_{i,t-1}$, which is the firm's sales scaled by total assets.

$\text{LEND}_{i,t-1}$ is a dummy variable equal to 1 when a firm has lenders during a year, and 0 otherwise. Potential conflicts of interest between creditors and shareholders can motivate managers to hide bad news. Upon revealing previously hidden bad news, creditor actions might exacerbate a negative market response, resulting in a positive relationship between $\text{LEND}_{i,t-1}$ and the stock price crash risk proxies. Moreover, because Chen et al. (2001) report that firms with a high stock price crash risk in year $t-1$ are also likely to have a high crash risk in year t, we control for the corresponding lagged stock price crash risk measures.[13]

[13]It is possible that the unobserved panel-level effects are correlated with the lagged stock price crash risk proxies, resulting in inconsistent point estimators in the dynamic panel regressions. We use Arellano and Bond's (1991) approach to correct for bias in the dynamic panel regressions and find a significant negative association between the CDS trading indicator ($\text{CDS\_ACTIVE}_{i,t-1}$) and stock price crash risk ($\text{NCSKEW}_{i,t}$ and $\text{DUVOL}_{i,t}$). The results are untabulated but available from the authors.

B. Baseline Results

Table 3 reports the multivariate regression results for equation (4). We report the t-values, which are calculated using robust standard errors and corrected for firm clustering (Petersen (2009)). We document a significantly negative coefficient on $\mathrm{CDS\_ACTIVE}_{i,t-1}$ for $\mathrm{NCSKEW}_{i,t}$. This result indicates that the onset of CDS trading of firm i in year $t-1$ alleviates the stock crash risk in year t, which is consistent with our conjecture in Hypothesis 1. Next, we perform the same multivariate analysis using $\mathrm{DUVOL}_{i,t}$ and $\mathrm{CRASH}_{i,t}$ as alternative stock price crash risk measures. $\mathrm{CRASH}_{i,t}$ is an indicator of the occurrence of an actual stock price crash for firm i in year t. We then conduct probit regressions for $\mathrm{CRASH}_{i,t}$. We find a negative relationship between CDS trading in year $t-1$ and the stock price crash risk in year t, reinforcing the evidence we document with $\mathrm{NCSKEW}_{i,t}$.

TABLE 3

Credit Default Swap Trading and Stock Price Crash Risk

Table 3 reports the regression that examines the impact of credit default swap (CDS) trading on stock price crash risk from 1996 to 2014. $\mathrm{CRASH\_PROXIES}_{i,t-1}$ denotes $\mathrm{NCSKEW}_{i,t-1}$, $\mathrm{DUVOL}_{i,t-1}$, and $\mathrm{CRASH}_{i,t-1}$, respectively, in each model. Please refer to the Appendix for the variable definitions. We use OLS regressions in the first and second columns and a probit regression in the third column. The marginal effects of the variables are reported in the third column. The regression coefficients of CDS trading proxies are bolded. Standard errors are robust and clustered at the firm level. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable		
	$\mathrm{NCSKEW}_{i,t}$	$\mathrm{DUVOL}_{i,t}$	$\mathrm{CRASH}_{i,t}$
$\mathrm{CDS\_ACTIVE}_{i,t-1}$	**−0.099***** **(−6.38)**	**−0.058***** **(−5.91)**	**−0.023***** **(−3.00)**
$\mathrm{CDS\_FIRM}_{i,t-1}$	0.009 (0.64)	0.005 (0.51)	−0.003 (−0.38)
$\mathrm{CRASH\_PROXIES}_{i,t-1}$	0.023*** (4.59)	0.019*** (4.03)	0.026*** (5.89)
$\mathrm{OPAQUE}_{i,t-1}$	0.146*** (7.04)	0.023*** (7.99)	0.016*** (7.19)
$\mathrm{DTURN}_{i,t-1}$	0.039*** (8.24)	0.026*** (13.81)	0.543** (1.99)
$\mathrm{SIGMA}_{i,t-1}$	1.801*** (4.52)	0.943*** (3.83)	0.121*** (3.76)
$\mathrm{RET}_{i,t-1}$	0.207*** (5.40)	0.114*** (4.73)	0.006*** (4.30)
$\mathrm{SIZE}_{i,t-1}$	0.045*** (15.11)	0.003*** (5.99)	0.001** (2.31)
$\mathrm{MB}_{i,t-1}$	0.006*** (6.24)	−0.004 (−0.25)	0.020* (1.68)
$\mathrm{LEV}_{i,t-1}$	−0.013 (−0.49)	0.175*** (8.30)	0.124*** (7.55)
$\mathrm{ROA}_{i,t-1}$	0.271*** (7.89)	0.082*** (6.46)	0.051*** (5.48)
$\mathrm{PPE}_{i,t-1}$	−0.092*** (−4.01)	−0.049*** (−3.44)	−0.052*** (−4.77)
$\mathrm{SALE}_{i,t-1}$	0.000 (0.01)	0.003 (0.78)	0.001 (0.45)
$\mathrm{LEND}_{i,t-1}$	0.040*** (4.26)	0.015** (2.52)	0.014*** (3.03)
CONSTANT	−0.568*** (−7.73)	−0.335*** (−7.33)	−1.195*** (−10.19)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.036	0.021
N	55,447	55,447	55,447

To evaluate the economic significance of the effect of CDS trading on stock price crash risk, we estimate the marginally expected decrease in the probability of a crash as a function of the occurrence of CDS trading, with all other variables at their sample mean. Numerically, the coefficients on $\text{CDS\_ACTIVE}_{i,t-1}$ in Table 3 are −9.9% for $\text{NCSKEW}_{i,t}$ and −5.8% for $\text{DUVOL}_{i,t}$. In contrast to the means of the unconditional $\text{NCSKEW}_{i,t-1}$ and $\text{DUVOL}_{i,t-1}$, which are approximately 2.4% and 1.3%, respectively, the economic magnitude of CDS trading on the likelihood of a stock price crash risk increase is economically significant. Because of the nonlinearity of the probit function, we report the marginal effect of $\text{CDS\_ACTIVE}_{i,t-1}$ on $\text{CRASH}_{i,t}$ in the third column of Table 3. We find that the marginal effect of $\text{CDS\_ACTIVE}_{i,t-1}$ on $\text{CRASH}_{i,t}$ is approximately −2.3%.[14] This outcome suggests that the probability of future stock price crashes decreases about 2.3% after the inception of CDS trading.

In addition, the coefficients on $\text{CDS\_FIRM}_{i,t-1}$ are not significantly different from 0, which suggests that there is no significant difference in the means of the stock price crash risk proxies between CDS-referenced and non-CDS-referenced firms. As expected, the coefficients on the control variables are generally consistent with previous studies. For example, consistent with Hutton et al. (2009), we find a positive coefficient on $\text{OPAQUE}_{i,t-1}$, suggesting that firms with high financial reporting opacity have a higher stock price crash risk. In general, we find significantly positive coefficients on $\text{DTURN}_{i,t-1}$, $\text{SIGMA}_{i,t-1}$, $\text{RET}_{i,t-1}$, $\text{SIZE}_{i,t-1}$, and $\text{MB}_{i,t-1}$ in year $t-1$, which is consistent with prior research (e.g., Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a), (2011b)). We also find a positive relationship between the profitability measure, ROA, and crash risk, which is consistent with Callen and Fang (2013) and Kim et al. (2014). Moreover, we document a significantly positive coefficient on $\text{LEND}_{i,t-1}$, which suggests that the presence of a lender is positively associated with the likelihood of experiencing a future stock price crash.

C. Robustness Checks on the Baseline Results

In the previous section, we use a multivariate regression model and find a significantly negative relationship between the onset of CDS trading and the firm's future stock price crash risk. We control for the firm's lagged crash risk measure, fundamental characteristics, equity performance, creditor information, year, and industry fixed effects. Nevertheless, concurrent or omitted factors may still affect the future stock price crash risk. In this section, we first determine the robustness of our findings by controlling for various variables that, according to the literature, are associated with stock price crash risk or CDS trading.

First, we consider financial markets' style factors associated with stock price crash risk. In particular, we focus on equity illiquidity (Chang, Chen, and Zolotoy (2017)) and the short interest ratio (Callen and Fang (2015)). We use Amihud's (2002) illiquidity ratio to measure equity illiquidity, denoted by STOCK_ILLIQ, and we measure short interest by the number of shares sold short divided by the total

[14]We use the STATA command "margins, dydx(*)" to calculate the marginal effect in the probit regression.

shares outstanding, denoted by SHORT_INTEREST. Panel A of Table 4 reports the results after adding these variables as controls, one by one.[15] Our findings on how stock illiquidity and short interest affect stock price crashes are consistent with prior studies. Most importantly, the coefficients on CDS_ACTIVE$_{i,t-1}$ are significant and negative in all models with additional controls, consistent with our primary finding that CDS trading reduces stock price crash risk.

Next, we add controls for firm characteristics. Specifically, we focus on CEO compensation incentives and a firm's expected default probability. Recent studies document that managers are increasingly more likely to be compensated by additional option grants in the wake of CDS introduction (Lee, Oh, and Yermack (2017), Hong, Ryou, and Srivastava (2018)). There is evidence that managerial incentives are associated with stock price crash risk (Kim et al. (2011b)). Hence, we control for CEO incentives (CEO_INCENTIVE). Following Kim et al. (2011b), we use the incentive ratio for executive option holdings to reflect CEO incentives. We control for the expected default probability (EDP) because CDS introduction could increase the distress risk caused by the empty creditor problem (Subramanyam et al. (2014)).[16] Bankruptcy threats can have a disciplinary effect on managers that affects their incentives to hide bad news. We use the implied expected default probability according to Merton's structural model to reflect a firm's default risk. Panel B of Table 4 reports the results of controlling for CEO_INCENTIVE and EDP. We find that the expected default risk is negatively associated with future stock price crashes. One possible explanation is that a higher expected default risk leads to more scrutiny of the firm, which, in turn, constrains its ability to hide bad news. More importantly, the coefficients on CDS_ACTIVE$_{i,t-1}$ are significant and negative in all models, which is consistent with our primary finding that CDS trading reduces stock price crash risk.

Finally, we consider possible changes in the post-CDS-trading information environment that could confound our results. Kim et al. (2018) show that analyst coverage and managerial earnings guidance increase after the inception of CDS trading. Hence, we check whether our results are robust to controlling for analyst coverage and managerial earnings guidance. Panel C of Table 4 reports the results of controlling for these variables. We find that analyst coverage and managerial earnings guidance are positively associated with future stock price crashes. One possible explanation is that higher analyst coverage and more guidance increase pressure on firms to hide bad news, which in turn increases the stock price crash risk. More importantly, the coefficients on CDS_ACTIVE$_{i,t-1}$ are significant and negative in all models, which is consistent with our primary finding that CDS trading reduces the stock price crash risk.

Next, we employ alternative proxies for stock price crash risk to reexamine the relationship between CDS trading and stock price crash risk. Specifically, we use industry-adjusted firm-specific returns to calculate the stock price crash risk

[15]Because of significant changes in the sample sizes with different variables, we add those control variables one at a time. We find similar results when we include these variables in one common regression.

[16]CDS price discovery is also more effective prior to rating downgrades and for highly leveraged companies (Lee, Naranjo, and Sirmans (2021b)).

TABLE 4
Robustness Check with Additional Controls

Table 4 presents the regression results to check the robustness of the relationship between credit default swap (CDS) trading and stock price crash risk with additional controls. In Panel A, we use stock illiquidity and short interest as additional controls. In Panel B, we use CEO incentives and the firm's expected default probability as additional controls. In Panel C, we use analysts' coverage and managerial guidance as additional controls. Panel D reports the regression results on the relationship between CDS trading and the stock price crash risk proxies that are calculated by industry-adjusted firm-specific returns. Please refer to the Appendix for the variable definitions. The regression coefficients of CDS trading proxies are bolded. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Markets' Style Factors

Additional Control	STOCK_ILLIQ			SHORT_INTEREST		
Dependent Variable	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.070*** (−4.48)**	**−0.042*** (−4.31)**	**−0.053* (−1.90)**	**−0.084*** (−4.84)**	**−0.049*** (−4.54)**	**−0.053* (−1.71)**
$ADDITIONAL\_CONTROL_{i,t-1}$	−0.048*** (−14.56)	−0.025*** (−12.47)	−0.055*** (−8.67)	0.768*** (6.75)	0.451*** (6.44)	1.480*** (8.63)
$CDS\_FIRM_{i,t-1}$	0.014 (0.94)	0.007 (0.77)	−0.006 (−0.21)	0.020 (1.25)	0.012 (1.19)	0.008 (0.26)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.038	0.039	0.023	0.031	0.036	0.023
N	55,447	55,447	55,447	40,911	40,911	40,911

Panel B. Firm Characteristics

Additional Control	CEO_INCENTIVE			EDP		
Dependent Variable	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.099*** (−6.33)**	**−0.057*** (−5.83)**	**−0.084*** (−2.95)**	**−0.099*** (−6.37)**	**−0.058*** (−5.93)**	**−0.089*** (−3.12)**
$ADDITIONAL\_CONTROL_{i,t-1}$	0.032 (0.64)	0.011 (0.35)	0.145* (1.80)	−0.308*** (−7.62)	−0.186*** (−7.42)	−0.353*** (−4.36)
$CDS\_FIRM_{i,t-1}$	−0.004 (−0.25)	−0.004 (−0.38)	−0.040 (−1.43)	0.004 (0.26)	0.002 (0.24)	−0.015 (−0.55)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.035	0.037	0.022	0.035	0.038	0.025
N	55,447	55,447	55,447	53,272	53,272	53,272

Panel C. External Informational Environment

Additional Control	ANALYST_COVERAGE			MANAGE_GUIDE		
Dependent Variable	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.064*** (−3.81)**	**−0.042*** (−3.93)**	**−0.054* (−1.77)**	**−0.105*** (−6.71)**	**−0.061*** (−6.18)**	**−0.094*** (−3.30)**
$ADDITIONAL\_CONTROL_{i,t-1}$	0.100*** (12.36)	0.059*** (11.70)	0.138*** (9.80)	0.020*** (6.89)	0.011*** (6.10)	0.039*** (8.36)
$CDS\_FIRM_{i,t-1}$	−0.014 (−0.89)	−0.009 (−0.95)	−0.035 (−1.21)	0.004 (0.27)	0.002 (0.19)	−0.020 (−0.73)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.030	0.034	0.023	0.035	0.037	0.025
N	44,607	44,607	44,607	55,447	55,447	55,447

Panel D. CDS Trading and Stock Price Crash Risk: Industry-Adjusted Firm-Specific Returns

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.111*** (−6.99)**	**−0.061*** (−6.09)**	**−0.035*** (−4.31)**
$CDS\_FIRM_{i,t-1}$	0.016 (1.11)	0.006 (0.65)	0.007 (0.84)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.030	0.032	0.021
N	54,404	54,404	54,404

TABLE 5

Analysis for Different Time Horizons, Specifications, and Subsamples

Table 5 reports the regression results that examine the relationship between credit default swap (CDS) trading and longer-term stock price crash risk (Panels A and B), after controlling for firm fixed effects (Panel C), and in the subsample with financial leverage (Panel D). Panels A and B report the impact of CDS trading on the 2- and 3-year-ahead stock price crash risk measures, respectively. Panel C reports the regression results that control for firm fixed effects. Panel D reports the regression results for firms with positive financial leverage. Other controls include all the control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of CDS trading proxies are bolded. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Long-Term Impact: 2-Year-Ahead

	Dependent Variable		
	$NCSKEW_{i,t+2}$	$DUVOL_{i,t+2}$	$CRASH_{i,t+2}$
$CDS\_ACTIVE_{i,t-1}$	**−0.115***** **(−6.67)**	**−0.069***** **(−6.45)**	**−0.102***** **(−3.36)**
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.028	0.030	0.017
N	46,997	46,997	46,997

Panel B. Long-Term Impact: 3-Year-Ahead

	Dependent Variable		
	$NCSKEW_{i,t+3}$	$DUVOL_{i,t+3}$	$CRASH_{i,t+3}$
$CDS\_ACTIVE_{i,t-1}$	**−0.122***** **(−6.69)**	**−0.072***** **(−6.34)**	**−0.108***** **(−3.47)**
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.027	0.030	0.016
N	40,365	40,365	40,365

Panel C. Controlling for Firm Fixed Effects

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.073***** **(−3.03)**	**−0.044***** **(−2.95)**	**−0.020*** **(−1.76)**
Other controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
R^2/pseudo R^2	0.033	0.038	0.018
N	52,394	52,394	52,394

Panel D. Firms with Debts Outstanding

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1}$	**−0.086***** **(−5.35)**	**−0.052***** **(−5.13)**	**−0.064**** **(−2.21)**
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.037	0.020
N	43,641	43,641	43,641

measures. Industry-adjusted, firm-specific returns refer to the residuals from the regressions of the weekly stock returns for a year on the equal-weighted industry returns in the current week, 2 weeks forward, and 2 weeks back, using the Fama–French 48 industry classifications. As reported in Panel D of Table 4, we document significantly negative coefficients on the CDS trading indicators for all new stock price crash risk measures, which further supports CDS trading's negative influence on the likelihood of future stock price crashes.

We also examine whether the initiation of CDS trading has a long-term reductive impact on stock price crash risk by using measures of the 2- and

3-year-ahead stock price crash risk. As reported in Panels A and B of Table 5, we find a negative association between CDS trading and stock price crash risk, which suggests that the price discovery role of CDS trading is not temporary. Furthermore, we report the regression results after controlling for firm fixed effects in Panel C of Table 5. We still document a significantly negative relationship between the CDS trading indicator and the stock price crash risk proxies. Additionally, because the reference entity of CDS contracts is based on corporate debts or bank loans, it is less likely to initiate CDS trading for firms without outstanding debt. To determine the robustness of our baseline findings, we conduct a multivariate regression after removing firms with no outstanding debt. We find consistent results, as reported in Panel D of Table 5.

To summarize, the results in Tables 3–5 offer evidence in support of the argument that CDS trading alleviates future firm-specific crash risk after controlling for the opacity of financial reports (Hutton et al. (2009)), investor heterogeneity (Chen et al. (2001)), and other known determinants of crash risk. This result is robust to the use of two alternative proxies for stock price crashes and to various subsamples.

D. Addressing Endogeneity in CDS Trading

We document a significant and robust relationship between the inception of CDS trading activities and a decrease in the likelihood of the firm experiencing extremely negative stock returns 1 year later. In this section, we address the possible endogeneity concerns on CDS trading. A primary concern is unobserved confounding variables driving both the inception of CDS activities and the firm's stock price crash risk. Following Frank (2000), we employ the impact threshold of a confounding variable (ITCV) analysis to evaluate how large the endogenous problem has to be to make the CDS effect statistically insignificant. Next, we use the propensity score matching method to provide further evidence on the effect of CDS trading on stock crash risk. Finally, we conduct a three-stage estimation with instrumental variables to establish the causality of CDS trading with regard to a decrease in stock price crash risk.

1. Impact Threshold of a Confounding Variable

Although we include a large array of control variables in our model specification, we may still omit some unobserved confounding variables. If the unobserved confounding variables are strongly correlated with both the covariates and the residuals in our baseline model, the resulting endogeneity problem could make the coefficients in our baseline regressions statistically insignificant. To evaluate the severity of this endogeneity problem, we follow Frank (2000) to estimate the ITCV needed to turn a statistically significant result into an insignificant one (or even to flip the sign). Specifically, ITCV is defined as the lowest product of the partial correlation between the dependent variable and the confounding variable and the partial correlation between the independent variables and the confounding variable that makes the coefficient statistically insignificant. A high ITCV suggests a lower likelihood that a significant result can turn into an insignificant one because of

TABLE 6

Analyzing the Impact Threshold of a Confounding Variable

Table 6 reports the results of the analysis to determine the sensitivity of the earlier regression results to omitted variable bias. The impact threshold value for each test is reported in the bottom row and bolded, which serves as a benchmark. The impact threshold value is the lowest product of the partial correlation between CDS_ACTIVE$_{i,t-1}$ and the confounding variable and the partial correlation between the dependent variable (NCSKEW$_{i,t}$ or DUVOL$_{i,t}$) and the confounding variable that is required to overturn the significant results. The partial impact is calculated as the product of the partial correlation between CDS_ACTIVE$_{i,t-1}$ and the control variable and the partial correlation between the dependent variable (NCSKEW$_{i,t}$ or DUVOL$_{i,t}$) and the control variable.

	NCSKEW$_{i,t}$	DUVOL$_{i,t}$
	Impact	Impact
CRASH_PROXIES$_{i,t-1}$	−0.0002	−0.0002
CDS_FIRM$_{i,t-1}$	−0.0110	−0.0111
DTURN$_{i,t-1}$	0.0004	0.0004
SIGMA$_{i,t-1}$	−0.0012	−0.0010
RET$_{i,t-1}$	−0.0015	−0.0013
SIZE$_{i,t-1}$	0.0165	0.0160
MB$_{i,t-1}$	−0.0021	−0.0020
LEV$_{i,t-1}$	0.0002	0.0001
ROA$_{i,t-1}$	−0.0013	−0.0015
OPAQUE$_{i,t-1}$	0.0004	0.0004
PPE$_{i,t-1}$	0.0008	0.0005
SALE$_{i,t-1}$	0.0001	0.0001
LEND$_{i,t-1}$	−0.0005	−0.0003
Impact threshold	**0.0189**	**0.0169**

potential omitted variables. Thus, an ITCV analysis can be a useful diagnosis for the causal effect of CDS trading on stock crash risk.

We report the results of the ICTV analysis in Table 6.[17] Because ITCV is a correlation-based approach, the ITCV analysis applies only to the linear regression model (Call et al. (2018); Xu, Frank, Maroulis, and Rosenberg (2019).[18] Thus, we focus on the linear regressions using NCSKEW$_{i,t}$ and DUVOL$_{i,t}$ as proxies for stock price crash risk. As reported in Table 6, the impact thresholds of our variable of interest, CDS_ACTIVE$_{i,t-1}$, using NCSKEW$_{i,t}$ and DUVOL$_{i,t}$ as dependent variables are 0.0189 and 0.0169, respectively. The results suggest that the partial correlation between NCSKEW$_{i,t}$ and the confounding variable and the partial correlation between CDS_ACTIVE$_{i,t-1}$ and the confounding variable should be greater than 0.1375 (= $\sqrt{0.0189}$); the corresponding value would be 0.1300 (= $\sqrt{0.069}$) for DUVOL$_{i,t}$ to overturn the significant results. Further, the variable with the largest impact is SIZE$_{i,t}$, with values of 0.165 and 0.160 using NCSKEW$_{i,t}$ and DUVOL$_{i,t}$ as the respective dependent variables. To overturn the significant result, a confounding variable has to be more highly correlated with CDS_ACTIVE$_{i,t-1}$ and the stock price crash proxies than it is with SIZE$_{i,t}$. Moreover, the impact of the

[17]We use the STATA command "konfound" to estimate ITCV. An alternative method is to use the raw correlations. Similar to Larcker and Rusticus (2010), Fu, Kraft, and Zhang (2012), Badertscher, Katz, and Rego (2013), and Call, Martin, Sharp and Wilde (2018), we find that in general, the raw correlations are larger than the corresponding partial correlations. Most importantly, we still document that the majority of raw correlations are consistently smaller than the impact thresholds, which suggests that it is unlikely that the possibly omitted variable could overturn the significant results.

[18]Xu et al. ((2019), p. 533) state that "the impact of an omitted variable necessary to invalidate an inference should not be used, because it is correlation based and thus applies only to linear cases." To circumvent the problem of nonlinearity, Call et al. ((2018), p. 161) switch to OLS for their ITCV analysis because their dependent variable, regulatory enforcement outcome, is also a dummy variable.

possibly omitted variable would need to be more than 8 times stronger than the rest of control variables except $\text{SIZE}_{i,t}$ and $\text{CDS\_FIRM}_{i,t-1}$ to invalidate the results. Hence, the ITCV results lend credence to the argument that the negative impact of CDS trading on the future stock price crash risk is unlikely to be affected by possible omitted variables.

2. Propensity Score Matching

The negative relationship between the CDS trading indicator and the stock price crash risk measures may be driven by unobserved factors that simultaneously induce both actions, albeit in opposite directions. In this case, we expect to observe the comovement of CDS trading and stock price crash risk, regardless of the exact timing of the initiation of CDS trading. To conduct the placebo test, we first use a propensity score matching approach to compose the treated (CDS-referenced) and control (non-CDS-referenced) groups.

We match the treated and control groups based on a 5-year event window. Specifically, we define a treated firm as one that initiates CDS trading in the third year of a 5-year window. In other words, there are no CDS activities in the first and second years (years $t-2$ and $t-1$), because CDS trading begins in the third year (year t) and continues in the fourth and fifth years (years $t+1$ and $t+2$). We then select a corresponding control firm from the group of firms that do not engage in CDS trading during that 5-year window. Each control firm is matched to a treated firm in year $t-1$ if it shares the same 2-digit SIC industry code and has the closest propensity score for the initiation of CDS trading in year t. Panel A of Table 7 compares the firm characteristics of the CDS-referenced firms and the propensity-score-matched firms; we find that the differences in NCSKEW, leverage, ROA, and other variables become insignificant after matching.

We compute the propensity score for the inception of CDS trading in year t using the following multivariate regression:

$$\text{(5)} \qquad \text{CDS\_ACTIVE}_{i,t} = \alpha_0 + \sum_{j=1}^{m} \gamma_j(\text{ITH\_DETERMINANTS}_{i,t-1}) + \varepsilon_{i,t},$$

where $\text{CDS\_ACTIVE}_{i,t}$ is an indicator that equals 1 if there are CDS activities in year t, and 0 otherwise. Following Subrahmanyam et al. (2014), we consider several firm characteristics as determinants of the inception of CDS trading, including the logarithm of firm size (SIZE), financial leverage (LEV), the return on total assets (ROA), the market-to-book ratio (MB), the ratio of total sales to total assets (SALE), and the ratio of tangible assets to total assets (PPE) in year $t-1$. We also incorporate equity market characteristics, including the means and standard deviations of the weekly returns and the detrended average monthly stock turnover (DTURN) for the previous year. Subrahmanyam et al. (2014) show that the lender's assets significantly affect the likelihood of trading CDS. To identify the lender's assets, we merge our CDS data set with Mergent FISD and Thomson Reuters' DealScan, so we can respectively identify bond and syndicated loan information. We incorporate the logarithm of the average size of the lenders (LASSET) for a firm in a year and the square of LASSET (LASSET2) into our prediction model. In addition, equation (5) also controls for year and industry fixed effects.

TABLE 7
Propensity Score Matching

Table 7 reports the regression results that use a propensity score matching approach to check the robustness of the relationship between credit default swap (CDS) trading and stock price crash risk. The matched sample of treated and control firms is constructed as follows: i) a treated firm is defined as having CDS trading in and after year t and as having no CDS trading before year t; ii) a control firm is defined as having no CDS trading throughout the sample period; and iii) a control firm is matched with a treated firm in year $t-1$ if they are in the same industry and their propensity scores for CDS trading are closer to each other than to any other potential match. The propensity score for CDS trading is calculated using equation (5) in Section IV.D.2. Panel A reports firm characteristics before and after propensity score matching. Panel B reports the regression results using the treated and control samples with the actual CDS initiation time. The placebo-treated firms are defined as having CDS trading 2 (or 3) years before the actual year of treatment. Panels C and D report the regression results using the treated and control samples with the wrong CDS initiation time. TREATED is a dummy variable that equals 1 for the treated firms, and 0 otherwise. Other controls include all the control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of interested interaction terms are bolded. Standard errors are robust and clustered at the firm level. The p-statistics are reported in parentheses in Panel A. The t-statistics are reported in parentheses in Panels B–D. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Firm Characteristics Before and After Propensity Score Matching

	Full Sample			PSM Sample		
	Non-CDS-Referenced Firms	CDS-Referenced Firms	Diff (p-Value)	Non-CDS-Referenced Firms	CDS-Referenced Firms	Diff (p-Value)
$PSM\_SCORE_{i,t-1}$	0.1210	0.5470	−0.4260*** (0.0000)	0.3084	0.3346	−0.0262 (0.1547)
$NCSKEW_{i,t-1}$	−0.005	0.072	−0.077*** (0.000)	0.097	0.105	−0.008 (0.656)
$SIZE_{i,t-1}$	5.655	8.744	−3.089*** (0.000)	8.219	8.390	−0.171* (0.091)
$MB_{i,t-1}$	3.470	4.467	−0.998*** (0.000)	3.681	3.837	−0.156 (0.114)
$LEV_{i,t-1}$	0.156	0.271	−0.005*** (0.000)	0.253	0.274	−0.021 (0.109)
$ROA_{i,t-1}$	−0.009	0.039	−0.047*** (0.000)	0.032	0.036	−0.004 (0.111)
$OPAQUE_{i,t-1}$	0.277	0.168	0.108*** (0.000)	0.149	0.155	−0.006* (0.051)

Panel B. Actual Time (t)

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1} \times TREATED_{i,t-1}$	**−0.104**** **(−2.30)**	**−0.061**** **(−2.15)**	**−0.060***** **(−2.66)**
$CDS\_ACTIVE_{i,t-1}$	0.010 (0.24)	−0.000 (−0.01)	0.027 (1.23)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.061	0.070	0.027
N	6,395	6,395	6,395

Panel C. Placebo Time ($t-2$)

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1} \times TREATED_{i,t-1}$	**−0.049** **(−0.90)**	**−0.021** **(−0.62)**	**−0.052*** **(−1.91)**
$CDS\_ACTIVE_{i,t-1}$	0.060 (1.27)	0.023 (0.80)	0.052** (2.17)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.060	0.073	0.037
N	6,395	6,395	6,395

Panel D. Placebo Time ($t-3$)

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
$CDS\_ACTIVE_{i,t-1} \times TREATED_{i,t-1}$	**−0.060** **(−0.80)**	**−0.030** **(−0.63)**	**−0.026** **(−0.71)**
$CDS\_ACTIVE_{i,t-1}$	0.078 (1.25)	0.052 (1.38)	0.021 (0.65)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.060	0.073	0.036
N	6,395	6,395	6,395

Using this matching procedure, we construct a control group that is similar to the treated group in terms of industry and the likelihood of initiating CDS trading in year *t* but for which no CDS trading occurs. Thus, the change in the stock price crash risk for the control group is equivalent to the change in the crash risk that would have occurred during the event window had the treated group not received the treatment. Consequently, the difference between the change in the stock price crash risk in year $t + 1$ of the 5-year window for the treated group and that for the control group reflects the causal effect of CDS trading on stock price crash risk. Panel B of Table 7 reports the results using the correct time of CDS initiation. We find significantly negative coefficients on the interaction term using all three stock price crash measures, which is consistent with the baseline results and further supports Hypothesis 1.

Next, for the placebo test, we incorrectly assign the timing of the treatment (the initiation of CDS trading) to the 2 or 3 years before the actual event. If the negative relationship between CDS trading and stock price crash risk is driven by a pre-determined trend or an unobserved variable, we would expect to observe a similar effect when using the wrong date for CDS trading. However, if the decrease in stock price crash risk is driven by the inception of CDS trading, this negative relationship should disappear when we assign the wrong date to CDS trading. Panels C and D of Table 7 report the regression results, which respectively and incorrectly assign the CDS trading date to 2 and 3 years before the actual event. We find that the coefficients on the interaction term are both negative but not significant at the 5% significance level, alleviating the concern that unobserved variables are responsible for our results and lending credence to CDS trading's negative effect on future firm-specific stock price crash risk.

3. Three-Stage Instrumental Variable Estimation

In this section, we address any remaining endogeneity concerns by employing an alternative specification (the instrumental variable regression approach). We choose instrumental variables that directly affect the initiation of CDS trading but not the equity market stock price crash risk. To be precise, these instrumental variables can affect stock price crash risk only through the channel of CDS trading. Specifically, we use FX_HEDGE and BORROWER_CDS to perform a two-stage regression. FX_HEDGE is the amount of FX derivatives a firm's lender uses for hedging purposes, scaled by the lender's total assets; it thus reflects the lenders' hedging preference. Saretto and Tookes (2013) are the first to use FX_HEDGE as an IV for CDS trading. Minton, Stulz, and Williamson (2009) find that banks that use interest rates, FX, equity, and commodity derivatives are more likely to use CDS contracts, indicating that their hedging preferences extend across a variety of financial markets, including the credit derivatives market. Therefore, we conjecture that the amount of FX derivatives used for hedging should be positively related to the likelihood of initiating CDS trading. Furthermore, as the hedging preference of a firm's lender is unlikely to directly affect the firm's risk of a stock price crash in the equity market, FX_HEDGE also has no direct effect on stock price crash risk.

To calculate FX_HEDGE, we link our data set with Mergent FISD and Thomson Reuters' DealScan to extract issuance information about bonds and syndicated loans. We extract all the bond underwriters and leading lenders of syndicated loans over the previous 5 years. To calculate the ratio of the amount of FX derivatives to total assets, we collect data on the use of FX derivatives and the fundamental lenders' data from Call Reports at the FDIC. Because a firm could have more than one lender in a year, we use the average ratio of FX derivatives to total assets for all the lenders of an individual firm (FX_HEDGE).

Our second instrumental variable, BORROWER_CDS, reflects the lender's preference for the use of CDS from the perspective of borrowers' CDS-referenced status. A bank can lend to many firms simultaneously. If the bank prefers or is willing to use a CDS contract to hedge its credit risk position, we expect to observe more CDS-referenced borrowers on its list. Thus, if a high percentage of a bank's borrowers are CDS-referenced, excluding the focal firm, the probability of future CDS trading is high. Similar to the argument made for the hedging preference reflected by FX_HEDGE, our argument here is that the ratio of a lender's CDS-referenced borrowers to its total borrowers is less likely to directly affect stock price crash risk in the equity market, which satisfies the exclusion condition.

First, we use the lender–borrower relationship from the bonds and loans extracted from Mergent FISD and DealScan to identify all borrowers for a given lender in the past 5 years. We then examine the CDS trading status, including both CDS transactions and CDS quotes for each borrower in the current year. After removing the firm of interest, we calculate the percentage of borrowers that are CDS-referenced for each lender in every year. Because a firm could have multiple lenders, we use the mean of the percentage of CDS-referenced borrowers as BORROWER_CDS.

We use the two previously described instrumental variables to conduct a three-stage regression following Adams et al. (2009), which is also used by Lee et al. (2017). In the first stage, we use the regression model from equation (5) to conduct a probit regression to examine the effect of the introduction of CDS trading. The lender dummy always equals 1 after incorporating these instrumental variables, which reflect lenders' characteristics. To avoid a multicollinearity problem, both regressions employ lenders' size as a substitute for the lender dummy. According to the first-stage probit regression results in Panel A of Table 8, we find significant and positive coefficients on both FX_HEDGE$_{i,t-1}$ and BORROWER_CDS$_{i,t-1}$. Furthermore, the chi-square tests for weak instruments reject the null hypothesis that the instruments are weak. We use the predicted probability of CDS trading (PREDICT_CDS_ACTIVE) from the first stage as an instrumental variable to CDS_ACTIVE in the second- and third-stage regressions.[19] As reported in Panel B of Table 8, we find that the IVPREDICT_CDS_ACTIVE$_{i,t-1}$ is negatively related to the stock price crash risk proxies, which indicates that CDS trading activities in the current year reduce the probability of experiencing extremely negative stock returns in the following year. These outcomes further strengthen Hypothesis 1.

[19]We use the STATA command "probit" to run the first-stage regression and calculate the predicted CDS_ACTIVE$_{i,t-1}$. Then, we employ the predicted CDS_ACTIVE$_{i,t-1}$ from the first-stage regression as an instrumental variable and use "ivprobit" to run the second- and third-stage regressions for CRASH$_{i,t}$ and "ivreg" to run the second- and third-stage regressions for NCSKEW$_{i,t}$ and DUVOL$_{i,t}$.

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TABLE 8

Three-Stage Instrumental Variables Approach

Table 8 reports the regression results that use the instrumental variable approach to examine the relationship between credit default swap (CDS) trading and stock price crash risk. We employ two instrumental variables: FX_HEDGE and BORROWER_CDS. FX_HEDGE is the mean of firm lenders' foreign currency exchange hedging scaled by lenders' total assets. BORROWER_CDS is the mean of the ratio of CDS-referenced borrowers to all borrowers for all lenders that have a lending relationship with a firm in the previous 5 years. The ratio of CDS-referenced borrowers equals the number of CDS-referenced borrowers to the total number of borrowers who borrowed money from a lender in the previous 5 years. We perform the regressions using a three-stage approach. Panel A reports the first-stage regression results on the relationship between the instrumental variables and CDS trading. Panel B reports the third-stage regression results on the relationship between IVPREDICT_CDS_ACTIVE$_{i,t-1}$ and the stock price crash risk proxies. IVPREDICT_CDS_ACTIVE$_{i,t-1}$ is the predicted CDS_ACTIVE$_{i,t}$ in the second-stage regressions. Other controls include all the control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of instrumental variables are bolded in Panel A. The regression coefficients of the predicted CDS trading proxies are bolded in Panel B. Standard errors are robust and clustered at the firm level. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Relationship Between the Instrumental Variables and CDS Trading

	Dependent Variable	
	IV: FX_HEDGE	IV: BORROWER_CDS
	CDS_ACTIVE$_{i,t}$	CDS_ACTIVE$_{i,t}$
IV$_{i,t-1}$	**4.106***** **(2.96)**	**1.242***** **(6.78)**
CDS_FIRM$_{i,t-1}$	2.417*** (27.79)	2.380*** (26.98)
Other controls	Yes	Yes
Pseudo R^2	0.721	0.725
N	31,613	31,613
χ^2-Statistic (IV)	8.79	46.01
p-Value (χ^2-statistic)	0.0030	<0.0001

Panel B. CDS Trading and Stock Price Crash Risk

	Dependent Variable					
	IV: FX_HEDGE			IV: BORROWER_CDS		
	NCSKEW$_{i,t}$	DUVOL$_{i,t}$	CRASH$_{i,t}$	NCSKEW$_{i,t}$	DUVOL$_{i,t}$	CRASH$_{i,t}$
IVPREDICT_CDS_ACTIVE$_{i,t-1}$	**−0.183***** **(−6.44)**	**−0.113***** **(−6.40)**	**−0.237***** **(−4.75)**	**−0.184***** **(−6.52)**	**−0.114***** **(−6.57)**	**−0.231***** **(−4.67)**
CDS_FIRM$_{i,t-1}$	0.074*** (3.98)	0.044*** (3.67)	0.109*** (3.17)	0.075*** (4.00)	0.044*** (3.75)	0.106*** (3.09)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2/pseudo R^2	0.027	0.032	0.023	0.027	0.032	0.023
N	31,613	31,613	31,613	31,613	31,613	31,613

V. Channels and Mechanisms

This section discusses further results that uncover the channels and mechanisms driving the CDS effect on stock price crash risk.

A. Direct Evidence on Information Flow from CDS to Stocks

In this section, we provide some evidence that bad news signals from the CDS market are indeed incorporated into equity prices in a timelier manner. According to the price discovery argument, the presence of CDS trading facilitates the timelier incorporation of bad news about firm fundamentals into the equity price, thus mitigating the risk of a stock price crash when the firm's attempts to hoard bad news are eventually revealed. Based on this argument, we expect a smoother equity price response (i.e., less volatile stock returns)

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related to the future public revelation of bad news. Because the focus of our analysis is on smoothness in capitalizing bad news, we adopt the downside return volatility, which is the volatility of the negative daily equity returns in the days around a firm's revelation of bad news (e.g., Barndorff-Nielsen, Kinnebrock, and Shephard (2010)).

1. Downside Return Volatility Around the Future Revelation of Bad News

In this section, we employ two approaches to identify the revelation of bad news, particularly extremely negative news: extremely negative earnings surprises and negative credit watches. Our focus on negative earnings surprises is motivated by Batta et al. (2016).[20] They show that post CDS trading, the dispersion of and errors in EPS forecasts decrease and that downgrades by both types of analysts become more frequent and timelier ahead of large negative earnings surprises. These outcomes indicate that the CDS market conveys information that is valuable to financial analysts. From the perspective of smoothness in capitalizing bad news, the findings of Batta et al. (2016) that informed market participants learn from the CDS market suggest that there is less downside return volatility around the time a firm announces bad earnings news.

We measure earnings surprise as the actual EPS value minus the median of financial analysts' EPS forecasts (90 days before the actual EPS announcement), scaled by the equity price on the announcement day. To facilitate our analyses, we divide firms into quintiles based on the distribution of earnings surprises within a year. Because we focus on the revelation of negative news, we construct a ranked variable that captures negative earnings surprises, NES, by assigning the firms with the most positive (negative) earnings surprises to the bottom (top) quintile. Panel A of Table 9 reports the summary statistics of the earnings surprises in each quintile. The mean and standard deviation of the earnings surprises in the top quintile of NES are −0.0187 and 0.0573, respectively.

Panel B of Table 9 reports the results of multivariate regressions that examine the impact of CDS trading on equity returns' downside volatility around earnings announcements, conditional on extremely negative earnings news. The downside volatility is denoted by VOLD. Because CDS trading could affect how analysts cover a firm (Batta et al. (2016)) and the amount of analyst coverage might affect the downside return volatility, we use the logarithm of the total number of analysts plus 1 (ANALYST_COVERAGE) as a control variable. We find significant and negative coefficients on the interaction term between CDS_ACTIVE and NES before earnings announcements. This finding indicates that the presence of CDS trading reduces the downside volatility of daily equity returns within the 10 or 5 days before an earnings announcement. This finding provides direct evidence that the onset of CDS trading smooths the incorporation of bad news into the equity price, which reduces the likelihood of extremely negative equity returns.

[20] Zhang and Zhang (2013) document evidence that negative earnings surprises are anticipated in the CDS market prior to any announcement.

TABLE 9

Downside Stock Return Volatility Around the Future Public Revelation of Bad News

Table 9 examines the impact of credit default swap (CDS) trading on the downside stock return volatility, VOLD, around the future revelation of bad news: extremely negative earnings surprises and negative credit watches. Panel A presents the summary statistics of earnings surprises across the NES quintiles; NES is a ranked variable such that firms with higher ranks are those with more negative earnings surprises. An earnings surprise is computed as the actual EPS value minus the median of financial analysts' EPS forecasts (90 days before the actual EPS announcement), scaled by the equity price on the announcement day. Panel B reports the results of the regressions that examine the impact of CDS trading on the downside return volatility around earnings surprises. Panel C presents the distribution of negative credit rating watches; RATING is the numerical value of S&P's credit rating; a higher number represents a higher credit rating. Panel D reports the results of the regressions that examine the impact of CDS trading on the downside return volatility around the announcement of negative credit watches. Please refer to the Appendix for the variable definitions. The regression coefficients of interested interaction term are bolded in Panels B and D. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics of Earnings Surprises in Each NES Quintile

NES	N	Mean	Std. Dev.	25%	Median	75%
5	5,607	−0.0187	0.0573	−0.0135	−0.0053	−0.0025
4	5,793	−0.0004	0.0005	−0.0006	−0.0002	0.0000
3	5,401	0.0005	0.0003	0.0003	0.0004	0.0006
2	5,597	0.0017	0.0007	0.0012	0.0016	0.0022
1	5,590	0.0147	0.0380	0.0041	0.0065	0.0122

Panel B. Downside Return Volatility Around Negative Earnings Surprises

	Dependent Variable: $VOLD_{i,t}$			
	10 Days Before Earnings Announcement	5 Days Before Earnings Announcement	5 Days After Earnings Announcement	10 Days After Earnings Announcement
$CDS\_ACTIVE_{i,t-1} \times NES_{i,t-1}$	**−0.023****	**−0.033*****	**0.013**	**−0.001**
	(−2.24)	**(−2.70)**	**(0.79)**	**(−0.11)**
$CDS\_ACTIVE_{i,t-1}$	−0.216***	−0.175***	−0.376***	−0.312***
	(−6.37)	(−4.25)	(−7.04)	(−8.01)
$NES_{i,t-1}$	0.029***	0.041***	0.104***	0.078***
	(6.29)	(7.15)	(14.17)	(14.56)
$ANALYST\_COVERAGE_{i,t-1}$	−0.029***	−0.030***	−0.070***	−0.073***
	(−4.14)	(−3.49)	(−6.33)	(−9.04)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R^2	0.79	0.70	0.70	0.78
N	27,960	27,129	26,954	27,952

Panel C. Distribution of Negative Credit Rating Watches

Rating	No. of Obs.	Percentage (%)
AAA	11	0.31
AA+	11	0.31
AA	28	0.79
AA−	47	1.33
A+	73	2.06
A	137	3.86
A−	594	16.76
BBB+	174	4.91
BBB	262	7.39
BBB−	268	7.56
BB+	187	5.28
BB	252	7.11
BB−	335	9.45
B+	357	10.07
B	267	7.53
B−	211	5.95
CCC+	102	2.88
CCC	74	2.09
CCC−	41	1.16
CC	107	3.02
C	7	0.20
Total	3,545	100

(continued on next page)

TABLE 9 (continued)

Downside Stock Return Volatility Around the Future Public Revelation of Bad News

Panel D. Downside Return Volatility Around Negative Credit Rating Watches

	Dependent Variable: $VOLD_{i,t}$			
	6 Months Before a Negative Credit Watch	3 Months Before a Negative Credit Watch	3 Months After a Negative Credit Watch	6 Months After a Negative Credit Watch
$CDS\_ACTIVE_{i,t-1}$ × $RATING_{i,t-1}$	**0.006*** (3.72)**	**0.007*** (3.10)**	**0.008** (2.15)**	**0.010*** (3.14)**
$CDS\_ACTIVE_{i,t-1}$	−0.117*** (−4.09)	−0.127*** (−3.43)	−0.132** (−2.12)	−0.172*** (−3.23)
$RATING_{i,t-1}$	−0.031*** (−25.60)	−0.035*** (−23.03)	−0.043*** (−22.24)	−0.041*** (−21.83)
$RET\_MONTH_{i,t-1}$	−0.051*** (−21.50)	−0.055*** (−19.19)	−0.036*** (−6.02)	−0.028*** (−3.38)
$DISTANCE_{i,t-1}$	−0.023*** (−19.42)	−0.044*** (−17.33)	−0.032*** (−12.20)	−0.016*** (−7.84)
Year FE	Yes	Yes	Yes	Yes
R^2	0.499	0.523	0.426	0.380
N	24,654	14,134	13,664	22,744

Next, we use a negative credit rating watch as an indicator of the public revelation of bad news.[21] Because Lee et al. (2021b) show that CDS spreads move a couple of months ahead of credit rating changes, we use negative credit rating watch changes as an alternative proxy for bad news so that we can examine the impact of CDS trading on information flow in the long run. We extract negative credit rating watch data from S&P's credit rating database. After matching these data with the equity information, we have 3,545 negative credit rating watches for our sample across ratings from AAA to C. Panel C of Table 9 reports the distribution of negative credit rating watches across credit ratings.

Panel D of Table 9 reports the results of the multivariate regressions that examine the impact of CDS trading on the monthly volatility of negative equity returns 3 and 6 months before and after the announcement of a negative credit rating watch. The annualized downside volatility is calculated using the negative daily equity returns for a month. In the regressions, we control for the number of months from a specific month to the month when the negative credit watch is announced (DISTANCE) and the annualized means of the daily equity returns for a month (RET_MONTH). We document significant and negative coefficients on $CDS\_ACTIVE_{i,t-1}$ for all time intervals around negative credit rating watches, which suggests that CDS trading facilitates the flow of negative information to the equity markets. We also find positive coefficients on the interaction term between $CDS\_ACTIVE_{i,t-1}$ and $RATING_{i,t-1}$. This outcome suggests that the impact of CDS trading on the volatility of negative equity returns is more pronounced for firms with a lower credit rating.

[21]We recognize a strand of literature on various issues with credit ratings (e.g., Griffin and Tang (2011), Griffin and Tang (2012), and Griffin, Nickerson, and Tang (2013)).

TABLE 10

Stock Returns After a Large Increase in the CDS Spreads

Table 10 reports the equity returns response after positive increases in the credit default swap (CDS) spread (CDS_INCREASE). $CDS\_INCREASE_{i,d}$ is the magnitude of the positive abnormal daily CDS spread change for firm *i* on day *d*. CDS_INCREASE equals zero when the abnormal CDS spread change is nonpositive. A daily abnormal CDS spread change is the difference between a firm's daily CDS spread change and the average daily CDS spread change for all firms in the same credit rating category. $RETD_{i,d}$ is the firm-specific daily stock return for firm *i* on day *d*. $CONSEC_{i,d}$ is the number of consecutive days with negative firm-specific daily stock returns for firm *i* starting from day *d*. We report the point estimates of OLS regressions. Please refer to the Appendix for the variable definitions. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable						
	$RETD_{i,d+1}$	$RETD_{i,d+2}$	$RETD_{i,d+3}$	$RETD_{i,d+4}$	$RETD_{i,d+5}$	$RETD_{i,d+6}$	$CONSEC_{i,d}$
	1	2	3	4	5	6	7
$CDS\_INCREASE_{i,d}$	−0.083***	−0.034*	−0.044**	−0.047**	0.018	−0.033	0.755***
	(−4.08)	(−1.66)	(−2.18)	(−2.37)	(0.89)	(−1.63)	(33.94)
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01
N	200,914	200,914	200,914	200,914	200,914	200,914	200,914

2. Stock Returns After a Large Increase in the CDS Spread

We now examine how the stock returns of firms with CDS contracts respond to bad news, as indicated by an increase in the CDS spread. $CDS\_INCREASE_{i,d}$ is the positive difference between firm *i*'s daily CDS spread change and the average daily CDS spread change for all firms in the same credit rating category on day *d*. A larger value for $CDS\_INCREASE_{i,d}$ indicates more bad news. We focus on bad news by setting $CDS\_INCREASE_{i,d}$ to 0 when the abnormal changes are nonpositive. We use a linear regression model to examine the response of the equity return from days $d+1$ to $d+6$, and we report the regression results in Table 10.[22] We find significant and negative coefficients on $CDS\_INCREASE_{i,d}$ on days $d+1$ to $d+4$, with the magnitude of the coefficients declining over the course of the days. There is no significant relationship between $CDS\_INCREASE_{i,d}$ and daily stock returns on days $d+5$ and $d+6$. These results imply that it takes approximately 4 days for bad news from CDS markets to be incorporated into equity prices and that price discovery from the CDS market to the equity market occurs over a short time.

To provide further evidence of price discovery, we examine whether bad news that first appears in the CDS market takes more time to be incorporated into the equity price. For the dependent variable, we use the number of consecutive days for which the stock return is negative in response to an abnormal increase in the CDS spread. Column 7 of Table 10 reports a positive relationship between an abnormal increase in the CDS spread and the number of consecutive days with subsequent negative equity returns. The coefficient estimate on $CDS\_INCREASE_{i,d}$, 0.755, is statistically significant at the 1% level. This finding supports the conjecture that it takes a longer time to incorporate more pronounced bad news that first appears in CDS markets into the equity price. The economic magnitude of the point estimate is large: An abnormal CDS spread increase of 4 BPS relative to the average spreads in

[22]Note that $CDS\_ACTIVE_{i,t-1}$ is not in the regression specification because the independent variable of interest in this analysis is a change in the CDS spread, which can be constructed only for firms with active CDS trading.

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TABLE 11
Credit Default Swap Market Activity

Table 11 reports the regression results that examine the relationship between credit default swap (CDS) market activity and stock price crash risk. We use two proxies to reflect CDS market activities: CDS_QUOTES (Panel A) and CDS_SPIKE (Panel B). $\text{CDS\_QUOTES}_{i,t}$ is the logarithm of the total number of firm i's distinct dealers plus 1 in fiscal year t. The number of distinct dealers that provide the CDS quotes is collected by Markit. A higher number of distinct dealers indicates more CDS activities. $\text{CDS\_SPIKE}_{i,t}$ is the logarithm of the number of CDS spread spikes of firm i in year t. We define a CDS spread spike as a positive abnormal weekly CDS spread change. The weekly abnormal CDS spread change is the difference between a firm's CDS spread change in a week and the average weekly CDS spread change for all firms in the same credit rating category. CRASH_PROXIES represents NCSKEW, DUVOL, and CRASH. Other controls include all the control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of CDS market activity proxies are bolded. Standard errors are robust and clustered at the firm level. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable		
	$\text{NCSKEW}_{i,t}$	$\text{DUVOL}_{i,t}$	$\text{CRASH}_{i,t}$
Panel A. Number of Credit Default Swap Quotes			
$\text{CDS\_QUOTES}_{i,t-1}$	**−0.041*** **	**−0.026*** **	**−0.018*** **
	(−3.69)	**(−3.77)**	**(−3.15)**
$\text{CRASH\_PROXIES}_{i,t-1}$	0.022***	0.019***	0.030***
	(3.76)	(3.31)	(5.39)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.027	0.031	0.019
N	38,941	38,941	38,941
Panel B. Spikes in Credit Default Swap Spreads			
$\text{CDS\_SPIKE}_{i,t-1}$	**−0.015** **	**−0.010** **	**−0.022* **
	(−2.24)	**(−2.29)**	**(−1.74)**
$\text{CDS\_ACTIVE}_{i,t-1}$	−0.089***	−0.051***	−0.070**
	(−5.48)	(−5.00)	(−2.42)
$\text{CRASH\_PROXIES}_{i,t-1}$	0.023***	0.019***	0.093***
	(4.58)	(4.02)	(5.90)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.036	0.021
N	55,447	55,447	55,447

the same rating class is associated with approximately 3 additional consecutive days with negative firm-specific daily stock returns.

B. CDS Quantities

After presenting a comprehensive set of analyses on the relationship between CDS trading and stock price crash risk, we now test our second hypothesis on the impact of CDS market activity on the relationship between CDS trading and future stock price crash risk. To measure CDS market activity, we rely on two proxies: CDS liquidity and the CDS spread. First, we use the logarithm of the number of distinct dealers that provide valid quotes on a CDS contract plus 1, denoted by CDS_QUOTES, to measure CDS contracts' endogenous liquidity (e.g., Qiu and Yu (2012)). A larger number of dealers providing quotes on a CDS contract indicates that the contract has better liquidity. Better liquidity for a contract facilitates its price discovery role by reflecting bad news in a timely fashion, as discussed in Hypothesis 2. Thus, we expect CDS trading to have a more pronounced reductive impact on stock price crash risk when the liquidity of the CDS contract is high. Because Markit provides CDS quote information only from 2001 to 2014, we conduct our analyses using observations from this subperiod; we report the results in Panel A of Table 11.

TABLE 12

The Role of CDS Market Dealers

Table 12 reports the regression results that examine the impact of credit default swap (CDS) dealers on the relationship between CDS trading and the stock price crash proxies. We extract the list of CDS dealers from the International Swap and Derivatives Association. We extract the list of financial institutions with trading subsidiaries in the United States from the Federal Reserve Bank. DEALER_TRADING$_{i,t-1}$ is an indicator that equals 1 when a firm *i*'s syndicated loans or corporate bonds lenders involve a financial institution that is a CDS dealer with a securities trading subsidiary in year $t-1$, and 0 otherwise. Other controls include all the control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of interested interaction term are bolded. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable		
	NCSKEW$_{i,t}$	DUVOL$_{i,t}$	CRASH$_{i,t}$
CDS_ACTIVE$_{i,t-1}$ × DEALER_TRADING$_{i,t-1}$	**−0.049****	**−0.028***	**−0.012**
	(−1.99)	**(−1.84)**	**(−0.28)**
DEALER_TRADING$_{i,t-1}$	0.002	0.003	0.017
	(0.11)	(0.27)	(0.64)
CDS_ACTIVE$_{i,t-1}$	−0.082***	−0.048***	−0.082***
	(−4.76)	(−4.43)	(−2.69)
Other controls	Yes	Yes	Yes
R^2	0.034	0.036	0.022
N	55,447	55,447	55,447

We find that CDS_QUOTES$_{i,t-1}$ is negatively related to all measures of crash risk, which supports Hypothesis 2.

To further analyze the role of CDS market activity, we use the weekly abnormal change in the CDS spread, which we term a CDS spike.[23] The weekly abnormal CDS spread change is the difference between a firm's CDS spread change in a week and the average weekly CDS spread change for all firms in the same credit rating category. A greater number of spikes in a CDS contract over the course of a year indicates higher potential for price discovery. We compute the logarithm of the number of CDS spikes plus 1 in a fiscal year, denoted by CDS_SPIKE. As reported in Panel B of Table 11, we document significant and negative coefficients on CDS_SPIKE$_{i,t-1}$, which suggests that the negative impact of CDS trading on stock price crash risk is more pronounced for CDS contracts with more activities. Overall, the results on CDS market activity lend support to price discovery driving the negative relationship between CDS trading and stock price crash risk.

C. Bad News Hoarding

In this subsection, we present findings relating to circumstances that lead to stronger or weaker price discovery effects as a result of CDS trading. The analyses test Hypotheses 3 and 4. Specifically, we examine the interaction effects with CDS market dealers, firms' financial reporting opacity, and managerial incentives.

1. CDS Market Dealers

First, we examine whether the negative relationship between CDS trading and stock price crash risk is stronger for firms with main lenders that are CDS market

[23]We use the weekly CDS spread change to maintain consistency with the weekly stock return that we use to compute the stock price crash measures. We also use the daily CDS spread change as a robustness check and find consistent results, which are available from the authors.

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dealers with securities trading subsidiaries. To identify these firms, we extract the list of CDS dealers from the International Swaps and Derivatives Association and the list of financial institutions with securities trading subsidiaries in the United States from the Federal Reserve Board. We identify CDS dealers with securities trading subsidiaries in the United States by merging these lists and then matching CDS dealers with syndicated loan information extracted from DealScan.

Table 12 reports the regression results that examine the influence of CDS dealers on the relationship between CDS trading and stock price crash risk. First, we focus on CDS dealers that participate in syndicated loans. DEALER_TRADING denotes CDS dealers with securities trading subsidiaries in the United States. We document significant and negative coefficients on the interaction term using $\text{NCSKEW}_{i,t}$ and $\text{DUVOL}_{i,t}$ as the price crash proxies. This outcome suggests that the presence of CDS dealers with securities trading subsidiaries enhances the negative influence of CDS trading on stock price crash risk, which supports Hypothesis 3.

2. Financial Reporting Opacity

We examine whether the negative relationship between CDS trading and stock price crash risk is stronger when firms are more opaque in their financial reporting. Following Hutton et al. (2009), we calculate information opaqueness as the moving sum of the absolute value of discretionary accruals over the previous 3 years. We use the modified Jones (1991) model in Dechow, Sloan, and Sweeney (1995) to estimate discretionary accruals. Then, we divide all firms into high- and low-opaqueness groups according to the median of the information opaqueness measure. Next, we construct an indicator, D_OPAQUE, that equals 1 for firms in the high-opaqueness group, and 0 otherwise.

Table 13 reports the multivariate regression results of the interaction between accounting accruals and CDS trading. We find negative and significant coefficients

TABLE 13

The Role of Financial Reporting Opacity

Table 13 reports the regression results that examine the impact of actual bad news hoarding on the relationship between credit default swap (CDS) trading and stock price crash risk. We use financial reports' information opaqueness to measure negative information hoarding. $\text{D\_OPAQUE}_{i,t}$ is an indicator that equals 1 for firms with highly opaque financial reports in year t. We separate the full sample into high- and low-opaqueness groups according to the median of the financial reports' opaqueness. Other controls include all control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of interested interaction term are bolded.Standard errors are robust and clustered at the firm level. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable		
	$\text{NCSKEW}_{i,t}$	$\text{DUVOL}_{i,t}$	$\text{CRASH}_{i,t}$
$\text{CDS\_ACTIVE}_{i,t-1} \times \text{D\_OPAQUE}_{i,t-1}$	**−0.061*** ** **(−2.65)**	**−0.037**** **(−2.56)**	**−0.056** **(−1.41)**
$\text{CDS\_ACTIVE}_{i,t-1}$	−0.021 (−0.64)	−0.011 (−0.53)	−0.013 (−0.21)
$\text{D\_OPAQUE}_{i,t-1}$	0.043*** (4.98)	0.024*** (4.54)	0.057*** (3.95)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.036	0.022
N	55,447	55,447	55,447

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on the interaction term CDS_ACTIVE$_{i,t-1}$ × D_OPAQUE $_{i,t-1}$, using NCSKEW$_{i,t}$ and DUVOL$_{i,t}$ to measure crash risk. This finding suggests that the influence of CDS activities on stock price crash risk is stronger for firms with highly opaque accounting information, which is consistent with CDS trading playing a price discovery role in constraining bad news hoarding when the firm is more publicly opaque.

3. Managerial Incentives to Hide Bad News

Bad news hoarding is a choice made by top management. Some managers have stronger incentives than others to hoard bad news. Therefore, we examine how managerial incentives moderate the relationship between CDS trading and stock price crash risk. We base managerial incentives to hoard bad news on managerial earnings guidance optimism and CEO overconfidence. Managers have various incentives to issue biased guidance (e.g., Rogers and Stocken (2005)). To determine guidance optimism, we obtain from IBES managerial guidance and actual EPS information at the fiscal year-end. If the guidance is a range estimate, we use the lower, more conservative bound. We then compare the guidance with the actual EPS to measure managerial guidance optimism. We construct an indicator variable, D_MOPT, that is equal to 1 when firm *i*'s manager issues optimistic guidance (i.e., guidance exceeds the actual EPS) in year *t*, and 0 otherwise. To measure CEO overconfidence, we use a stock-option-based indicator inspired by Malmendier and Tate's (2005) findings. In contrast to risk-averse CEOs, who may exercise their own firm's stock options early if the options are deep-in-the-money (Hall and Murphy (2002)), overconfident CEOs postpone their deep-in-the-money option exercise because they overestimate the future returns of their investment projects (Malmendier and Tate (2005)).

Detailed information about CEO compensation packages is not available for our large sample. We thus adopt the modified version of the CEO overconfidence measure developed by Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011). We extract CEO compensation information from the ExecuComp database and then classify CEOs as overconfident if they hold stock options that are more than 67% in-the-money at least twice during our sample period. We construct an indicator variable, D_OVER, which equals 1 when the CEO of firm *i* is overconfident in year *t*, and 0 otherwise.

Table 14 provides the results of the interaction between CDS trading and managerial incentives to hide bad news. In Panel A, the coefficient on the interaction term CDS_ACTIVE$_{i,t-1}$ × D_MOPT$_{i,t-1}$ is negative and statistically significant. This result suggests that the reductive impact of CDS trading on stock price crash risk is enhanced when managers tend to hide bad news by issuing optimistic guidance, which further supports a price discovery role for CDS contracts. Similarly, Panel B reports significant and negative coefficients on the interaction term CDS_ACTIVE$_{i,t-1}$ × D_OVER$_{i,t-1}$, which implies that CDS trading has a more pronounced impact on stock price crash risk when managers hide bad news because of overconfidence. Taken together, the results in Table 14 support our fourth hypothesis that the negative association between CDS trading and stock price crash risk is stronger when managers have incentives to hoard bad news.

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TABLE 14

The Role of Managerial Incentives to Hide Bad News

Table 14 reports the regression results that examine the impact of managers' internal incentives to withhold bad news on the relationship between credit default swap (CDS) trading and stock price crash risk. We categorize the external pressures into three groups: managerial optimism, CEO overconfidence, and CEO age. In Panel A, $D\_MOPT_{i,t-1}$ is an indicator that equals 1 when managers issue optimistic guidance, and 0 otherwise. In Panel B, $D\_OVER_{i,t-1}$ is an indicator that equals 1 when the CEO is overconfident, and 0 otherwise. Other controls include all control variables in equation (4). Please refer to the Appendix for the variable definitions. The regression coefficients of interested interaction terms are bolded. Standard errors are robust and clustered at the firm level. The *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable		
	$NCSKEW_{i,t}$	$DUVOL_{i,t}$	$CRASH_{i,t}$
Panel A. Managerial Optimism			
$CDS\_ACTIVE_{i,t-1} \times D\_MOPT_{i,t-1}$	**−0.106*** (−3.08)**	**−0.065*** (−3.06)**	**−0.170*** (−2.84)**
$CDS\_ACTIVE_{i,t-1}$	−0.087*** (−5.41)	−0.050*** (−5.01)	−0.063** (−2.20)
$D\_MOPT_{i,t-1}$	0.030** (2.22)	0.014 (1.63)	0.056*** (2.62)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.036	0.022
N	55,447	55,447	55,447
Panel B. CEO Overconfidence			
$CDS\_ACTIVE_{i,t-1} \times D\_OVER_{i,t-1}$	**−0.068*** (−3.21)**	**−0.043*** (−3.19)**	**−0.087** (−2.35)**
$CDS\_ACTIVE_{i,t-1}$	−0.064*** (−3.54)	−0.035*** (−3.01)	−0.036 (−1.02)
$D\_OVER_{i,t-1}$	0.077*** (7.76)	0.041*** (6.90)	0.137*** (8.59)
Other controls	Yes	Yes	Yes
R^2/pseudo R^2	0.034	0.038	0.028
N	17,990	17,990	17,990

VI. Conclusion

As one of the most important innovations in financial history, CDSs have attracted significant public scrutiny and extensive academic debate. However, little is known about the impact of CDS trading on stock price dynamics. We show that the inception of CDS trading significantly reduces the likelihood of future stock price crashes. This finding is robust to a large battery of tests. Further cross-sectional analyses suggest that the crash-reduction effect is channeled through CDS trading's price discovery role, which can uncover bad news that corporate managers try to hide. The negative relationship between CDS trading and stock price crash risk is stronger when the CDS market is more active or when the main lenders of the reference firms are CDS market dealers with securities trading subsidiaries. Moreover, CDS trading reduces the stock price crash risk for firms that are more likely to hide bad news.

Our article is the first to systematically investigate the impact of CDS trading on stock price crash risk. We provide novel evidence of information transmission from the CDS market to the related equity market. Overall, our findings shed light on how financial innovations in the debt market facilitate equity market price discovery and how credit derivative trading helps to stabilize the stock market.

Appendix. Variable Definitions

ANALYST_COVERAGE: The logarithm of the total number of financial analysts following a firm in a fiscal year according to the IBES data set plus 1.

BORROWER_CDS: The ratio of CDS-referenced borrowers in year $t-1$, which equals the number of CDS-referenced borrowers to the total number of borrowers who borrowed money from a lender in the previous 5 years.

CDS_ACTIVE: An indicator that equals 1 after the inception of CDS trading for a firm, and 0 otherwise.

CDS_FIRM: An indicator that equals 1 for all of a firm's observations if a CDS transaction or a quote on the firm is documented during the sample period, and 0 otherwise.

CDS_INCREASE: The magnitude of the positive abnormal daily CDS spread change. A daily abnormal CDS spread change is the difference between a firm's daily CDS spread change and the average daily CDS spread change for all firms in the same credit rating category. Zero or negative changes are set to 0.

CDS_QUOTES: The logarithm of the number of distinct dealers that provide valid CDS quotes on a CDS contract plus 1 in a fiscal year. Markit collects CDS quotes from dealers on a daily basis. If a greater number of distinct dealers provide quotes on the same CDS contract, it suggests the contract has better liquidity. We use the average number of distinct dealers in a fiscal year.

CDS_SPIKE: The logarithm of the number of CDS spikes plus 1 in a year. We define a CDS spike as a positive abnormal weekly CDS spread change. The weekly abnormal CDS spread change is the difference between a firm's CDS spread change in a week and the average weekly CDS spread change for all firms in the same credit rating category.

CEO_INCENTIVE: The incentive ratio for executive option holdings, measured as ONEPCT_OPT/(ONEPCT_OPT + SALARY + BONUS). ONEPCT_OPT is the dollar change in the value of the executive option holdings that results from a 1% increase in the firm's stock price. SALARY is the CEO's salary. BONUS is the CEO's stock bonus.

CONSEC: The number of consecutive days with negative firm-specific daily stock returns.

CRASH: A variable that equals 1 if a firm experienced 1 or more crash weeks in a year, and 0 otherwise. A crash week is a week when a firm-specific weekly return falls 3.09 standard deviations below the mean of the firm-specific weekly returns over a fiscal year; 3.09 standard deviations generate a frequency of 0.1% in the normal distribution.

CRASH_PROXIES: A variable that represents the stock price crash risk proxies.

DEALER_TRADING: An indicator that equals 1 when a firm's syndicated loans or corporate bonds lenders involve CDS market dealers with securities trading subsidiaries, and 0 otherwise.

DISTANCE: The number of months between an indicated month and a month when a negative credit watch is announced.

D_MOPT: An indicator that equals 1 when the manager of a firm issues optimistic guidance, and 0 otherwise.

D_OPAQUE: An indicator that equals 1 for firms with highly opaque financial reports. We separate the full sample into high- and low-opaqueness groups according to the median of the financial reports' opaqueness.

D_OVER: An indicator that equals 1 when the CEO is overconfident, and 0 otherwise.

DTURN: The change in the share turnover in fiscal year t relative to that in year $t-1$. The change equals the share turnover in fiscal year t minus that in fiscal year $t-1$.

DUVOL: The down-to-up volatility, calculated as the natural logarithm of the standard deviation of weekly stock returns during the weeks when the returns are lower than their annual mean (down weeks) over the standard deviation of weekly stock returns during the weeks when they are higher than their annual mean (up weeks).

EDP: A firm's expected default probability according to Merton's structural model.

FX_HEDGE: The average of the FX derivative hedging ratio of all of a firm's lenders. The FX derivative hedging ratio equals the sum of the FX derivatives scaled by the lenders' total assets.

IV: Instrumental variables. We employ two instrumental variables: FX_HEDGE and BORROWER_CDS.

IVPREDICT_CDS_ACTIVE: The predicted CDS_ACTIVE in the second stage regressions using a three-stage instrumental variables approach.

LASSET: The logarithm of the average size of the lenders.

LASSET2: The square of LASSET.

LEND: A dummy variable that equals 1 if there are lenders for a firm in a year, and 0 otherwise. Bond and loan lenders are identified from Mergent FISD and Deal-Scan, respectively.

LEV: The ratio of long-term debts to total assets.

MANAGE_GUIDE: An indicator that equals 1 when there is managerial guidance in a fiscal year according to IBES, and 0 otherwise.

MB: The market-to-book ratio.

NCSKEW: The negative coefficient on skewness, calculated by taking the negative of the third moment of the firm-specific weekly returns for each sample year and dividing it by the standard deviation of the firm-specific weekly returns raised to the third power. See equation (2) for details.

NES: An indicator of the negativity of earnings surprises. We measure the earnings surprise using the difference between the median of financial analysts' EPS forecasts (90 days before the actual EPS announcement) and the actual EPS value. We assign all earnings surprises to 1 of 5 quintiles; the highest quintile contains firms with the most negative earnings surprises.

OPAQUE: The sum of the absolute value of discretionary accruals in the previous 3 fiscal years.

PPE: Property, plant, and equipment divided by total assets.

PSM_SCORE: The propensity score for the inception of CDS trading in a year calculated using equation (5) in Section IV.D.2.

RATING: A series of consecutive numbers from 1 to 25 that measures the Standard and Poor's credit rating. A higher number indicates a higher credit rating. The highest number (25) represents an AAA rating, whereas the lowest number (1) signifies a C rating.

RET: The mean of the firm-specific weekly returns over a fiscal year.

RET_MONTH: The annualized daily return within a calendar month.

RETD: Firm-specific daily stock return.

ROA: Income before extraordinary items divided by total assets.

SALE: Sales divided by total assets.

SIGMA: The standard deviation of the firm-specific weekly returns over a fiscal year.

SHORT_INTEREST: The number of shares sold short divided by the total shares outstanding, with a range from 0 to 1.

SIZE: The natural logarithm of a firm's total assets.

STOCK_ILLIQ: Stock illiquidity is proxied by Amihud's (2002) measure of a stock's price impact on trade. This stock illiquidity measure in a fiscal year is computed as $\frac{1}{D_{iy}}\sum_{t=1}^{D_{iy}}\frac{|R_{it}|}{\text{VOL}_{it}}$, where D_{iy} is the number of trading days in a fiscal year, and R_{it} and VOL_{it} are the daily return and the daily dollar trading volume, respectively, for stock i on day t.

TREATED: A dummy variable that equals 1 for the treated firms in the propensity-score-matched sample, and 0 otherwise.

VOLD: The volatility of the negative daily returns within a certain time period.

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