Are Credit Ratings Still Relevant? *

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Abstract

We show that firms' stock prices react significantly less to credit rating downgrade announcements when they have Credit Default Swap (CDS) contracts trading on their debts. We find that information in CDS spreads predict firms' future rating downgrades and defaults, and document a significant information flow from the CDS to equity and bond markets before firms are downgraded. Further, term structures of CDS can be used to construct a more reliable measure of default risk premium for firms undergoing rating revisions. While the CDS market is not a perfect substitute for credit ratings, our results suggest that credit rating revisions have become less informative to equity investors in the presence of the CDS market.

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1 Introduction

Credit rating agencies that specialize in assessing the credit worthiness of bond issuers are an integral component of the financial landscape. Investors, regulators, and managers have historically relied on credit ratings, yet they are also frequently criticized for their slow response in predicting corporate defaults (e.g., Enron, Worldcom), accuracy of their ratings, and the conflicts of interest inherent in the agencies' business model (see White (2010)). As a consequence of these criticisms, regulators have initiated proposals in the Dodd-Frank Act to reduce regulatory and supervisory reliance on credit rating agencies.

A firm's credit rating is the opinion of a particular credit rating agency about the firm's credit worthiness, and it reflects the agency's view on the firm's physical default probability $PD^{\mathbb{P}}$. The prevailing consensus is that such opinion by a rating agency is relevant as documented by negative stock market reactions to rating downgrade announcements (see for example Hand, Holthausen, and Leftwich (1992); Dichev and Piotroski (2001); Jorion, Liu, and Shi (2005)). In contrast, CDS contracts are a market-based measure of a firm's default risk, and provide an estimate of the firm's risk-neutral default probability $PD^{\mathbb{Q}}$ (see Longstaff, Mithal, and Neis (2005)). Although credit ratings and CDS spreads provide an assessment of the firm's default risk under two different probability measures ($\mathbb{P}$ versus $\mathbb{Q}$), insights from the structural model suggest they share common information about the firm's fundamentals. If CDS spreads provide information about the underlying firm, in lieu of, or in addition to that conveyed by credit ratings, rating change announcements should become less pricing relevant to equity investors. In this paper, we analyze whether the stock market still reacts to credit rating agencies' downgrade announcements after CDS trades on their underlying firm's debt.

We use a comprehensive sample of credit rating change announcements from the three major credit rating agencies — Standard and Poor's, Moody's, and Fitch, and we find that, consistent with the prior literature, stock and bond markets react significantly negatively to credit rating downgrades. However, when CDS contracts are introduced on the firm's debt, the stock market reaction to credit rating downgrades is muted compared with the period before CDS contracts start trading on a firm's debt. Also, stock and bond prices of firms with traded CDS contracts react significantly less to rating downgrades relative to those of firms without traded CDS contracts. These results are robust to a number of tests such as instrumental variable regressions and propensity score matching analysis, which were used to mitigate endogeneity concerns.

In order to understand the information content of CDS contracts relative to credit ratings, we first construct CDS-implied credit ratings non-parametrically following the approach in Breger, Goldberg, and Cheyette (2003) and Kou and Varotto (2008) and find that they start deteriorating 180 days prior to a downgrade. Second, using a semi-parametric hazard model (See Shumway (2001) and Chava and Jarrow (2004)), we find that CDS spreads contain information that significantly predict the likelihood of rating downgrade announcements. In the same vein, we show that information in CDS spreads complements credit ratings by enhancing corporate default prediction models.

Bond yields also reflect the market's assessment of a firm's default risk. However, CDSs are standardized credit derivative contracts that generally trade more liquidly than bonds and allow investors to more easily short or hedge credit risk. Further, Longstaff, Mithal, and Neis (2005) and Ericsson, Jacobs, and Oviedo (2009) show that CDS spreads are a "more pure" measure of a firm's default risk than corporate bond spreads (also see Veronesi and Zingales (2010) and Stulz (2010)). Using the Hasbrouck's (1995) information share measure, we show the CDS market, on average, dominates the bond market in credit price discovery (see also, Blanco, Brennan, and Marsh (2005)). However, before rating downgrades, the CDS market's information share increases substantially to about 90% relative to the bond market. Thus, the CDS market is a leading venue for credit price discovery before rating downgrade announcements.

The presence of the CDS market can also helps improve equity valuation. Examining the information flow between the CDS and stock markets, we find that unanticipated changes in CDS spreads lead stock returns, predominantly before firms are downgraded. In support of our main conclusion, we find evidence suggesting that stock prices react less to rating change announcements because a bulk of their price adjustment occurred in the pre-announcement period.

An important channel through which the CDS market improves equity pricing is by providing investors with information that can be used to better estimate the default risk premium. In particular, Avramov, Chordia, Jostova, and Philipov (2009) find that the distress risk puzzle, i.e., lower rated firms earn lower returns, is most pronounced around rating downgrades.[1] We test this implication by examining the value of the CDS market in explaining the cross-section of stock returns for firms that are about to be re-rated. We follow the method developed in Friewald, Wagner, and Zechner (2014). Their general idea is that the firm's equity risk premium can be extracted using the term

[1] For the review of literature, see Campbell, Hilscher, and Szilagyi (2008) and Chava and Purnanandam (2010).

structure of CDS spreads over time. Our results, based on portfolio sorting, show a strong, positively monotonic relationship between CDS-implied equity risk premia and average one-year equity returns. Importantly, this finding holds when we focus our samples on firms that are about to be downgraded. However, we observe the opposite pattern — i.e., firms with higher default risk have lower returns, when sorting firms based on credit rating levels.

Our paper contributes to two strands of literature. The first is the literature documenting abnormal stock and bond market returns to credit rating downgrades, but not for upgrades.[2] Jorion, Liu, and Shi (2005) argue that the Regulation Fair Disclosure (Reg FD) might have bestowed upon the credit rating agencies an informational advantage owing to the exemption of the rating agencies the regulation.[3] Our results show that even after Reg FD, the onset of CDS trading significantly reduces the importance of these rating change announcements.

The second strand of literature two which we contribute is related to studies that examine whether the CDS market helps in price discovery. For example, Hull, Predescu, and White (2004), and Norden (2011) show that CDS spreads anticipate credit rating downgrades, and some evidence exists that CDS spreads lead the stock (Acharya and Johnson (2007)) and bond market (Blanco, Brennan, and Marsh (2005)) in price discovery. Motivated by these studies, we examine whether stock and bond markets perceive credit rating announcements to be less pricing relevant when the underlying firm has a CDS contract traded on its debt.

Any market based benchmark of default risk, such as CDS, provides a risk-neutral assessment of default risk. However, credit ratings which convey the agency's objective view of a firm's default risk are built "through the cycle" and may be more suitable from a corporate policy or a risk-management perspective. So, without making additional assumptions, CDS contracts and credit ratings are not completely equivalent and hence not a perfect substitute. Similar to credit ratings, CDS can convey many false positives. Furthermore, as with any market-based measures, changes in CDS spreads can be volatile, which may make them less suitable for use as a benchmark in financial contracts such has bond covenants or rating triggers. Credit rating agencies can still play an important role in financial markets, but the increased competition from the CDS markets and the availability of a market-based benchmark for default risk can potentially improve the performance of rating agencies.

[2]For examples, see Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), Goh and Ederington (1993), and Dichev and Piotroski (2001).

[3]We confirm the finding in Jorion, Liu, and Shi (2005) on the effect of Reg FD introduced in August 2000.

The rest of this paper is organized as follows. Section 2 develops hypotheses that motivate empirical tests in this paper. Section 3 describes the data. Section 4 presents the main empirical tests of stock price reactions to rating revisions. Sections 5 and 6 examine why stock prices react significantly less to credit rating downgrades in the presence of CDS contracts. Section 7 examines the value of CDS contracts for explaining the cross-section of stock returns in relation to default risk premia. Finally, Section 8 concludes.

2 Hypotheses development

In this section, we develop hypotheses that motivate subsequent empirical tests using insights based on static analysis of the Merton (1974) structural model. Merton (1974) assumes the firm value V follows a geometric Brownian motion with drift μ and volatility σ. The model values equity E as a call option on the firm value with the strike price equal to the face value D of a non-coupon paying bond with maturity T. The firm can default only at the maturity T of its debt. It can be shown that the expected excess equity return over the risk-free rate $\mu_E - r$ (i.e. equity risk premium), and the equity volatility σ_E are given by

$$\mu_E - r = (\mu - r)\left(\frac{V}{E}E_V\right) \tag{1}$$

$$\sigma_E = \sigma\left(\frac{V}{E}E_V\right), \tag{2}$$

where E_V denotes the partial derivative of E with respect to V. Using standard call option pricing notation for E, and noting that E_V is the call option delta, we can rewrite equation (1) as

$$\mu_E - r = \frac{\mu - r}{1 - Le^{-rT}\left[\frac{\Phi(d_2)}{\Phi(d_1)}\right]}, \tag{3}$$

where $L = \dfrac{D}{V}$ is the firm's leverage, and Φ denotes the cumulative distribution function of the standard normal random variable.[4] Equation (3) shows that the firm's equity risk premium is a function of its asset return, asset return volatility, and leverage. For instance, ceteris paribus, a shock to the firm's asset return μ is amplified when translated to a change in the firm's equity return

[4] In the standard Black-Scholes option pricing formula, $d_1 = \frac{log(V/D)+(r+\frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}$, and $d_2 = d_1 - \sigma\sqrt{T}$

due to the leverage effect.

The default probabilities under the physical measure ($PD^{\mathbb{P}}$) and the risk-neutral measure ($PD^{\mathbb{Q}}$) are respectively given by

$$PD^{\mathbb{P}} = \Phi\left(-\frac{log(1/L) + (\mu - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}\right) \tag{4}$$

$$PD^{\mathbb{Q}} = \Phi\left(-\frac{log(1/L) + (r - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}\right). \tag{5}$$

Combining equations (4) and (5) and using the relationships shown in equations (1) and (2), we can write the equity risk premium as

$$\mu_E - r = \left(\Phi^{-1}(PD_t^{\mathbb{Q}}) - \Phi^{-1}(PD_t^{\mathbb{P}})\right)\frac{\sigma_E}{\sqrt{T}}. \tag{6}$$

Equation (6) shows that changes to $PD^{\mathbb{P}}$ and $PD^{\mathbb{Q}}$ can affect the equity risk premium thereby resulting in the stock price reaction. Therefore, we expect the stock price to react to new information about the firm's physical and risk-neutral default probabilities.

A credit rating, by definition, conveys the rating agency's opinion about the firm's ability to meet its financial obligations on time.[5] Therefore, a rating change reflects the change of an agency's view on the firm's physical default probability $PD^{\mathbb{P}}$. A related question is what new information about the firm's fundamentals does it contain? Equations (3) and (4) provide some insights. For instance, a rating downgrade, which corresponds to an increasing $PD^{\mathbb{P}}$ can be due to a deterioration in the firm's performance (decreasing μ, $\frac{\partial PD^{\mathbb{P}}}{\partial \mu} < 0$) or uncertainty of its cash flows (increasing σ, $\frac{\partial PD^{\mathbb{P}}}{\partial \sigma} > 0$), or both. As a result, stock prices react negatively to unanticipated bad news about μ and σ because $\frac{\partial ERP}{\partial \mu} > 0$, and $\frac{\partial ERP}{\partial \sigma} < 0$. An increase in $PD^{\mathbb{P}}$ can also arise due to the change in firm leverage L as seen from $\frac{\partial PD^{\mathbb{P}}}{\partial L} > 0$, but this leads to a positive stock market reaction as $\frac{\partial ERP}{\partial L} > 0$. Distinguishing between which information change conveyed by rating agencies is more relevant to equity investors can be difficult.[6] Because we do not observe the exact reason in terms of the change in fundamentals that drives the rating change event, we include all the rating change announcements in our analysis.

[5] For instance, Standard & Poor's website states that credit ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time.

[6] Goh and Ederington (1993) documented that rating changes – specifically downgrades – due to a deterioration in firm's financial prospects are informative and produce a negative abnormal stock return while those due to an increase in leverage are uninformative.

Our first hypothesis relates to the information relevance of credit rating agencies. If credit ratings provide equity investor with pricing-relevant information about that firm's physical default probability, then rating change events should elicit stock market reactions.

Hypothesis 1 *The stock market reacts to a firm's credit rating change announcement as the news reveals changes in the firms physical default probability.*

The simple structural model offers us insights into how the presence of the CDS market may affect the value of credit rating changes. CDS spreads embody a risk-neutral assessment of the firm's default probability $PD^{\mathbb{Q}}$. Taking partial derivatives of $PD^{\mathbb{P}}$ and $PD^{\mathbb{Q}}$ (see equations (4) and (5)) with respect to σ, L, and μ, respectively, shows that (1) $\frac{\partial PD^{\mathbb{Q}}}{\partial \sigma} > 0$, $\frac{\partial PD^{\mathbb{P}}}{\partial \sigma} > 0$; (2) $\frac{\partial PD^{\mathbb{Q}}}{\partial L} > 0$, $\frac{\partial PD^{\mathbb{P}}}{\partial L} > 0$; and (3) $\frac{\partial PD^{\mathbb{Q}}}{\partial \mu} = 0$, $\frac{\partial PD^{\mathbb{P}}}{\partial \mu} > 0$. These relationships suggest that the risk-neutral default probability $PD^{\mathbb{Q}}$ and the physical default probability $PD^{\mathbb{P}}$ contain correlated information about the firm's fundamentals (i.e., regarding σ and L). Therefore, if the CDS market provides information about the underlying firm's fundamentals, in lieu of, or in addition to that conveyed by credit ratings (through $PD^{\mathbb{P}}$), then rating change announcements should become less pricing relevant to equity investors.

Hypothesis 2 *Stock market reactions to a firm's rating change events are attenuated if CDS contracts trade on the underlying firm's debt.*

The hypothesis above tests for the effect of CDS trading on the value of rating changes, which is the main conclusion of this paper. In the remaining hypotheses, we focus on how and why the CDS market may affect the magnitude of stock market reactions to credit rating changes.

As discussed previously, static analyses of the structural model show that CDS spreads and credit ratings convey common information about the firm's fundamentals. If CDS spreads contain information about the firm that anticipates changes in $PD^{\mathbb{P}}$ associated with rating revisions, then rating change announcements should become less informative about the firm's equity risk premium. This, in turn, implies a smaller stock market reaction to rating change announcements.

Hypothesis 3 *CDS spreads contain information that predict credit rating revisions.*

We test the hypothesis above by examining whether CDS spreads predict rating changes on a firm, and whether they improve the model for predicting defaults.

The presence of CDS market can improve equity valuation, if it contains new information about the firm's risk-neutral default probabilities (see equation (6)). Although CDS and corporate bond spreads provide a risk-neutral assessment of their underlying firm's default risk, existing evidence suggests that the CDS market leads the bond market in credit price discovery (see Blanco, Brennan, and Marsh (2005)). CDS contracts also provide a feasible way to short credit risk, thereby helping complete the credit risk market.[7] Until then, shorting corporate bonds was limited to the repo market which typically has very short maturity. Whereas CDS contracts are standardized and can be used for shorting credit risk for longer periods ranging from one to ten years. Further, the CDS market generally trades more frequently relative to the corporate bond market. This enables market participants to construct high frequency estimates of risk-neutral default probability.

Equity prices also contain information about the firm's credit risk. However, Acharya and Johnson (2007) find that changes in CDS spreads lead stock returns especially around negative credit events. They argue that unlike the stock market, trading in the CDS market is dominated by large institutions, mostly banks, which explains why the information revelation may occur in the CDS market before the equity market. In relation to credit rating changes, if the CDS market provides new information about the firm's credit risk before rating change announcements, we expect unanticipated changes in CDS spreads to lead stock and bond returns during this period. As a result, stock prices react less to rating change announcements because a bulk of their price adjustment occurred in the pre–announcement period.

Hypothesis 4 *CDS spreads lead other market measures that embody risk-neutral default probabilities before rating change announcements.*

We test the hypothesis above by examining whether the CDS market contributes to price discovery in the stock and bond markets before rating change announcements.

Arguments in Hypotheses 2–4 posit that the presence of CDS market improves equity valuation by providing investors with new (or more reliable) information about the firm's credit risk. This statement has an important implication in light of the well documented distress risk puzzle, i.e., lower rated firms earn lower returns, because the structural model shows that risk premia in equity and credit markets are related (see equation (6)). In particular, Avramov, Chordia, Jostova, and Philipov (2009) find that the puzzle is most pronounced around rating downgrades. Therefore, if the CDS

[7] See Flannery, Houston, and Partnoy (2010) for supporting arguments.

market provides information that improves equity valuation, we expect equity risk premia estimated using CDS information to relate better to firms' default risks than credit ratings, particularly for firms that are about to be re-rated. We test this important implication in the next hypothesis.

Hypothesis 5 *The CDS market provides investors with a more reliable measure of default risk premium than credit ratings for firms undergoing rating revisions.*

To test the hypothesis above, we examine whether the equity risk premia extracted from CDS data can explain the cross-section of stock returns of firms that are undergoing rating revisions.

3 Data and descriptive statistics

We use a CDS database that is widely used among financial market participants (CMA Datavision database (CMA)) to identify all firms for which we observe CDS quotes on their debt. CMA contains consensus data sourced from 30 buy-side firms, including major global investment banks, hedge funds, and asset managers which is disseminated through Bloomberg since October 2006.[8] We further ensure the accuracy in the coverage of CDS quotes by augmenting the CMA database with CDS data obtained from Bloomberg. The earliest quotes were then taken as the first sign of active CDS trading on a firm's debt.

Data on bond ratings were gathered from the Mergent Fixed Income Securities Database (FISD). FISD provides comprehensive data on issue-level details on over 140,000 corporations, U.S. agencies, and U.S. Treasury debt securities. The data contains detailed information for each issue, including the issuer name, rating date, rating level, agency that rated the issue, and credit watch status, etc. We include only those ratings issued by the top three NRSROs – S&P, Moody's, and Fitch. We restrict our sample to U.S. domestic corporate debentures, and exclude yankee bonds, and bonds issued via private placements, preferred stocks, mortgage-backed, trust preferred capital, convertible bonds and bonds with credit enhancements. We also consider only the issuers whose stocks are traded on either the NYSE, AMEX, or NASDAQ. Approximately 18% of the ratings are from Fitch, and the remaining ratings are split evenly between S&P and Moody's.

We consider a rating change for an issuer as one observation. When there are rating changes on

[8] Mayordomo, Pena, and Schwartz (2010) compare the data qualities of the six most widely used databases – GFI, Fenics, Reuters, EOD, CMA, Markit and JP Morgan – and find that the CMA database quotes lead the price discovery process.

multiple bond issues for an issuer on the same day, we use the issue with the greatest absolute rating scale change because such changes are likely to create the strongest impact on bond and stock prices. We consider only the rating announcements that are associated with either "DNG" (downgrade) or "UPG" (upgrade), which constitute about 90% of the total rating events.[9] The main sample is from January 1996 to December 2010 and consists of 4665 downgrades and 2171 upgrades; we refer to it as the "Full sample" for the remainder of this paper. The Full sample consists of 1142 unique firms, of which 390 have CDS trading at some point during the sample period. There are about 2.1 downgrades for every upgrade, which is line with the findings in Dichev and Piotroski (2001). More details on the sample are provided in the internet appendix.

Many of the firms in our sample never experienced CDS trading over the 1996-2010 period. In order to control for the differences between firms with and without CDS contracts traded on their debt, we consider a subsample of firms for which CDS starts trading at some point during our sample period. We refer to this sample as the "Traded-CDS". We use firms' rating changes in this subsample to compare their stock reactions to rating change announcements made between their pre-CDS and post-CDS trading periods. The average size of rating change for the sample is 1.45 before CDS trading starts and 1.49 after CDS trading starts. The distribution of the rating changes are provided in the internet appendix.

We obtain corporate bond price data from TRACE, which contains individual bond transactions starting on July 1, 2002. Corporate bond data prior to July 2002 is obtained from Mergent FISD historical NAICS database. We apply a number of standard filters to the data set. Following Bessembinder, Kahle, Maxwell, and Xu (2009), we eliminate trades that have been canceled or corrected, trades that have commissions, and non-institutional trades because they show that they help increase the power of the test for detecting abnormal performance. Therefore, consistent with Edwards, Lawrence, and Piwowar (2007), we remove observations in which the par value of the transaction is less than or equal to $\$100,000$ because smaller trades tend to be non-institutional trades.[10]

[9] The FISD ratings database reports the reason for the rating change on an issue. About 4.8% of the total rating change reasons are "IR" (Internal Review), while about 2% are "AFRM" (Affirmed).

[10] The prices reported in the TRACE bond database are the "clean" prices. They do not include the accrued coupon payment. We add the accrued coupon payment to the clean prices by merging in variables from the Mergent FISD database. The final bond prices that we use are therefore settlement prices.

4 Stock price reaction to rating changes

This section tests Hypotheses 1 and 2 of the paper. First we provide univariate evidence that the stock market reacts to rating downgrades, but the magnitude significantly decreases when CDS contracts trade on the firm's debt. We then confirm our results using multivariate regressions. Subsequently, we address endogeneity concerns regarding to the timing of the CDS introduction.

4.1 Abnormal stock returns

We study changes in daily abnormal stock returns on the date of rating change announcements for CDS and non-CDS firms. We carry out the analysis separately for upgrades and downgrades. We define the daily abnormal stock return of firm i on day t, AR_{it}, as the residual estimated from the market model:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}),$$

where R_{it} is the raw return for firm i on day t, and R_{mt} is the value-weighted NYSE/AMEX/NASDAQ index return. We examine whether the mean cumulative abnormal return (CAR) around the event period is significantly different from zero. Following Holthausen and Leftwich (1986), we compute CAR using the three-day window centered on the announcement date. That is, $CAR_i(-1,1) = \sum_{t=-1}^{+1} AR_{it}$. Kothari and Warner (2007) show that short–horizon event studies such as ours are not highly sensitive to the assumption of cross-sectional or time-series dependence of abnormal returns, as well as the benchmark model used for computing abnormal returns.[11]

4.2 Univariate analysis

Table 1 presents the mean of cumulative adjusted return (CAR) for the pre- and post-CDS trading periods. The results in Panel A are based on the "Full-sample" which, consists of traded-CDS and non-traded-CDS firms. The results in Panel B are based on the "Traded-CDS–sample". Traded-CDS firms are those that have CDS traded at some point during our sample period. However, non-traded-CDS firms are those that do not have CDS trading in our sample period, which is from 1996 to 2010. Results obtained using the "Traded-CDS–sample" can be usefully thought of as fixed-effects tests

[11] We estimate $\hat{\alpha}_i$ and $\hat{\beta}_i$ using a rolling window over a period of 255 days from -91 to -345 relative to the event date. Using a shorter estimation window and a different factor model do not affect our conclusions. Table I.A1 in the Internet Appendix shows that we obtain similar findings when using the Fama-French 3-factor model to calculate abnormal return.

because only firms that experience CDS trading are considered. Consistent with previous studies, Panel A shows that overall, stock price reacts significantly to downgrades (-4.31%) but only weakly to upgrades (0.14%).[12] This finding supports of Hypothesis H1.

The results in Panel A show the mean CARs over the three-day window around rating downgrades is negative and significant at the 1% level for the pre- and post-CDS periods. However, the magnitude is significantly weaker for the post-CDS period. The mean CAR in the post-CDS period is -2.51%, compared to -5.10% in the pre-CDS period. The difference in CAR between these two groups is 2.58% and is statistically significant at the 1% level. On the other hand, we do not find that stock prices react significantly differently to rating upgrades in the post-CDS period. The difference in CAR to credit rating upgrades do not differ significantly between the pre- and post-CDS periods.

In Panel B of Table 1, we report univariate results for firms that eventually have CDS contracts traded on its debt. Restricting our analysis to the Traded-CDS sample mitigates the concern that traded-CDS firms are inherently different from non-traded-CDS firms. We find that stock price reaction to credit rating downgrades is significantly weaker in the post-CDS period. The difference in the mean CAR values is -0.95% between the pre-CDS and post-CDS periods, and is statistically significant.[13]

4.3 Regression analysis

We employ multivariate regressions to control for factors that could affect stock price reactions to rating changes. Following previous studies (e.g., Holthausen and Leftwich (1986)), we run the regressions separately for upgrades and downgrades. The results are reported in Table 2. The regression model that we estimate is

$$\begin{aligned} CAR_i = &\beta_0 + \beta_1 dCDS_i + \sum \gamma_i \textit{Rating-level characteristic}_{it} + \\ &\sum \delta_i \textit{Firm-level characteristic}_{it} + \sum \phi_i \textit{CDS-trading control}_{it} + \varepsilon_i \end{aligned} \tag{7}$$

where for bond issue i, CAR is the 3-day cumulative abnormal return centered on the date of rating change announcements – i.e., event window (-1,1). The main variable of interest is $dCDS$, an

[12]The magnitude of CAR to rating downgrades is in line with existing studies that examine announcement returns to rating changes using the more recent sample, e.g. Jorion, Liu, and Shi (2005).

[13]Jorion, Liu, and Shi (2005) find that stock price reactions to rating downgrades is significantly stronger after Regulation Fair Disclosure (Reg FD) was implemented in Oct 2000 because rating agencies are exempt from Reg FD and could still access private information on the rated firms. For a robustness check, we eliminate rating changes prior to the year 2001 (before Reg FD was put in place) and find that our conclusions remain unchanged.

indicator variable equal to one if the rating change takes place when CDS trades on the underlying firm and 0 otherwise. Panel A of Table 2 reports results for rating downgrades, while Panel B reports results for rating upgrades. Each panel reports results for three regression specifications. Regression models (I) and (II) are run on the full sample, while regression model (III) is estimated using the traded-CDS sample. All variables are defined in Appendix B.[14]

If rating changes are less informative in the presence of CDS trading, we would expect the coefficient of $dCDS$ in equation (7) to be positive for downgrades and negative for upgrades. Panel A of Table 2 shows the coefficients on $dCDS$ are positive and statistically significant across the three regression specifications. Controlling for industry- and year-fixed effects in specification (II), we find the difference in CARs between firms that have and do not have CDS trading is 1.70%. Looking only at the traded-CDS sample, (i.e. model (III)), we find the evidence is stronger. Stock prices react significantly less to credit rating downgrades by an average of 2.59% in the traded-CDS sample. The results in Panel B, however, show that all three coefficients on $dCDS$ are not significantly different from zero. Overall, our regression results in Table 2 confirm our univariate results (see Table 1) that stock price reaction is significantly weaker to credit rating downgrades, and not upgrades, when CDS contracts trade on the firms' debt.

The coefficients on the control variables are in line with the results documented in the literature (see Hand, Holthausen, and Leftwich (1992), and Jorion, Liu, and Shi (2005)). Table 2 shows the coefficients on *Previous Rating* and *AbsRating Change* are negative and highly significant, suggesting that ratings downgrades on lower-rated firms, as well as downgrades across multiple cardinal scales, lead to larger stock price reactions. The time since the previous credit rating does not seem to impact how the new rating change influences stock response. However, rating downgrades accompanied by firms' earnings announcements elicit a larger stock price reaction. Among the firm-level characteristics, we find that firms' recent return performances, (i.e. *Avg Return*), robustly predict the magnitude of stock price reactions to rating downgrades. *Leverage,* as well as *Avg Trading Volume* appear to be negatively related to CAR for downgrades, though, their statistical significance

[14] All regression models include three sets of control variables to account for potential factors affecting the magnitude of stock price reactions. The first set of control variables are rating-level characteristics: previous rating level, the size of rating change, how long has the previous rating been outstanding for, and whether rating change occurs in relation with the company's earnings announcement. The second set of control variables includes various firm-level characteristics. The third set of control variables account for characteristics that may be related to the propensity that firms that have CDS trading. All variables are defined in Appendix B. All firm-level characteristics and CDS-trading controls are lagged by one period, i.e. a month or a quarter, depending on the frequency of data sources.

disappears when we restrict our regressions to traded-CDS firms.

We confirm that our regression results are robust to a series of robustness checks, which are reported in the Internet Appendix. Table IA3 Panel A reports regression results showing that our main conclusion holds when we allow for Industry×Year fixed effects, which helps controlling for time-varying industry risk factors. Table IA3 Panel B shows our regression results hold when using a subsample of only non-financial firms. We find that the coefficients on *dCDS* are slightly larger in magnitude for downgrades when we focus our analysis only non-financial firms. Further, to ensure that our results are unaffected by the financial crisis, we focus on rating changes prior to 2008 and find that our conclusions remain intact. Table IA4 Panel A replicates the results in Table 2 using the Fama-French 3-factor model to compute CARs and Table IA4 Panel B conducts a pooled analysis on downgrades and upgrades together. In both cases we verify that our results are robust.

4.4 Instrumental variable analysis

A potential concern with any study on the impact of the CDS market is that the timing of CDS introduction is not exogenous. CDS contracts may have been introduced during a period when the firm's credit quality improves, thereby affecting how its stock price reacts to rating changes. In this section, we address the concern that the emergence of the CDS market is not exogenous using the instrumental variable method.

We follow Saretto and Tookes (2013) to find an instrument that correlates with the firm's likelihood of having CDS contracts traded on its debt, while being directly unrelated to how the firm reacts to its credit rating changes. Saretto and Tookes (2013) use the foreign exchange derivatives traded for hedging purposes by banks that have a lending relationship with a given firm as the instrument for CDS market introduction. The choice of this instrument is motivated by Minton, Stulz, and Williamson (2009) who show that banks that use interest rate, foreign exchange, equity, and commodity derivatives are more likely to be net buyers of CDS, and hence related to the emergence of the CDS market. Among banks' various derivatives activities, their foreign exchange position is arguably least likely to directly influence the credit risk of firms with which they conduct business. Importantly, the amount of foreign exchange derivatives used by banks reflect their hedging need for macro risk, and hence should not affect the credit risk of domestic firms (i.e., U.S. entities) in our sample. We further exclude non-financial firms from the instrumental variable regression results for two reasons. First, financial firms are more likely to act as borrowers and lenders amongst themselves and with several banks simultaneously, which makes their nature and the extent of relationship difficult to identify. Second, we want to maintain consistency with Saretto and Tookes (2013) who motivated the use of the instrumental variable.

Our instrumental variable, *Forex Derivative Hedging*, is defined as the average foreign exchange derivatives amount used for hedging (i.e., non-trading purposes) relative to total assets by the lead syndicate banks and bond underwriters that the firm has conducted business with over the past five years. We use the Dealscan syndicated loan database to identify firms' lenders (i.e., lead syndicates), and Mergent FISD database to identify firms' bond underwriters. Banks' derivatives usage data is obtained from the Bank Holding Company (BHC) Y9-C filings. We lag *Forex Derivative Hedging* by one quarter when including it in the instrumental variable (IV) estimation. The average *Forex Derivative Hedging* at the firm-level in our full sample is 1.98% of the total assets with a standard deviation of 1.54%. These values are in line with Saretto and Tookes (2013).

In order to address concerns that CDS introduction is endogenous, we re-estimate the main regression results using *Foreign Derivative Hedging* to instrument for *dCDS*. We follow Wooldridge (2001) and apply the fitted variable from a probit model for *dCDS* to the regression model in equation (7); see also Bharath, Dahiya, Saunders, and Srinivasan (2007) and Saretto and Tookes (2013) for similar applications. We include firm-level characteristics and CDS-trading controls in the probit model. The instrument that we use is available quarterly and therefore the model is estimated at the firm-quarter level. Table B2 in the Appendix reports the probit model from the IV estimation. After accounting for various firm-level characteristics and variables that may influence CDS trading, we find that the amount of foreign derivatives usage significantly predicts the likelihood that a firm will have CDS trading on its debt (t-statistic of 4.84).[15]

Table 3 reports the regression results using the fitted instrumental variable, *dCDS IV* for 1966 downgrades and 886 upgrades belonging to 609 unique firms. The number of observations are lower compared to Table 2 because we restrict our sample to non-financial firms with lending or underwriting relationships with banks that are active in the *forex derivatives* market. Further, bank *forex derivatives* activities are reported in the BHC Y-9C filings and call reports are from 2001 onwards.

[15] The incremental psuedo-R^2 of the instrument is about 1.1%. The economic impact of foreign exchange derivatives usage on the probability of CDS trading is reasonably large. We find that a one-standard deviation increase in *Forex Derivative Hedging* increases the likelihood that a firm has CDS traded on its debt by 4.2. Overall, consistent with Saretto and Tookes (2013), we find that the instrument is not weak.

Table 3 shows the coefficients on *dCDS IV* are positive and statistically significant for downgrades, but not for upgrades, which is largely consistent with our previous findings. A one-standard deviation change in the *dCDS IV* is related to a 2.26 and 2.01 percent attenuation in CAR response to credit rating downgrades for the regressions specifications with industry-fixed effects (I) and year- and industry-fixed effects (II), respectively. The estimated coefficients on the other variables in Table 3 are similar to those in Table 2 . Overall, we conclude that our main results hold when using *Foreign Derivative Hedging* as an instrument to address the potential bias associated with the endogeneity of CDS market introduction.

4.5 Matched sample analysis

In addition to the instrumental variable regression, we carry out a matched-sample analysis to mitigate concerns that traded-CDS and non-traded-CDS firms are different on some observable dimensions. A traded-CDS firm is matched with a firm that does not have a CDS traded on its debt at any point in our sample period (i.e., a non-traded-CDS firm). We use a propensity score matching method that can incorporate a large number of matching dimensions (Rosenbaum and Rubin (1983)). The matching is carried out in the month when CDS starts trading on a traded-CDS firm based on 15 observable characteristics. These matching characteristics are motivated by Ashcraft and Santos (2009), Saretto and Tookes (2013), and include other factors that might affect the introduction of CDS trading.

We estimate firms' propensity of having CDS trading using a probit model, in which the dependent variable, *dCDS*, is an indicator variable equal to one starting on the month when CDS begins trading on the firm, and zero otherwise. All explanatory variables in the probit model are lagged by one period and defined in Appendix B. We require that firms entering the matching sample have complete time-series information on their observable variables. This requirement leaves us with 376 traded-CDS firms and 418 non-traded-CDS firms for estimating the propensity score model, which we refer to as the before-matching sample. In the Appendix, Table B3 reports diagnostics of the propensity score matched sample. In Panel A, the column labeled "Before matching" reports results for the probit model estimated at the firm-month level using the before-matching sample. Most of the estimated coefficients are significant with the magnitude roughly in line with the probit model estimated using firm-quarter observations for the instrumental variable estimator (see Table B2). The fitted probability from the probit model is then used as the propensity score to match traded-CDS firms to non-traded-CDS firms.

For each traded-CDS firm, we use its propensity score in the month that CDS starts trading to identify a non-traded-CDS firm with the closest propensity score in the same month. We require that the propensity score of the matched non-traded-CDS firm be within ±5% of the propensity score of the traded-CDS firm. The matching technique used for this is the nearest-neighborhood caliper method of Cochran and Rubin (1973). We match one traded-CDS (treated) firm with five non-traded-CDS firms (control), i.e., one-to-five matching, in order to increase our sample of matched control firms (see Dehejia and Wahba (2002), and Smith and Todd (2005)). The matching is carried out with replacement.[16] This exercise leaves us with 354 unique traded-CDS firms each matched to five eligible control firms.

We report various diagnostics of the matched sample in Table B3 in the Appendix. The column labeled "After matching" in Panel A reports results derived from estimating the probit model using the matched observations. Overall, the explanatory power of the probit model decreases significantly with the pseudo R^2 of 14% relative to 49% observed in the "Before matching" sample. We find that four observable characteristics remain statistically significant in the probit model for the matched sample. Given the large observable dimensions used for matching, i.e., 15 dimensions, we do not expect to find a perfect match. Nevertheless, Panel A shows that all the probit coefficients in the after-matching sample either lost statistical significance or have become substantially less significant relative to the before-matching sample. We further report the quality of our matched sample in Panels B and C in the Appendix Table B3. In Panel B, we report univariate means of the 15 observable dimensions for the before-matching and after-matching samples. The findings echo the results reported in Panel A, which show that the propensity-score matching significantly reduces observable differences between the traded-CDS firms (treatment group) and the non-traded-CDS firms (control group). Nevertheless, traded-CDS firms in the matched sample still tend to be larger, better rated, and have greater bond debt outstanding. In order to control for the differences in these remaining observable dimensions, we include all the matching controls in our matched sample regressions. Additionally, in Panel C we report the industry distribution of firms in the treatment

[16] We also verify that our results are similar when using one-to-one matching *without replacement*. In this case, we have 242 uniquely matched pairs. Table IA5 in the Internet Appendix reports difference-in-difference regression results verifying our main finding using the one-to-one matched sample without replacement.

and control samples. Overall, we find that industry distributions of the two samples do not differ greatly.

Using the matched sample, we estimate the following difference-in-difference regression

$$
\begin{aligned}
CAR_i = {} & \beta_0 + \beta_1 dCDS_i + \beta_2 dTreatment_i + \beta_3 \; dTreatment_i \times dCDS_i \\
& + \sum \gamma_i Rating\text{-}level\ characteristic_{it} + \sum \delta_i Firm\text{-}level\ characteristic_{it} \\
& + \sum \phi_i CDS\text{-}trading\ control_{it} + \varepsilon_i,
\end{aligned} \tag{8}
$$

where the dependent variable CAR_i is the cumulative abnormal stock return of firm i to a credit rating downgrade. Table 4 reports the results. To save space, we do not report results for credit rating upgrades as our previous evidence suggests that CAR to credit rating upgrades are, on average, not significant. The above regression model in (8) is similar to the baseline regression model in (7), with the additions of two new variables. The first is $dTreatment_i$, which is an indicator variable equal to one if the firm corresponding to the observation is from the treatment group, i.e. a traded-CDS firm in the matched sample, and zero otherwise. The second variable we introduce is $dTreatment_i \times dCDS_i$, which is the difference-in-difference (DID) estimator and is our key variable of interest. It is an interaction term of the $dTreatment_i$ with the indicator variable for CDS trading, $dCDS_i$. For firms in the treatment group, $dCDS_i$ simply takes the value of 1 when CDS starts trading on the firm's debt, and zero otherwise. Control-group firms are assigned counterfactual $dCDS_i$ variables that are identical to their matched traded-CDS firms. The coefficient on the DID estimator therefore captures the difference in CARs to credit rating downgrades between the traded-CDS firms and their matched non-traded-CDS firms over the two periods: before and after CDS introduction.

Panel A of Table 4 reports difference-in-difference regression results using the matched sample. Industry-fixed effects are included in the first regression specification (I), while both industry- and year-fixed effects are included in the second regression specification (II). In both cases, we find the coefficient on the DID estimator is positive and highly significant. Looking at a more conservative regression specification (II), the coefficient on DID estimator is 1.72. This finding suggests that stock prices of firms with CDS trading react less to credit rating downgrades by about 1.72% relative to firms sharing similar characteristics, yet without CDS trading. Overall, the results suggest that the information content in rating announcements has decreased for downgrades after the onset of CDS trading.

In Panel B of Table 4, we run regression diagnostics based on equation (8) for four different subsamples. The regression model (III) reports results for firms that are in the treatment group ($dTreatment = 1$), while regression model (IV) reports results for firms that are in the control ($dTreatment = 0$). Because the regressions are estimated separately for the treatment and control groups, the variable $dTreatment$ is dropped from the regressions as it is not identified. In these two subsamples, the variable of interest is $dCDS$, which examines the impact of the $dCDS$ variable on CAR to bond downgrades for treatment-group firms and control-group firms, respectively. We expect coefficients on $dCDS$ to be positive and significant for the treatment group because this dummy variable indicates when the firms have CDS trading. In fact, the regression model (I) is similar to the regression model (III) for the traded-CDS sample in Table 2. However, we do not expect $dCDS$ to be significant for the subsample consisting only of control-group firms because they do not actually have CDS trading. The coefficients on $dCDS$ in the regression models (III) and (IV) confirm our expectation. We do not find that firms in the control sample, which have similar characteristics as traded-CDS firms, experience weaker stock price reactions to credit rating downgrades.

The regression models (V) and (VI) in Table 4 report results for firms in both the treatment and control groups estimated using two different subsample periods. The regression model (V) uses only firms that are in the post-CDS period ($dCDS = 1$), while the regression model (VI) uses firms in the pre-CDS period ($dCDS = 0$). In these two regression models, the variable $dCDS$ is excluded because it is not identified. The main variable of interest is $dTreatment$ which tests for the difference in CAR values between treatment-group firms and control-group firms in the post-CDS period (V) and pre-CDS period (VI). We expect the coefficient on $dTreatment$ to be positive and significant for the post-CDS period, if CAR to rating downgrades is weaker for firms that have CDS trading relative to control-group firms. Recall that control-group firms do not actually have a traded CDS but are assigned to the post-CDS period because their observable characteristics resemble those of traded-CDS firms. The positive coefficient on $dTreatment$ in the regression model (V) is 1.66 and statistically significant, which confirms our expectation. However, the statistically insignificant coefficient on $dTreatment$ in the regression model (VI) shows that firms in the treatment and control groups do not react differently to rating downgrades, and thus suggest parallel trends in the pre-CDS period. Overall, results in the regression models (V) suggest that firms the in the treatment and control groups are well matched in how they respond to rating changes in the pre-CDS period, while results in (VI) suggest the difference in post-CDS CARs between the treatment and control groups is due to the introduction of CDS contracts on the treatment-group firms.

5 Information in CDS spreads about credit ratings

This section tests Hypothesis 3 of the paper. Insights from the simple structural model show that CDS spreads and credit ratings convey common information about the firm's fundamentals. If CDS spreads contain information that anticipates changes in the physical default probability $PD^{\mathbb{P}}$ associated with rating revisions, then rating change events should become less informative. We provide three sets of empirical results to support Hypothesis 3. First, we back out CDS-implied ratings using a non-parametric method and show that they significantly lead rating downgrades issued by credit rating agencies. Second, we show the predictive power of CDS spreads on credit rating downgrades in a multivariate framework using a hazard model. Third, we show that information in CDS spreads improve the model for predicting historical defaults.

5.1 CDS-implied ratings

One reason why CDS spreads appear more information-relevant than credit ratings is their timely response to changes in the underlying firm's credit condition. Acharya and Johnson (2007) find that information discovery occurs in the CDS market prior to negative credit news. In this subsection, we back out the rating levels implicit in CDS spreads (CDS-implied ratings) and compare them with those issued by rating agencies. Our objective is to examine the dynamics of CDS-implied ratings around the rating downgrades. If trading in the CDS market reveals information about changes in a firm's default risk, we expect CDS-implied ratings to significantly change prior to a downgrade issued by credit rating agencies.

We calculate CDS-implied ratings following the approach in Breger, Goldberg, and Cheyette (2003) and Kou and Varotto (2008). The basic idea is to estimate the CDS boundaries separating two adjacent rating classes in a non-parametric manner. Once the boundaries are determined, we assign each firm to a rating class corresponding to its CDS spread level. We estimate CDS boundaries by minimizing the penalty function with the objective of reducing the number of misclassifications, which we define as the discrepancy between the firm's CDS spread level and its rating class. For instance, missclassification occurs when the CDS spread of a higher-rated firm is larger than the spread of a lower-rated firm. Following this intuition, the penalty function for estimating the boundary between the A and BBB ratings classes, b_{A-BBB}, is

$$F(b_{A-BBB}) = \frac{1}{m}\sum_{i=1}^{m}[\max(s_{i,A} - b_{A-BBB}, 0)]^2 + \frac{1}{n}\sum_{j=1}^{n}[\max(b_{A-BBB} - s_{j,BBB}, 0)]^2, \qquad (9)$$

where $s_{i,A}$ is the CDS spread of A-rated firm i, and $s_{j,BBB}$ is the CDS spread of BBB-rated firm j. When the spread of A-rated firm is higher than the boundary b_{A-BBB}, the firm's CDS spread is considered misclassified with the error equal to their difference. Similarly, when the spread of BBB-rated firm is lower than the boundary b_{A-BBB}, the firm's CDS is considered misclassified. The objective is then to minimize the error from misclassifications by minimizing the penalty function described in equation (9). The numbers of firms in the A and BBB rating classes are denoted as m and n, respectively, and the penalty function for estimating boundaries between other adjacent rating classes are defined similarly. We estimate CDS spread boundaries for all adjacent rating classes daily.[17] The estimation uses all CDS spreads on firms that have CDS spreads traded on each day.

Figure 1 plots average CDS-implied ratings over the interval [-360,180] days centered on the rating change events. The solid line plots the official ratings issued by credit rating agencies and the dotted line plots average CDS-implied ratings. The rating levels are plotted on the rating class scale. A higher rating class corresponds to a higher credit risk. To save space, we plot the results for three adjacent rating classes that have the most rating change events: A-BBB, BBB-BB, and BB-B. Figure 1 shows that CDS-implied ratings started increasing at least 180 days prior to a downgrade announcement. This finding suggests that the CDS market responds to the firm's deteriorating credit quality significantly faster than credit rating agencies. However, Figure 1 shows that CDS-implied ratings do not change significantly prior to an upgrade announcement. In fact, CDS-implied ratings were already at the level that represents the future rating class of the soon-to-be upgraded firm. This finding is consistent with the prevailing consensus, as well as our previous results that rating upgrades have little pricing relevance.

[17] The mapping between rating codes and rating classes is shown in the Appendix Table B1. Due to the large number of daily observations required to precisely estimate the boundary, we do not consider adjacent rating levels that are in the same rating classes. For instance, AA+, AA, AA- are considered to be rated AA. Fitch estimates CDS-implied ratings based on a method similar to ours but with a slightly different penalty function. As a robustness check, we implement Fitch's penalty function and obtain roughly the same boundaries.

5.2 Predictability of credit rating changes

So far, we have visually shown in Section 5.1 that credit ratings backed out from CDS spreads anticipate rating downgrades issued by credit rating agencies. An important question is whether CDS spreads provide additional predictability of rating downgrades after controlling for variables such as accounting measures and bond spreads that have been shown to anticipate credit rating changes. We test the hypothesis that information derived from the CDS market can predict future downgrades using the hazard model.[18]

We estimate the extended Cox model commonly used for survival analysis in epidemiological studies (e.g. Platt et al. (2004)). The survival time in our analysis is the number of months from current time to the next rating change event. Let t be the current time period, and $T \geq t$ be when rating change occurs, the hazard rate associated with future rating changes is given by

$$h(t) = \lim_{y \to 0} \frac{\mathbb{P}(t \leq T < t + y | T \geq t)}{y}.$$

In our analysis, the hazard function is represented by

$$h(t, \mathbf{x}, \mathbf{z}(t)) = h_q(t) \exp\left(\sum_{i=1}^{p_1} \beta_i x_i + \sum_{j=1}^{p_2} \delta_j z_j(t) \right), \tag{10}$$

where $\mathbf{x} = (x_1, x_{2,}, \ldots, x_{p_1})'$ is a time-independent vector of variables, i.e., industry, rating agency, and year-fixed effects, and $\mathbf{z}(t) = (z_1(t), z_2(t), \ldots, z_{p_2}(t))'$ is a time-dependent vector of covariates affecting the hazard rate of having rating changes (i.e., CDS spreads, bond spreads, and accounting variables). When $\delta_j = 0$ for all j's, the above equation (10) is known as the Cox proportional hazard (Cox PH) model, where $h_q(t)$ is the baseline hazard function. The baseline function is semi–parametric and hence we do not need to define the functional form for $h_q(t)$. We further allow $h_q(t)$ to be different for different rating levels, i.e. strata. Arguably, a one unit rating change for a lower-rated firm and a higher-rated firm may be perceived differently by investors. This intuition is supported by our results in Table 2, which shows that *Previous Rating* robustly explains the difference in firms' stock price reactions to credit rating downgrades. Therefore, credit rating agencies may use a

[18] Our approach is similar to Hull, Predescu, and White (2004) who use a logistic model to show that changes in CDS spreads increase the likelihood of future rating events. However, our analysis differs from theirs as we use a much longer and more extensive set of firms in our sample, and control for a number of variables that can potentially predict future rating changes.

different model to decide when to revise their ratings on a lower-rated firm relative to a higher-rated firm. The use of stratification controls for a predictor that does not satisfy the proportional hazard assumption.[19] In our estimation, we allow firms in different rating levels to have different baseline hazard functions $h_q(t)$, while sharing the same coefficients β_i and δ_j. The model is estimated using maximum likelihood at the issue-month level.

Table 5 presents the results from estimating the hazard model in equation (10) separately for downgrades (Panel A) and upgrades (Panel B). All explanatory variables are described in Appendix B and are lagged by one period. We also control for credit watch announcements in all regression models using the indicator variable *Credit watch dummy*, which indicates whether the firm (or bond issue) is put on credit watch prior to a credit rating change.[20]

The variables of interest in Table 5 are average CDS spreads, bond yields and their changes. Bond yields are calculated as the trade-weighted average monthly bond yield at the issue level. We require that firms in the estimation sample have CDS spreads currently traded on their debt. We use 5-year to maturity CDS spreads as they are the most liquid. Our primary CDS data are from CMA Datavision. We also supplement CMA data with CDS quotes from Markit. We obtain corporate bond data from TRACE, which contains individual bond transactions starting from July 1, 2002. Corporate bond data prior to July 2002 is obtained from Mergent FISD historical NAICS database. We also include industry, year and rating agency-fixed effects in all hazard model regression specifications.

In Table 5 regression model (I), we test whether recent changes in CDS spreads and bond yields are informative about future rating changes. We find a positive and significant coefficient on *CDS Spread Change*, suggesting that an increase in CDS spreads in the prior month increases the likelihood that the firm will be downgraded. The coefficient on *CDS Spread Change* is negative, but not statistically significant for upgrades. Our findings that CDS spread changes are predictive of rating downgrades, but not upgrades, are consistent with prior results shown in Figure 1. Interestingly, we find that the coefficient on *Bond Yield Change* is negative and weakly significant for downgrades, which is

[19] We confirm the importance of using rating scale as the strata by testing whether the proportional hazard (PH) assumption holds. Following the test of Grambsch and Therneau (1994), we reject the PH assumption when using rating scale as a predictor for downgrades at the 5% level.

[20] This monthly indicator variable is equal to one from the month of the watch announcement to the month of the rating change event, or until "Off Watch" or "Not On Watch" is announced. For downgrades, only negative watches are considered while for upgrades, only positive watches are considered. Credit watch announced 180 days or more prior to when a firm is re-rated is not considered to be related to the rating change event. Credit watch data is obtained from Mergent FISD and Moody's Default Risk Database (MDRS).

counter-intuitive from the credit risk perspective. A possible explanation could be the relatively low liquidity and high trading costs in the corporate bond market, which might cause the prices between these two instruments to diverge. Because of the relative liquidity advantage, the CDS market is likely the more attractive trading venue for hedgers, speculators, and short-term investors as opposed to long-term investors in the bond market (see Martin and Zawadowski (2013)). The heterogeneous investor base in these two markets and their different trading frequencies in response to information-related events could further render bond yields stale.

Regression model (II) in Table 5 compares the predictive power of CDS spreads versus bond yields on rating downgrades and upgrades. We again find that the coefficient on *CDS spread* is positive and significant only for downgrades, but not upgrades. This suggests that a higher CDS spread level in the current month increases the likelihood that the firm will be downgraded in the following month. However, the coefficient on *CDS spread* is negative for predicting rating upgrades, which is consistent with the general observations that higher rated firms have lower CDS spreads, though it is not statistically significant. The sign on the coefficient for *Bond Yield*, for both upgrades and downgrades, which is somewhat unexpected. As discussed previously, this could be due to the low bond market liquidity. The regression model (III) includes both CDS spreads, bond yields and their changes. Overall, the results remain qualitatively similar for this specification too. We conclude that the level of CDS spread and the change in CDS spreads have incremental predictive power for future rating downgrades, after controlling for credit watch events and other standard accounting variables.

5.3 Predicting default

We examine whether the information embedded in CDS spreads can improve the estimation of default risk under the physical measure using the hazard model. We follow the approach similar to the hazard model for predicting rating changes described in Section 5.2, however, the event of interest here is the firm's actual default date. Data on firms' default history is obtained from Moody's Ultimate Recovery Database (Moody's URD), which contains information on all bonds rated by Moody's during our sample period 1996–2010. Moody's URD has information on default history of the bonds and recovery rates in the event of default (Duffie, Saita, and Wang (2007), and Chava, Stefanescu, and Turnbull (2011)). We restrict our attention to firms that are in the intersection of Moody's

URD, CRSP, COMPUSTAT, and the CDS databases during 1996-2010. We use Moody's definition of default in our analysis. The sample includes 616 firms of which about 6 percent of them experienced default.

We estimate the extended Cox model similar to equation (10) at the firm-month level. Because the number of defaults observed is small, we do not allow for stratification. Table 6 reports the results. All regression models include accounting variables that have been shown to predict default. The first regression model (I) shows that credit rating levels, defined as the average ratings of the three agencies, significantly predict future default. The pseudo R^2 is about 60% suggesting that credit ratings along with standard accounting variables can explain a significant variation of default risks across firms.

In the regression models (II)–(IV), we test whether the level of CDS spread, and the change in CDS spread can improve default risk estimation. Based on the R^2, we find that each of these two pieces of information extracted from CDS spreads do not improve default risk modeling relative to the model that relies on credit ratings (model (I)). The coefficients *CDS Spread* and *CDS Spread Change* are positive, which is consistent with the prediction of the structural model that the risk-neutral and physical default probabilities are positively correlated (see equations (4) and (5)). However, only the coefficient on *CDS Spread* is significant.

The regression model (V) in Table 6 reports estimation results of the hazard rate model when both credit ratings and CDS-related variables are included. We find a substantial increase in pseudo R^2 from 69% to about 78%. Importantly, we find the coefficients on credit ratings, as well as on the two CDS variables are mostly significant with their signs consistent with the prediction of the structural model. Overall, the results in Table 6 show that both credit ratings and CDS spreads carry important information for modeling default probability. In other words, information extracted from CDS spreads substantially improves the default prediction model when used jointly with credit ratings.

6 Price discovery before rating change announcements

This section tests Hypothesis 4 of the paper. We examine whether the CDS market leads other market measures embodying risk-neutral default probabilities, e.g., stock and bond prices. We first show that the CDS market's information share of credit price discovery relative to the bond market increases substantially before credit rating downgrades. After, we show that unanticipated changes in CDS spreads lead stock returns particularly before rating downgrade announcements.

6.1 Credit price discovery in the CDS and bond markets

We examine how much the CDS market contributes to credit price discovery particularly in the period prior to credit rating downgrades. We follow the method in Blanco, Brennan, and Marsh (2005) and study lead-lag dynamics of CDS and bond spreads using the Vector Error Correction Model (VECM). We choose the VECM approach because the approach conveniently allows us to examine which of the two markets is more important for credit price discovery using the Hasbrouck's (1995) "information share" measure. Further, the theoretical equivalence between CDS and corporate bond spreads suggests that the two time-series are cointegrated through a long-run relationship. The VECM is therefore a suitable technique because it adjusts for their long-run changes, as well as deviations from equilibrium.

We estimate the VECM in two steps. First, we estimate the following first-stage regression model for each firm individually using all daily oberservations:

$$CDS_{i,t} = \alpha_{0i} + \alpha_{1i} CS_{i,t} + E_{i,t}, \tag{11}$$

where $CDS_{i,t}$ and $CS_{i,t}$ are CDS and corporate bond spreads of firm i with the same maturity observed on day t. The residual term, $E_{i,t}$, represents daily deviation to the long-run relationship between CDS and corporate bond spreads. It is also referred to as the error correction term. Next, we apply residuals from the first-stage regression in equation (11) to estimate the following panel regression specification:

$$\Delta CDS_{i,t} = \lambda_1 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{1j} \Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{1j} \Delta CS_{i,t-j} + \varepsilon_{1i,t} \tag{12}$$

$$\Delta CS_{i,t} = \lambda_2 E_{i,t-1} + \sum\nolimits_{j=1}^{5} \beta_{2j} \Delta CDS_{i,t-j} + \sum\nolimits_{j=1}^{5} \gamma_{2j} \Delta CS_{i,t-j} + \varepsilon_{2i,t}, \tag{13}$$

where $\Delta CDS_{i,t}$ and $\Delta CS_{i,t}$ are diferences in $CDS_{i,t}$ and $CS_{i,t}$ spreads for firm i between days t and $t-1$, respectively.

In equations (12) and (13), we are interested in the estimated coefficients λ_1 and λ_2, which show how CDS and bond spreads adjust after a deviation to their long-run relationship. When $E_{i,t-1}$ is positive, equation (11) suggests the CDS spread is too high relative to the bond spread and their long-run relationship predicts that the CDS spread will decrease ($\lambda_1 < 0$), while the corporate bond spread will increase ($\lambda_2 > 0$). A similar logic holds when $E_{i,t-1}$ is negative. The sign and magnitude of coefficients λ_1 and λ_2 are used to infer the information-flow direction and the adjustment speeds of the two securities. If both coefficients are significant with correct signs, i.e. $\lambda_1 < 0$ and $\lambda_2 > 0$, then both markets contribute to price discovery. However, when only λ_2 is positive and significant, the CDS market is the main contributor to price discovery because it suggests that corporate bond spreads adjust to reconcile their deviation from CDS spreads. Analogously, when only λ_1 is negative and significant, the bond market leads in the credit risk's price discovery.

We estimate the VECM system using daily CDS and bond spreads with constant 5-year maturity. We use CDS contracts that are written on senior debt and with no restructing clause. Unlike CDS contracts, corporate bonds do not trade at standardized maturities. Therefore, we need 5-year bond yields to match the constant 5-year CDS spreads. We follow the procedure similar to Blanco, Brennan, and Marsh (2005). On each day and for each reference entity, we search for a bond with maturities between three and five years, and another bond with maturity of 6.5 years of more. We then linearly interploate between these yields to estimate a 5-year yield to maturity bond. Bond spread is calculated by subtracting bond yield with the constant 5-year Treasury rate.

In order for firms to enter our sample, we require that they have CDS and bond data traded simultaneously and continuously for at least two calendar years. This filter ensures that we can precisely estimate the first-stage regression in (11). This requirement leaves us with 305 firms. In order to use VECM analysis, we apply the Johansen trace test for cointegration between CDS and bond spreads. We find for 210 reference entities, their CDS and bond spreads are cointegrated with order one, i.e., $I(1)$. Our empirical analysis in this section is therefore based on 210 reference entities.

Table 7 reports results from the second-stage panel regression model in equations (12)–(13). We report results estimated from three estimation samples.[21] The first estimation sample uses all $249,306$ daily observations. The second estimation sample uses only daily observations that fall in the window [-90,-2] days relative to firms' rating downgrade announcements. This estimation period is used to examine credit price discovery prior to rating downgrade announcements. Finally, the third estimation sample uses only daily observations that fall in the window [-90,-2] days relative to

[21] The first-stage regression (see equation (11)) is estimated for each firm individually using all available observations. To save space, we do not report their estimates.

firms' rating upgrade announcements.

Using all observations, we find the coefficient estimates of λ_1 and λ_2 are -0.017 and 0.033, respectively, and are statistically significant. This finding suggests that, on average, CDS and corporate bond spreads adjust toward their long-run relationship consistent with Blanco, Brennan, and Marsh (2005) who apply the VECM approach to 33 investment-grade firms. Using the VECM estimates in Table 7, we calculate the lower and upper bounds of Hasbrouck's (1995) measure of the CDS market contribution to price discovery. Their expressions are given by

$$\mathrm{HAS}_1 = \frac{\lambda_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}, \quad \mathrm{HAS}_2 = \frac{\left(\lambda_2\sigma_1 - \frac{\sigma_{12}}{\sigma_2}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}, \tag{14}$$

where HAS_1 and HAS_2 are the two bounds of Hasbrouck's measures. The remaining variables σ_1^2, σ_2^2, and σ_{12} in (14) are the covariance matrix terms between $\varepsilon_{1i,t}$ and $\varepsilon_{2i,t}$ in equations (12)–(13).

Table 7 shows that for the first estimation sample, the CDS market's contribution to price discovery of credit risk is between 81 and 85 percent, which is roughly in line with Blanco, Brennan, and Marsh (2005). However, prior to rating downgrades, the contribution from the CDS market increases to between 90 and 91 percent. We also find that the coefficient $\lambda_2 = 0.037$ is positive and significant, while the λ_1 is no longer significant. This finding suggests that prior to rating downgrades, bond spreads always adjust toward CDS spreads in order to maintain their equilibrium relationship. In other words, the CDS market is the leading venue for credit price dicovery prior to rating downgrades. Given our finding that bond prices adjust following CDS spreads before credit rating downgrades, we expect firms with CDS trading to experience a weaker bond price reaction to rating downgrade announcements. We test this conjecture in the Internet Appendix IA.3. Using the event-study method similar to our analysis for stock price reactions, we find that bond price reacts less to credit rating downgrades for firms with CDS trading.

We next turn to the VECM results for the period prior to rating upgrades. Table 7 shows the contribution of the CDS market to credit price discovery falls substantially, ranging between 51 and 56 percent. We also find the coefficient $\lambda_1 = -0.024$ is significant and negative, while λ_2 is not significant. This finding suggests that the bond market leads the CDS market in credit price discovery prior to rating upgrades.

Overall, the lead-lag analyses using the VECM show that on a day-to-day basis, both the CDS and corporate bond markets contribute to price discovery of their firm's credit risk. The contribution of the CDS market however, significantly increases over the quarter-period prior to rating downgrades where CDS spreads lead bond spreads in their daily changes. Whereas, in the quarter-period prior to rating upgrades, we find the opposite relation holds. Collectively, our results in Table 7 strongly support the main conclusion of this paper that the CDS market provides important information to equity and bond investors prior to rating downgrades, which explains why stock and bond prices react less to rating downgrades for firms with CDS trading on their debts.

6.2 Does information flow from the CDS to equity markets?

Following the empirical framework in Acharya and Johnson (2007), we study how the information flows between the CDS and equity markets by looking at the lead-lag relationships between CDS and stock returns. The objective is to test whether there is any incremental information in the CDS market that is not already contained in the equity market. An important concern with the lead-lag study between the credit and equity markets is that the two markets could be highly dependent. It is therefore important to remove components in CDS changes that are predictable using lagged CDS returns, contempraneous stock return, and lagged stock returns.

We regress daily CDS returns (i.e., percentage changes) for each firm i using past information up to five lags as follows:

$$
\begin{aligned}
\text{CDS return}_{i,t} = \alpha_i + \sum_{k=0}^{5} \beta_{i,t-k} \text{Stock return}_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k} \left(\frac{\text{Stock return}_{i,t-k}}{\text{CDS level}_{i,t}} \right) \\
+ \sum_{k=1}^{5} \delta_{i,t-k} \text{CDS return}_{i,t-k} + u_{i,t} \quad (15)
\end{aligned}
$$

Besides lagged CDS, lagged stock returns, and contemporaneous stock returns, we include the ratio of past stock return to the current CDS spread in equation (15) to capture the nonlinear elasticity between CDS spread and equity value. The above regression is estimated for each firm separately. The residuals $u_{i,t}$ from the regression represent the unexpected change in CDS spreads that is unanticipated by both the equity and CDS markets. We refer to $u_{i,t}$ as CDS innovation, which is used in the second-stage regression for studying the information flow from the CDS market to the stock market. However, consistent with Acharya and Johnson (2007), we find that R^2 from the unreported first-stage regressions are mostly in the single digits.

Next, we test whether the unanticipated component in CDS spread changes can predict future stock returns. We estimate the following panel regression specification:

$$\text{Stock return}_t = a + \sum_{k=1}^{5} \Big(b_k + b_k^d \text{ Rating-downgrade}_t + b_k^u \text{ Rating-upgrade}_t \Big) \times u_{i,t-k}$$
$$+ \sum_{k=1}^{5} \Big(c_k + c_k^d \text{ Rating-downgrade}_t + c_k^u \text{ Rating-upgrade}_t \Big) \times \text{Stock return}_{t-k} + \varepsilon_t \quad (16)$$

where $u_{i,t-k}$ is the CDS innovation on day $t-k$ estimated from equation (15). We also include lagged stock returns in the above equation to ensure that any relationships between past CDS innovations and future stock returns are not artifacts of stock return autocorrelations. We introduce two new variables in the above regression specification. *Rating-downgrade*$_t$ is an indicator variable equal to one on day t if it is within [-60,-2] days of credit rating downgrades, and zero otherwise. This variable is designed to capture information flow from the CDS to equity markets that occurs before rating downgrade announcements. Similarly, *Rating-upgrade*$_t$ is an indicator variable equal to one on day t if it is within [-60,-2] days of credit rating upgrades, and zero otherwise.[22] For our analysis, we use CDS spreads with the constant 5-year maturity because they are the most liquid. We also consider only CDS spreads that are written on senior debt and those without a restructuring clause. Table 8 reports results based on the regression model in equation (16).

The regression model (I) in Table 8 reports results based on equation (16) without *Rating-downgrade*$_t$ and *Rating-upgrade*$_t$. In this case, the coefficient $\sum_{k=1}^{5} b_k$ quantifies the amount of information discovered through the CDS market that is informative of future stock prices on the day-to-day basis. Table 8 shows that $\sum_{k=1}^{5} b_k = -0.0074$, which is negative and significant at the 10 percent confidence level. The negative sign on the sum of coefficients is consistent with Merton (1974), which shows that as default risk increases equity price falls. However, the magnitude of 0.74% is economically trivial, suggesting that the CDS market, on average, is not substantially informative of the equity price. On the other hand, we find that past stock returns significantly predict future stock returns with the coefficient of -7.23%. This strong negative auto-correlation that we observe is consistent with the well-established mean-reversion characteristic of stock returns.

The regression model (II) in Table 8 reports results without *Rating-upgrade*$_t$. In this case, $\sum_{k=1}^{5} b_k$

[22] Our results are robust to other event windows around credit rating downgrades and upgrades. For instance, we obtain similar conclusions when replicating the results with rating condition dummies defined over the following event windows [-90,-2], [-120,-2], [-60,+30], and [-30,+30] relative to rating change events.

and $\sum_{k=1}^{5} b_k^d$ quantify information flow from the CDS to equity markets in the periods that are outside and during rating-downgrades, respectively. We find that the flow measure during the rating-downgrade period $\left(\sum_{k=1}^{5} b_k^d\right)$ is negative and statistically significant, indicating an approximate 4.3% transmission of information from CDS innovation to future stock returns. We find the information flow measure outside the rating-downgrade period $\left(\sum_{k=1}^{5} b_k\right)$ is no longer significant, suggesting that the CDS market is not very informative of future stock returns outside the rating-downgrade period. Interestingly, estimates from regression model (II) show that past stock returns do not significantly predict future stock returns during the rating-downgrade period. This can be seen by the statistically insignificant estimates on $\sum_{k=1}^{5} c_k^d$.

Lastly, the regression model (III) reports results based on the model in equation (16) without *Rating-downgrade*$_t$. In this case, $\sum_{k=1}^{5} b_k^u$ captures the information flow from the CDS to equity markets during the rating-upgrade period. We do not find that the CDS market provides new information to the equity market during the period around credit rating upgrades. However, it is interesting to point out that stock returns are quite persistent when the firm experiences rating upgrades, which is observed through the positive and significant coefficients on $\sum_{k=1}^{5} c_k^u = 20.7\%$.

Overall, the results in Table 8 show that there exists significant information flow from the CDS to equity markets before the firm is being downgraded. We conclude that the CDS market is an important venue for equity price discovery prior to credit rating downgrades, providing support to explain why stock prices of firms with CDS trading react significantly less to credit rating downgrades. These results are consistent with Acharya and Johnson (2007) who document insider trading by privately informed parties in the CDS markets around negative events.[23]

7 CDS spreads and the cross-section of stock returns

The distress risk puzzle, i.e., lower-rated firms earn lower returns, has been documented by a number of empirical studies. In particular, Avramov, Chordia, Jostova, and Philipov (2009) find that the puzzle is most pronounced around rating downgrades. In this section, we test Hypothesis 5 by examining the value of the CDS market in explaining the cross-section of stock returns for firms that are about to be re-rated.

[23]For instance, these informed parties could be banks that have relationships with firms and simultaneously act as intermediaries in the CDS market.

We are motivated by Friewald, Wagner, and Zechner (2014) who estimate the equity risk premia from CDS spreads and show that they positively correlate with firms' stock returns. Their general idea is that the firm's equity risk premium is related their CDS spread dynamics under the risk-neutral ($\mathbb{Q}$) and physical ($\mathbb{P}$) measures, which can be extracted using the term structure of CDS spreads over time, i.e., panel CDS data. Building on the insight of the Merton's structural model, the equity risk premium, $\mu_E - r$, is related to the CDS excess return by

$$\mu_E - r = \frac{-\left(\mu_s^{\mathbb{P}} - \mu_s^{\mathbb{Q}}\right)}{\sigma_S}\sigma_E, \tag{17}$$

where $\mu_s^{\mathbb{P}} - \mu_s^{\mathbb{Q}}$ is the CDS spread excess return defined as the difference between the drifts under the physical and risk-neutral probability measures.[24] Equity volatility and CDS spread volatility are denoted by σ_E and σ_S, respectively. Friewald, Wagner, and Zechner (2014) suggest that equation (17), can be inferred from the CDS spread dynamics with constant maturity T as follows

$$ERP_{t+\tau}^{T} \equiv -\left(\frac{\log E_t^{\mathbb{P}}\left[S_{t+\tau}^T\right] - \log E_t^{\mathbb{Q}}\left[S_{t+\tau}^T\right]}{\sqrt{\int_t^{t+\tau}\sigma_{S,u}^2 du}}\right) \cdot \sqrt{\int_t^{t+\tau}\sigma_{E,u}^2 du}, \tag{18}$$

where $E_t^{\mathbb{Q}}\left[S_{t+\tau}^T\right]$ and $E_t^{\mathbb{P}}\left[S_{t+\tau}^T\right]$ denote the conditional time-t expectation of CDS spread at the future time $t+\tau$ under the $\mathbb{Q}$ and $\mathbb{P}$-measure, respectively. The denominator in the above equation (18) refers to the volatility of CDS spreads across the interval $[t, t+\tau]$, and $\int_t^{t+\tau}\sigma_{E,u}^2 du$ is the equity variance calculated over the same period. The term in brackets on the right-hand side of equation (18) can be usefully thought of as the Sharpe ratio of CDS spreads with constant maturity T.

We estimate equation (18) using the term structure of CDS spreads at various points in time. The method is based on the well-established approach of Cochrane and Piazzesi (2005) in the fixed income literature. To save space, we describe the procedure in Internet Appendix IA.5. We estimate one-year CDS-implied equity risk premium on a daily basis for each firm in the sample, i.e., $\tau = 1$ in equation (18). We refer to the estimate as ERP. In order for firms to be eligible for the equity risk premia estimation, they must have sufficient CDS quotes traded at maturities 1, 3, 5, 7, and 10 years. In Table IA9, we report portfolio characteristics sorted based on ERP, credit ratings, and CDS spreads. The sorting is done at the beginning of each month. We find that ERP positively

[24]The risk-neutral drift of the CDS spread $\mu_s^{\mathbb{Q}}$ does not need to be equal to the risk-free rate as the CDS spread is not a traded asset, only the CDS contract is.

and monotonically increases with average portfolio returns. This positively monotonic relationship, however, does not hold for portfolios sorted by either credit ratings or CDS spreads, confirming the findings in Friewald, Wagner, and Zechner (2014).

We next examine whether CDS implied ERP can explain the cross-section of equity returns of firms that are about to be downgraded. Panel A of Table 9 reports average one-year portfolio returns of firms before credit rating downgrades quintile–sorted based on ERP, credit ratings, and CDS spreads. Only firms that will be downgraded by one of the three rating agencies within the next 30 calendar days are kept in the sample. The average one-year returns of all portfolios in Panel A are negative, which is consistent with Dichev and Piotroski (2001) who documented negative stock returns persisting for a year after downgrades. However, importantly for this sample, we find that ERP monotonically increases with aveage one-year equity returns. The difference in average one-year returns between the highest and lowest ERP-sorted portfolio is 29.2% and statistically significant at the one percent level. On the other hand, we do not find that sorting firms prior to rating downgrades based on their rating scales result in a cross–sectional difference in one-year equity returns. The relationship between credit ratings and one-year equity returns is not monotonic, and the difference in equity returns between the worst-rated group and the best-rated group is not statistically significant.

Similar to sorting based on credit ratings, we do not find that CDS spreads alone can explain the cross–section of equity returns before rating downgrade announcements. Interestingly, sorting portfolios based on credit ratings and CDS spreads produces results that are synonymous with the distressed puzzle, i.e., firms with higher CDS spreads (lower credit ratings) have lower expected equity returns.

We replicate the results in Panel A using firms that will be upgraded in the next 30 days, i.e. prior to rating upgrade announcements. The results are reported in Panel B of Table 9. Sorting based on either ERP, credit ratings or CDS spreads, we do not observe a strictly monotonic relationship in returns unlike in the case of downgrades. Overall, the results in this section show that the ERP estimated from CDS spreads perform better than credit ratings in explaining equity returns, especially before rating downgrade announcements.

8 Conclusion

We present evidence that firms' stock prices react significantly less to credit rating downgrades when they have CDS contracts trading on their debt. Our results are robust to different model specifications such as the instrumental variable regression and the propensity-score-matched difference-in-difference analysis. Drawing insights from the simple structural model, we examine various economic channels that can potentially explain our results. We show that CDS spreads contain information that anticipates credit rating downgrades as far as 180 days ahead of the revision date. Using a hazard model for default, we find that CDS spreads provide information that significantly helps improve historical default prediction. Further, the CDS market significantly contributes to price discovery in the stock and bond markets before rating change announcements, and CDS term structures contain information that allow equity investors to construct a more reliable measure of default risk premium than credit ratings.

Overall, our findings suggest that the CDS market provides new and complementary information to that already conveyed by credit rating agencies. Therefore, it may be beneficial for regulators to design policies that can enhance the transparency and liquidity in the CDS market instead of focusing solely on regulating the credit rating agencies.

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Figure 1: CDS-implied credit ratings

We plot daily averaged CDS-implied ratings over the interval [-360,180] days centered on the rating change events. The left (right) panels plot results for downgrades (upgrades) for three adjacent rating classes: A-BBB, BBB-BB, and BB-B. On each day, we classify firms according to their CDS spread into six rating classes; see Table B1 in the appendix for the mapping. The CDS spread boundaries used to classify firms into rating classes are estimated non-parametrically following the method in Breger, Goldberg, and Cheyette (2003) and Kou and Varotto (2008). The plotted CDS-implied ratings are daily averaged values across rating–change events. The y-axis in each panel indicates the credit rating classes. Higher credit rating classes imply higher default probability. The x-axis indicates event days relative to the rating change date. In each panel, the solid line plots the official ratings, in rating class scale, issued by credit agencies, while the dotted line plots average CDS-implied ratings.

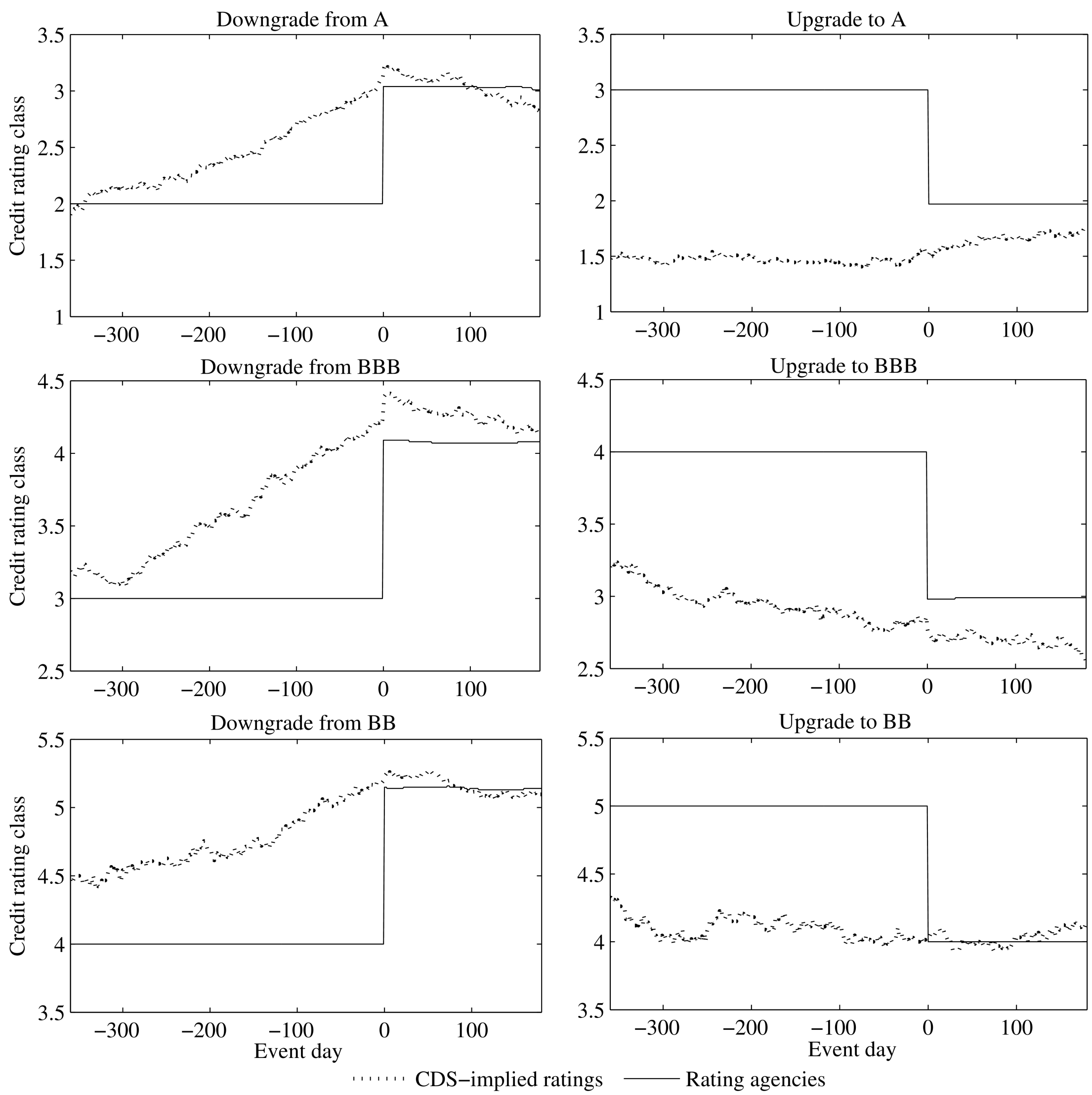

Table 1: Stock price reactions to bond rating changes

This table reports stock price reactions to bond downgrades and upgrades. The sample consists of credit rating downgrades and upgrades on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. Panel A reports results for the full sample, while Panel B reports results for the traded-CDS sample. The full sample consists of 4,665 credit rating downgrades and 2,171 credit rating upgrades. The traded-CDS sample (Panel B) consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010. In each panel, we report cumulative abnormal returns (CAR) calculated over the 3-day event window (-1,+1), where day 0 represents the rating change event day. CAR is calculated using the market model. *Count* reports the number of rating change observations used in each CAR calculation. We report averaged CAR values separately for the Pre–CDS period and the Post–CDS period. Rating changes that occur in the presence of CDS trading are considered to be in the post-CDS period, while rating changes that occur in the absence of CDS trading are considered to be in the pre-CDS period. *Difference* reports the difference in averaged CAR values between the Pre–CDS period and the Post–CDS period. T-statistics are reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Full sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-5.10***	3249	0.16*	1482
	(-19.72)		(1.60)	
Post-CDS	-2.51***	1416	0.09	689
	(-6.42)		(0.61)	
Difference (Post–Pre)	2.58***		-0.07	
	(5.51)		(-0.39)	
Total	-4.31***	4665	0.14*	2171
	(-19.93)		(1.67)	

Panel B: Traded-CDS sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-2.87***	803	0.18	300
	(-7.23)		(0.85)	
Post-CDS	-1.92***	1029	0.06	574
	(-5.48)		(0.39)	
Difference (Post–Pre)	0.95*		-0.12	
	(1.79)		(-0.46)	
Total	-2.34***	1832	0.10	874
	(-8.89)		(0.82)	

Table 2: Regression analysis of stock price reactions to bond rating changes

This table reports regression results of stock price reactions to bond rating changes. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in Appendix A. Robust t-statistics are clustered at the firm-level and reported in bracket. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Downgrades			*Panel B: Upgrades*		
	Full sample		**Traded-CDS**	**Full sample**		**Traded-CDS**
	(I)	(II)	(III)	(I)	(II)	(III)
dCDS	2.08***	1.70**	2.59***	-0.14	0.03	0.08
	(3.38)	(2.39)	(3.73)	(-0.65)	(0.11)	(0.19)
Rating-level controls						
Prev Rating (log)	-3.04***	-3.19***	-3.48***	-0.16	0.02	-0.41
	(-3.42)	(-3.45)	(-2.99)	(-0.40)	(0.05)	(-0.69)
Abs Rating Change	-2.24***	-2.27***	-1.87**	0.03	0.01	0.04
	(-5.03)	(-5.08)	(-2.22)	(0.33)	(0.16)	(0.20)
Days Since Last Rating (log)	0.13	0.12	-0.02	0.09	0.10	0.18
	(0.54)	(0.50)	(-0.09)	(0.74)	(0.84)	(1.10)
Earnings Ann Related	-2.09**	-2.15**	-1.44	0.78	0.80	0.12
	(-2.20)	(-2.25)	(-1.20)	(1.34)	(1.36)	(0.13)
Firm-level controls						
Sales (log)	0.62	0.66	-0.27	-0.14	-0.17	-0.27
	(1.55)	(1.61)	(-0.63)	(-1.11)	(-1.30)	(-1.55)
Profitability	0.44	0.38	-0.59	0.85	0.79	0.66
	(0.32)	(0.28)	(-0.39)	(1.08)	(1.00)	(0.59)
Leverage	-3.38	-3.73*	2.18	0.20	0.11	0.59
	(-1.58)	(-1.71)	(0.75)	(0.32)	(0.18)	(0.59)
Mkt-to-Book	0.19*	0.20**	0.10	-0.02	-0.02	-0.00
	(1.96)	(2.07)	(0.85)	(-0.94)	(-1.00)	(-0.08)
Avg Volatility (log)	-0.78	-0.68	-0.33	0.19	-0.04	0.53
	(-1.52)	(-1.01)	(-0.43)	(0.83)	(-0.19)	(1.53)
Avg Trading Volume (log)	-0.81***	-0.86**	-0.52	0.15	0.18	0.01
	(-2.64)	(-2.51)	(-1.06)	(0.94)	(1.09)	(0.03)
Avg Return	7.16***	6.71***	8.02***	-1.38	-1.20	-1.98
	(4.33)	(4.11)	(2.71)	(-1.25)	(-1.05)	(-1.29)
CDS-trading controls						
Analyst Coverage (log)	0.12	0.22	-0.19	-0.06	-0.06	0.08
	(0.28)	(0.51)	(-0.26)	(-0.44)	(-0.38)	(0.43)
Analyst Dispersion	0.00	0.00	0.00	-0.00	-0.00	-0.01*
	(1.20)	(1.28)	(0.47)	(-0.42)	(-0.49)	(-1.80)
Institutional Ownership	1.32**	1.31**	-1.12*	-0.22*	-0.19	-0.10
	(1.99)	(1.98)	(-1.77)	(-1.75)	(-1.41)	(-0.43)
Stock Illiquidity	1.33	1.51	-3.39	0.87	0.94	10.25
	(0.56)	(0.64)	(-0.21)	(0.23)	(0.25)	(1.10)
Bond Illiquidity	-0.28	-0.23	-0.39	0.11	0.11	0.32**
	(-0.68)	(-0.57)	(-0.85)	(1.01)	(0.96)	(1.99)
Debt Outstanding (log)	-0.44	-0.44	-0.14	0.05	0.06	0.31
	(-1.17)	(-1.16)	(-0.28)	(0.42)	(0.45)	(1.65)
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind & Year	Ind
Observations	4176	4176	1775	1972	1972	834
Adjusted R^2	0.123	0.124	0.091	-0.000	-0.004	0.000

Table 3: Instrumental variable regression of stock price response to bond rating changes

This table reports instrumental variable regression results of stock price reactions to bond rating changes. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in Appendix A. Robust t-statistics are clustered at the firm-level and reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Downgrades		***Panel B: Upgrades***	
	(I)	(II)	(I)	(II)
dCDS IV	6.10***	5.44*	0.13	1.44
	(4.44)	(1.76)	(0.17)	(1.23)
Rating-level controls				
Prev Rating (log)	-2.91**	-2.96**	-1.07	-0.76
	(-2.36)	(-2.35)	(-1.50)	(-0.99)
Abs Rating Change	-1.06*	-1.10*	0.20	0.23
	(-1.87)	(-1.94)	(1.35)	(1.57)
Days Since Last Rating (log)	0.21	0.19	0.22	0.27
	(0.75)	(0.71)	(1.13)	(1.30)
Earnings Ann Related	-1.25	-1.32	0.72	0.65
	(-1.01)	(-1.07)	(0.87)	(0.77)
Firm-level controls				
Sales (log)	0.15	0.11	-0.22	-0.38*
	(0.29)	(0.18)	(-1.02)	(-1.67)
Profitability	6.49*	6.52**	-0.03	-0.33
	(1.96)	(2.00)	(-0.02)	(-0.21)
Leverage	-0.01	-0.53	-0.14	-0.40
	(-0.00)	(-0.21)	(-0.16)	(-0.42)
Market-to-Book	0.03	0.03	0.03	0.04
	(0.29)	(0.33)	(1.16)	(1.34)
Avg Volatility (log)	-0.31	-0.35	0.96**	0.72*
	(-0.45)	(-0.44)	(2.39)	(1.83)
Avg Trading Volume (log)	-1.02**	-0.93**	-0.04	-0.02
	(-2.25)	(-1.99)	(-0.19)	(-0.09)
Avg Return	8.71***	8.15***	-0.97	-0.66
	(3.89)	(3.56)	(-0.63)	(-0.42)
CDS-trading controls				
Analyst Coverage (log)	0.40	0.45	-0.04	-0.02
	(0.74)	(0.83)	(-0.18)	(-0.06)
Analyst Dispersion	0.00	0.00	-0.00	-0.00
	(1.10)	(1.19)	(-0.90)	(-0.91)
Institutional Ownership	-0.02	0.08	-0.84***	-0.75***
	(-0.03)	(0.12)	(-3.22)	(-2.66)
Stock Illiquidity	-3.22	-2.70	-8.28	-8.03
	(-0.76)	(-0.63)	(-1.08)	(-0.95)
Bond Illiquidity	-0.77	-0.71	0.13	-0.02
	(-1.47)	(-1.14)	(0.67)	(-0.09)
Debt Outstanding (log)	-1.04**	-0.96	0.21	0.11
	(-2.04)	(-1.61)	(0.93)	(0.45)
Fixed effects	Ind	Ind & Year	Ind	Ind & Year
Observations	1966	1966	886	886
Adjusted R^2	0.128	0.133	0.014	-0.017

Table 4: Difference-in-difference regression of stock price reactions to bond downgrades: Propensity-score matched sample

This table reports difference-in-difference regression analysis of stock price response to bond downgrades for the propensity-score matched sample. The dependent variable is CAR (-1,+1) calculated over the 3-day event window around a rating change event using the market model. All the variables are defined in Appendix A. Robust t-statistics are clustered at the firm-level and reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Panel A: Matched sample		***Panel B: Subsamples (diagnostics)***			
			Treatment	Control	Post-CDS	Pre-CDS
	(I)	(II)	(III)	(IV)	(V)	(VI)
Diff-in-diff variables						
dTreatment×dCDS	2.07**	1.72*				
	(2.00)	(1.89)				
dCDS	0.09	-0.63	2.43***	0.20		
	(0.11)	(-0.81)	(3.46)	(0.22)		
dTreatment	-0.28	-0.33			1.66**	-0.27
	(-0.36)	(-0.44)			(2.02)	(-0.38)
Rating-level controls						
Prev Rating (log)	-4.01**	-3.85**	-2.76**	-4.61	-5.28*	-3.27**
	(-2.22)	(-2.10)	(-2.41)	(-1.43)	(-1.81)	(-2.41)
Abs Rating Change	-1.33***	-1.29***	-1.72**	-1.19***	-1.20*	-1.60***
	(-3.58)	(-3.54)	(-2.58)	(-2.74)	(-1.76)	(-6.95)
Days Since Last Rating (log)	0.65*	0.55	-0.09	1.05*	1.56*	-0.29
	(1.70)	(1.48)	(-0.35)	(1.81)	(1.93)	(-0.55)
Earnings Ann Related	-1.68	-1.61	-1.60	-1.63	-1.57	-1.34
	(-0.96)	(-0.92)	(-1.29)	(-0.60)	(-0.63)	(-1.04)
Firm-level controls						
Sales (log)	-0.41	-0.39	0.04	-0.47	-0.54	-0.19
	(-0.72)	(-0.75)	(0.09)	(-0.52)	(-0.66)	(-0.37)
Profitability	0.68	0.01	-3.39	4.12	2.39	-2.76
	(0.29)	(0.00)	(-1.35)	(1.26)	(0.75)	(-1.31)
Leverage	-1.22	-0.92	-2.45	-1.59	-4.11	0.05
	(-0.59)	(-0.46)	(-0.88)	(-0.49)	(-1.53)	(0.01)
Mkt-to-Book	0.11	0.10	0.28**	0.06	0.13	0.10
	(0.90)	(0.92)	(2.26)	(0.34)	(0.74)	(0.63)
Avg Volatility (log)	-0.27	0.10	-0.51	0.14	-1.59*	2.43*
	(-0.35)	(0.10)	(-0.74)	(0.11)	(-1.70)	(1.87)
Avg Trading Volume (log)	-0.30	-0.64	-0.60	0.01	0.51	-1.49***
	(-0.67)	(-1.39)	(-1.31)	(0.02)	(0.80)	(-2.70)
Avg Return	8.85***	8.95***	4.62*	11.27***	8.57**	9.26***
	(2.90)	(3.36)	(1.86)	(2.72)	(2.39)	(3.58)
CDS-trading controls						
Analyst Coverage (log)	-0.08	0.18	-0.02	-0.41	-0.77	0.26
	(-0.18)	(0.40)	(-0.03)	(-0.60)	(-1.05)	(0.53)
Analyst Dispersion	0.01**	0.01**	0.01	0.01**	0.01	0.01**
	(2.50)	(2.41)	(1.31)	(2.20)	(1.44)	(2.15)
Institutional Ownership	0.32	0.05	-0.52	1.00*	0.56	-0.25
	(0.89)	(0.16)	(-1.25)	(1.72)	(1.23)	(-0.46)
Stock Illiquidity	8.48	3.84	14.64	12.36	36.91**	-19.05
	(0.81)	(0.36)	(0.77)	(0.80)	(2.03)	(-1.30)
Bond Illiquidity	-0.74*	-0.55	-0.51	-0.62	-1.49**	-0.03
	(-1.81)	(-1.37)	(-1.19)	(-1.06)	(-2.23)	(-0.07)
Debt Outstanding (log)	-0.88	-0.71	-0.19	-1.38	-0.70	-1.07**
	(-1.50)	(-1.22)	(-0.40)	(-1.44)	(-0.84)	(-2.08)
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind	Ind
Observations	6159	6159	1995	4164	3154	3005
Adjusted R^2	0.156	0.169	0.084	0.202	0.167	0.191

Table 5: CDS, and the predictability of rating changes

This table reports results from estimating the extended Cox model for predicting bonds' credit rating change events. The sample consists of corporate bonds issued by U.S. firms that have CDS contracts trading on its debt. We estimate the hazard rate function (see equation (10)) for the time-to-rating change events (in months) at the bond-issuance level. We allow the baseline hazard functions to differ between different credit rating levels, i.e. strata. Panel A reports results for downgrades, while Panel B reports results for upgrades. *Observations* and *Nob. events* indicate the number of issuance-month observations and the number of rating change events used in the estimation, respectively. *CDS spread* is the average 5-year CDS spread in the prior month (in %). *Bond Yield* is the trade-weighted average bond yield in the prior month (in %). *CDS Spread Change* is the log difference in 5-year CDS spreads at the start and end of the previous month. *Bond Yield change* is the log difference in trade-weighted average bond yields at the start and end of the previous month. *Credit Watch dummy* is an indicator variable equal to one if the firm has been put on the credit watch list. We obtain credit watch announcements data from FISD, as well as from Moody's Default Risk Database (MDRS). We only consider negative watches for downgrades, and positive watches for upgrades. All remaining explanatory variables are described in Appendix A and are lagged by one month. All regressions include industry, rating agency and year fixed-effects. We report robust t-statistics clustered at the firm level in brackets below each estimate.

	Hazard rate of future rating change event					
	Panel A: Downgrades			***Panel B: Upgrades***		
	(I)	(II)	(III)	(I)	(II)	(III)
CDS Spread Change	0.42**		0.38**	-0.24		-0.23
	(2.56)		(2.36)	(-0.73)		(-0.68)
Bond Yield Change	-0.14*		-0.14*	0.11		0.05
	(-1.75)		(-1.75)	(0.50)		(0.23)
CDS Spread		0.01*	0.01*		-0.02	-0.02
		(1.95)	(1.70)		(-0.74)	(-0.76)
Bond Yield		-0.00	-0.00		0.01***	0.01***
		(-0.59)	(-0.44)		(4.19)	(4.74)
Credit watch dummy	1.69***	1.71***	1.70***	1.90***	1.89***	1.90***
	(19.65)	(20.11)	(19.83)	(11.44)	(11.53)	(11.43)
Market Cap (log)	-0.56***	-0.55***	-0.54***	0.37***	0.38***	0.38***
	(-6.30)	(-6.48)	(-6.21)	(2.75)	(2.83)	(2.78)
Profitability	-0.09	-0.08	-0.09	0.29	0.31	0.30
	(-1.56)	(-1.47)	(-1.54)	(1.47)	(1.56)	(1.48)
Long Term Debt-to-Assets	-0.02	-0.10	-0.10	-0.67	-0.63	-0.65
	(-0.04)	(-0.19)	(-0.18)	(-0.71)	(-0.66)	(-0.68)
Leverage	0.01***	0.01**	0.01***	0.03*	0.03**	0.03*
	(2.76)	(2.53)	(2.70)	(1.80)	(1.99)	(1.79)
Avg Trading Volume (log)	0.82***	0.80***	0.80***	0.23*	0.22*	0.23*
	(10.08)	(10.23)	(10.08)	(1.88)	(1.79)	(1.84)
Avg Volatility (log)	0.24**	0.21*	0.22*	-0.38	-0.37	-0.37
	(2.05)	(1.83)	(1.92)	(-1.62)	(-1.62)	(-1.62)
Avg Return	0.09	-0.13	0.08	-1.11*	-1.03	-1.12*
	(0.27)	(-0.38)	(0.24)	(-1.75)	(-1.59)	(-1.76)
Observations	206338	211259	206338	113639	115610	113639
Nob. events	7541	7640	7541	2251	2273	2251
Pseudo R-sq	0.088	0.087	0.089	0.057	0.057	0.058

Table 6: CDS and the predictability of defaults

This table reports results from estimating the extended Cox model for predicting default. We estimate the hazard rate function (see equation (10)) for the time-to-default events (in months) at the firm level. We obtain default and bankruptcy filing data from Moody's Ultimate Recovery Database (Moody's URD), FISD and Bankrupcy.com. The sample consists of U.S. firms that have CDS contracts trading on their debt at some point between January 1996 and December 2010 (i.e. traded-CDS firms). A firm is considered to be in default in the month that it misses a disbursement of interest and/or principal, as well as when it files for bankruptcy. *Observations* and *Nob. events* indicate the number of firm-month observations and default events used in the estimations. *Credit Rating* is the credit rating level, in cardinal scale, of the firm in the prior month averaged across the three rating agencies. *CDS spread* is the firm's average 5-year CDS spread in the prior month (in %). *CDS Spread Change* is the log difference in 5-year CDS spreads at the start and end of the previous month. *Predicted ERP* is the expected one-year equity risk premium calculated from CDS spreads (see section 7). All remaining explanatory variables are described in Appendix B and are lagged by one period. All regressions include industry and year fixed-effects. We report robust t-statistics clustered at the firm level in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Probability of default				
	(I)	(II)	(III)	(IV)	(V)
Credit Rating (Avg of 3 CRAs)	0.52***				0.61***
	(3.61)				(3.57)
CDS Spread Level (5yr)		0.16**		0.17***	0.12
		(2.12)		(2.73)	(1.55)
CDS Spread Change (5yr)			2.85**	3.23**	3.83**
			(2.27)	(2.13)	(2.18)
Net Income-to-Assets	-5.16	-8.08	-9.68*	-12.64**	-14.22
	(-0.77)	(-1.08)	(-1.69)	(-2.09)	(-1.35)
Total Liabilities-to-Assets	3.52**	1.64	2.37	1.58	1.83
	(2.24)	(1.02)	(1.54)	(0.97)	(0.85)
Relative Size	0.34	-0.14	-0.42*	-0.21	0.24
	(1.47)	(-0.44)	(-1.87)	(-0.72)	(0.50)
Excess Return	-3.68***	-2.06	-1.52	-1.77	-4.13*
	(-3.02)	(-1.27)	(-1.02)	(-1.02)	(-1.87)
Market-to-Book	-0.15***	-0.39**	-0.47***	-0.42***	-0.37***
	(-2.79)	(-2.54)	(-2.87)	(-2.67)	(-3.28)
Avg Volatility (log)	2.58***	1.55***	2.08***	1.31**	1.40*
	(5.39)	(2.79)	(3.96)	(2.35)	(1.93)
Observations	54215	46470	45897	45897	45203
Nob. events	37	33	33	33	32
Pseudo R-sq	0.690	0.661	0.646	0.675	0.775

Table 7: CDS contribution to credit price discovery

We report coefficient estimates from the Vector Error Correction Model (VECM), and Hasbrouck measures of CDS spreads' contribution to the credit price discovery process. The sample consists of 210 reference entities for which the Johansen trace test statistics conclude that their daily secondary bond yields and CDS spreads are cointegrated $I(1)$ variables. Secondary bond yields data are obtained from TRACE, which starts in July 2001. Our sample period ends in December 2010. Daily CDS spreads with 5-year maturity are obtained from MARKIT. We follow the method in Blanco, Brennan, and Marsh (2005) and estimate the constant 5-year maturity bond yield by interploating the daily bond yields curve. Corporate bond spread is the difference between the 5-year interpolated bond yield and the 5-year treasury yield. The coefficients λ_1 and λ_2 are estimates from the following second-stage panel regression

$$\Delta CDS_{i,t} = \lambda_1 E_{i,t-1} + \sum_{j=1}^{5} \beta_{1j} \Delta CDS_{i,t-j} + \sum_{j=1}^{5} \gamma_{1j} \Delta CS_{i,t-j} + \varepsilon_{1i,t}$$

$$\Delta CS_{i,t} = \lambda_2 E_{i,t-1} + \sum_{j=1}^{5} \beta_{2j} \Delta CDS_{i,t-j} + \sum_{j=1}^{5} \gamma_{2j} \Delta CS_{i,t-j} + \varepsilon_{2i,t},$$

where $\Delta CDS_{i,t}$, and $\Delta CS_{i,t}$ are daily diferences in CDS and corporate bond spreads for firm i between days t and $t-1$. The error correction term, $E_{i,t-1}$, is obtained from the following first-stage regression estimated firm-by-firm using all daily oberservations:

$$CDS_{i,t} = \alpha_{0i} + \alpha_{1i} CS_{i,t} + E_{i,t}.$$

The residual term, $E_{i,t}$, represents daily deviation to the long-run relationship between CDS and corporate bond spreads. This table reports from the second-stage panel regression for the three estimation samples. The first estimation sample uses all daily observations available. The second estimation sample uses daily observations over a quarter-period prior to the firm's credit rating downgrades, i.e. [-90,-2] days relative to the event date. Similarly, the third estimation sample uses daily observations over [-90,-2] days prior to the firm's credit rating upgrades. Hasbrouck's measure provides upper and lower bounds to the price discovery contribution made in the CDS market; see equation (14). The coefficients λ_1 and λ_2 measure the relationship between changes in CDS and corporate bond spreads in relation to their cointegrated relationship. Robust t-statistics are clustered at the firm level and reported in brackets beneath the λ_1 and λ_2 estimates. Superscripts ***, **, * indicate significance at the 1, 5, and 10 percent levels, respectively.

		Vector Error Correction Model (VECM)				
Estimation sample	Observations	Coefficient estimates		Hasbrouck share of CDS market		
		λ_1	λ_2	Lower	Mid	Upper
(1) All observations	249306	-0.017**	0.033***	0.81427	0.8327	0.85113
		(-2.24)	(3.85)			
(2) Prior to downgrades	22529	-0.011	0.037***	0.90007	0.90728	0.9145
		(-1.20)	(2.90)			
(3) Prior to upgrades	12449	-0.024*	0.094	0.50743	0.53243	0.55743
		(-1.90)	(1.46)			

Table 8: Lead-lag analysis of CDS and stock returns

This table reports results from the panel regression of daily stock returns on lagged CDS innovations, and lagged stock returns under different credit-rating conditions. We estimate the following panel regression model:

$$\begin{aligned}\text{Stock return}_t =& a + \sum_{k=1}^{5} \left(b_k + b_k^d \text{ Rating-downgrade}_t + b_k^u \text{ Rating-upgrade}_t\right) \times \text{CDS innovation}_{t-k} \\ &+ \sum_{k=1}^{5} \left(c_k + c_k^d \text{ Rating-downgrade}_t + c_k^u \text{ Rating-upgrade}_t\right) \times \text{Stock return}_{t-k} + \varepsilon_t.\end{aligned}$$

We surpress firm-level notation above for brevity. Stock return at time t is calculated as the daily difference between the log of stock prices. *CDS innovation*$_t$ represents daily changes to CDS returns due to shock in the credit markets that is not anticipated by stock markets at time t. We estimate *CDS innovation*$_t$ using the residual from the first-stage regression according to equation (15). We interact lagged CDS innovations and stock returns with dummy variables indicating when the firm is under different credit-rating conditions. Regression model (I) reports results for the baseline regression without a rating-condition dummy. For the regression model (II), *Rating-downgrade*$_t$ is equal to one on days [-60,-2] relative to when the firm's credit rating is downgraded, and zero otherwise. For the regression model (III), *Rating-upgrade*$_t$ is equal to one on days [-60,-2] relative to when the firm's credit rating is upgraded, and zero otherwise. We report robust t-statistics clustered at the firm level in brackets beneath each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Dependent variable: Stock return$_t$			
	(I) None	(II) Downgrade	(III) Upgrade
Intercept	0.0004***	0.0004***	0.0004***
	(8.58)	(8.72)	(8.38)
$\sum_{k=1}^{5}$ CDS innovation$_{t-k}$	-0.0074*	-0.0038	-0.0054
	(-1.76)	(-0.97)	(-1.39)
$\sum_{k=1}^{5}$ Stock return$_{t-k}$	-0.0723***	-0.0672***	-0.0796***
	(-4.41)	(-4.65)	(-4.83)
$\sum_{k=1}^{5}$ Rating-downgrade$_t \times$CDS innovation$_{t-k}$		-0.0428**	
		(-2.02)	
$\sum_{k=1}^{5}$ Rating-downgrade$_t \times$Stock return$_{t-k}$		-0.0306	
		(-0.48)	
$\sum_{k=1}^{5}$ Rating-upgrade$_t \times$CDS innovation$_{t-k}$			-0.0513
			(-0.93)
$\sum_{k=1}^{5}$ Rating-upgrade$_t \times$Stock return$_{t-k}$			0.2074***
			(3.30)
Observations	286777	286777	286777
No. of clusters	345	345	345
Adj. R^2	0.17%	0.31%	0.20%

Table 9: CDS-implied equity risk premia and the cross-section of stock returns: Before rating change announcements

This table reports means of one-year portfolio returns based on quintile monthly portfolio sorts. The sample consists of U.S. firms that have CDS contracts traded with maturity of 1, 3, 5, 7, and 10 years. The portfolios are formed at the beginning of each month based on three dimensions: CDS-implied equity risk premia (ERP), credit ratings, and CDS spreads. We calculate CDS-implied ERP for each reference entity using its CDS term structures following the method in Friewald, Wagner, and Zechner (2014) (see Section 7 & Appendix IA.5 for details). Average credit rating levels of the three rating agencies are used for portfolio sorting based on credit ratings. The level of 5-year CDS spreads are used for portfolio sorting based on CDS spreads. Panel A reports average one-year returns calculated using firms that are about to be downgraded. In Panel B, average one-year returns are calculated using firms that are about to be upgraded. Newey-West t-statistics adjusted for 11 lags are reported in brackets below the average portfolio returns. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Portfolio-sorted average one-year returns before rating downgrades

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.456***	-0.386***	-0.139***
	(-17.95)	(-11.47)	(-4.84)
2	-0.333***	-0.250***	-0.169***
	(-8.94)	(-8.16)	(-5.55)
3	-0.326***	-0.366***	-0.320***
	(-8.33)	(-10.33)	(-9.30)
4	-0.302***	-0.290***	-0.405***
	(-8.53)	(-7.98)	(-12.19)
5 (highest)	-0.164***	-0.454***	-0.492***
	(-3.59)	(-12.21)	(-15.73)
5−1	0.292***	-0.068	-0.353***
	(5.59)	(-1.36)	(-8.32)

Panel B: Portfolio-sorted average one-year returns before rating upgrades

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.027	-0.021	0.103***
	(-0.61)	(-0.30)	(3.85)
2	0.083**	0.103***	0.110***
	(2.21)	(2.81)	(3.74)
3	0.160***	0.114***	0.088***
	(4.97)	(3.91)	(2.58)
4	0.117***	0.054**	0.102***
	(4.57)	(1.82)	(3.11)
5 (highest)	0.254***	0.241***	0.220***
	(9.07)	(10.06)	(7.10)
5−1	0.281***	0.262***	0.118***
	(5.39)	(3.53)	(2.87)

Appendix

Appendix A Variable Definitions

Rating-level variables

- *dCDS* is an indicator variable equal to one if the rating change takes place when the CDS trades on the underlying firm, and 0 otherwise.
- *Previous Rating* is the credit rating level prior to the rating change. It is expressed as the natural logarithm of the cardinal rating scale; see Table B1 for the mapping
- *Abs Rating Change* is the absolute value of the difference in rating scale change between after and before rating change events.
- *Days Since Last Rating* is the natural logarithm of the number of days between the previous rating change in the same direction for the same bond issue, but by another rating agency. Following Jorion, Liu, and Shi (2005), the number of days is set to 60 (a) if both rating agencies rate on the same day, (b) if the rating by the second rating agency is in the opposite direction,or (c) if the rating change by the other rating agency is more than 60 days.
- *Earnings Ann Related* is an indicator variable equal to one if there is an earnings announcement within (-1,+1) days of the rating change event day, and 0 otherwise.
- *dDowngrade* is an indicator variable equal to one if the bond experiences a rating downgrade event, and 0 otherwise.

Firm-level variables: Firm fundamentals

- *Sales* is the firm's quarterly sales (saleq) reported in COMPUSTAT.
- *Assets* is the firms' quarterly total assets (atq) reported in COMPUSTAT.
- *Operating income* is the quarterly operating income (oiadpq) reported in COMPUSTAT.
- *Profitability* is the firm's quarterly ratio of *Operating income* to *Sales*.
- *Total debt* is the firm's total debts (dlcq + dlttq) reported in the quarterly COMPUSTAT.
- *Leverage* is the firm's *Total debt* divided by its *Assets*.
- *Market value of equity* is the market value of equity calculated using the monthly CRSP database, i.e. share price $\times$ total shares outstanding.
- *Book value of equity* is the book value of equity. It is the total assets minus total liability plus tax credit (atq−ltq + txditcq) calculated using quarterly COMPUSTAT.
- *Mkt-to-Book* is the monthly ratio of *Market value of equity* divided by the *Book value of equity*.
- *Avg Volatility* is the monthly standard deviation of daily stock returns caculated using data from CRSP.
- *Avg Trading Volume* is the monthly trading volume on the stock reported in CRSP.
- *Avg Return* is the monthly stock return obtained from CRSP.

Firm-level variables: CDS trading variables

- *Analyst Coverage* is the number of analyst EPS forecasts in the 90 days prior to the earnings announcement date. (source: I/B/E/S)

- *Analyst Dispersion* is the standard deviation of analyst EPS estimates made in the 90 days prior to the earnings announcement date scaled by the actual reported EPS. (source: I/B/E/S)

- *Institutional Ownership* is the ratio of total shares held by institutional investors to the total shares outstanding for a given stock. (source: Thomson-Reuters Institutional Holdings (13F) Database)

- *Stock Illiquidity* is the monthly average stock illiquidity defined as the squared root of the Amihud (2002) measure. It is the monthly average of the following daily values where Ret_t and Price_t are daily return and price of the stock: $\sqrt{1000000 * |\mathrm{Ret}_t| / (\mathrm{Volume} \times \mathrm{Price}_t)}$.

- *Bond Illiquidity* is the number of outstanding bond issues in a given month (see Martin and Zawadowski (2013)).

- *Debt Outstanding* is a proxy for hedging demand. It is the residual from regressing total amount debt outstanding on the number of bond issues. In other words, this variable measures the amount of debt outstanding that is orthogonal to the number of bond issues.

- *Forex Derivative Hedging* is the average amount of foreign exchange derivatives used for hedging purposes (i.e. non-trading purposes) relative to total assets of the lead syndicate banks and bond underwriters that the firm has done business with in the past five years. Banks' derivatives usage data is obtained from Bank Holding Company (BHC) Y9-C filings. Data on the firm's lead bank syndicate is obtained from LPC Dealscan, and the firm's unwriter information is obtained from Mergent FISD.

CDS & Bond variables

- *CDS Spread* is the average monthly 5-year CDS spread from CMA and MARKIT databases.

- *Bond Yield* is the trade-weighted average monthly bond yield calculated from the TRACE database.

- *CDS Spread Change* is the logarithmic difference in average monthly 5-year CDS spreads between the current and previous months.

- *Bond Yield Change* is the logarithmic difference in trade-weighted average bond yields between the current month and previous months.

- *CDS Slope* is the difference between the monthly average 10-year CDS spreads and the monthly average 1-year CDS spreads.

- *CDS-implied Rating Class* is the firm's credit rating class, on the scale of 1 to 6, that is backed out non-parametrically using CDS spreads. See Section 5.1 for more details.

- *Credit Rating Class* is the credit rating level mapped to the rating class scale. See Table Appendix B for the mapping.

- *Credit watch dummy* indicates whether the firm (or bond issue) is put on credit watch prior to a credit rating change. This monthly indicator variable takes the value 1 from the month of the watch announcement to the month of the rating change event or until "Off Watch" or "Not On Watch" is announced. For downgrades, only negative watches are considered while for upgrades, only positive watches were considered. A credit watch announced 180 days or more prior to when a firm is re-rated is not considered to be related to the rating change event. Credit watch data is obtained from Mergent FISD and Moody's Default Risk Database (MDRS).

- *Market Cap* is the monthly market value of equity.

- *Market Leverage* is defined as (Total debt + Market value of equity)/(Market value of equity) calculated at a quarterly frequency.

- *Long Term Debt-to-Asset* is the ratio of long term debt to total assets (dlttq/atq) calculated using quarterly COMPUSTAT.

- *ERP* is the firm's annualized equity risk premium implied by the dynamic of CDS term structure.

- *Subordinate* is an indicator variable equal to one if the bond is subordinated. We obtain bond characteristics from Mergent FISD, CUSIP Master file, and Moody's Default Risk Database (MDRS).

- *Callable* is an indicator variable equal to one if the bond is callable or redeemable, and zero otherwise.

- *Issue Size* is the offering amount of the bond at primary issue.

- *Maturity* is the maturity of the bond in years.

- *Treasury Slope* (10yr-1yr) is the difference between the 10-year and 1-year Treasury rates.

- *Bond return* is the raw bond return around the rating change event (t = 0) calculated over the $[-k, +k]$ event days as:

$$BondReturn_{t=0} = \frac{BondPrice_{t+k} - BondPrice_{t-k} + AccruedInterest}{BondPrice_{t-k}}.$$

  We use the shortest event window possible depending on the availability of bond trading history. The maximimum window of $k = 7$ days is used, otherwise bond event-period return is not computed.

- *Daily bond index* is the weighted (equal or value) index of bond returns grouped according to Moody's six major rating categories.

Bankruptcy & Distress regression variables

- *Bankruptcy* is defined as when the firm experiences a credit default event as defined in Moody's Ultimate Recovery Database (Moody's URD).

- *Net Income-to-Assets* is the ratio of net income to total assets (niq/atq) obtained from quarterly COMPUSTAT.

- *Total Liabilities-to-Assets* is the ratio of total liabilities to total assets (ltq/atq) obtained from quarterly COMPUSTAT.
- *Relative Size* is the logarithmic of the firm's market value of equity divided by the total NYSE/AMEX market equity value. It is calculated monthly using data from CRSP.
- *Excess Return* is the monthly return on the firm minus the value-weighted NYSE/AMEX index return.

Appendix B Additional Tables

Table B1: Classification of credit rating codes

The table presents the mapping of rating codes issued by S&P, Fitch, and Moody's to the cardinal scale, as well as to the rating class. The rating codes used by S&P and Fitch are similar but are different from those used by Moody's. Moody's uses code from Aaa down to C to rate bonds whereas S&P and Fitch rate bonds from AAA down to D. Within the 6 classes from AA to CCC for S&P and Fitch, the rating agencies have three additional gradations with modifiers (+,none,-). For examples, S&P's AA rating class is subdivided into AA+, AA, AA-. Similarly, Moody's has three additional gradations with modifiers 1,2,3 from Aaa to Caa. We transformed the credit ratings of the three rating agencies into a cardinal scale starting with 1 as AAA(Aaa), 2 as AA+(Aa1), 3 as AA(Aa2), and so on until 23 as the default category. The rating class mapping is from Jorion and Zhang (2007). Fitch differs from the other two agencies in that it provides three ratings for default. We follow Jorion, Liu, and Shi (2005) by using 23 instead of 22 as the cardinal scale for Fitch's default category, which is the average of three default ratings – i.e., DD.

Description	S&P	Moody's	Fitch	Cardinal scale	Rating class
Investment grade					
Highest grade	AAA	Aaa	AAA	1	1
High grade	AA (+,none,-)	Aa (1,2,3)	AA (+,none,-)	2, 3, 4	1
Upper-medium grade	A (+,none,-)	A (1,2,3)	A (+,none,-)	5, 6, 7	2
Medium grade	BBB (+,none,-)	Baa (1,2,3)	BBB (+,none,-)	8, 9, 10	3
Speculative grade					
Lower medium grade	BB (+,none,-)	Ba (1,2,3)	BB (+,none,-)	11, 12, 13	4
Speculative	B (+,none,-)	B (1,2,3)	B (+,none,-)	14, 15, 16	5
Poor standing	CCC (+,none,-)	Caa (1,2,3)	CCC (+,none,-)	17, 18, 19	6
Highly speculative	CC	Ca	CC	20	6
Lowest quality	C	C	C	21	6
In default	D		DDD/DD/D	23	6

Table B2: Probit model for CDS trading: First-stage IV model

We report probit regression results for the probability of CDS trading. The dependent variable is the firm-quarter indicator variable that is equal one if CDS contract trades on the underlying firm's debt in this quarter, and zero otherwise. The explanatory variables include firm-level characteristics, CDS-trading controls, and the instrument variable proxying for the probability of CDS trading. The instrumental variable (IV) that we use is *Forex Derivative Hedging* (see also Saretto and Tookes (2013)). It is defined as the average amount of foreign exchange derivatives used for hedging purposes relative to total assets of the lead syndicate banks and bond underwriters that firms have done business with in the past five years. We obtain data on firm's lead syndicate bank and underwriters from Dealscan and FISD, respectively. See Appendix B for description of other variables. Industry and year fixed-effects are included. Robust t-statistics are reported in bracket below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Probability of CDS trading
Instrumental variable	
Forex Derivative Hedging (%)	0.04***
	(4.84)
Instrumental variable	
Sales (log)	0.40***
	(21.14)
Profitability	-0.54***
	(-4.81)
Leverage	0.28***
	(3.19)
Market-to-Book	-0.01*
	(-1.89)
Rating Scale (log)	-0.30***
	(-6.01)
Avg Volatility (log)	-0.05
	(-1.58)
Avg Trading Volume (log)	0.12***
	(6.23)
Avg Return	0.15
	(1.16)
Instrumental variable	
Analyst Coverage (log)	0.03
	(1.53)
Analyst Dispersion	0.00**
	(1.96)
Institutional Ownership	0.26***
	(5.10)
Stock Illiquidity	-3.28***
	(-4.92)
Bond Illiquidity	0.66***
	(33.22)
Debt Outstanding (log)	0.40***
	(20.15)
Observations	17850
Incremental Pseudo R^2	1.1%
Pseudo R^2	0.4854

Table B3: The propensity score matched sample

This table presents matched sample diagonoistics. All variables are defined in Appendix B. Panel A shows the probit model used in the propensity score matching. We estimate firms' probability of having CDS trading in each month. The dependent variable in the probit model is the firm-month indicator that is equal one if CDS contract trades on the underlying firm's debt this month, and zero otherwise. All independent variables are lagged by one month. The first column in Panel A (Before matching) reports results estimated using the full sample for which data are available. The second column in Panel A (After matching) reports results estimated using the CDS-traded and propensity-score matched firms. Firms for which CDS contracts trade at any point in our sample period (1996-2010) are identified with the treatmeant group, i.e. traded-CDS firms. Firms in the control group used in the matching are those in the full sample that never have CDS contracts traded at any point in our sample period , i.e. non-traded-CDS firms. Each traded-CDS firm (treatment firm) is matched with up to five non-traded-CDS firms (control firms) based on their propensity scores of having CDS trading. Industry and year fixed effects are included in the regressions. Robust t-statistics clustered at the firm level are reported in bracket. *, **, and *** indicate statistical confidence greater than 10%, 5%, and 1%, respectively. Panel B reports pairwise comparisons of the variables used for matching for the CDS treatment firms, and the matched control firms. Panel C reports industry distributions (Fama-French 12 classification) for the CDS treatment firms, and the matched control firms.

Panel A: Propensity score matched sample

	Before matching	After matching
Sales (log)	0.40***	0.32***
	(36.44)	(4.03)
Profitability	-0.53***	-0.13
	(-8.14)	(-0.25)
Leverage	0.26***	0.14
	(5.05)	(0.40)
Mkt-to-Book	-0.01***	-0.01
	(-2.78)	(-0.43)
Rating Scale (log)	-0.26***	-0.72***
	(-9.10)	(-3.61)
Avg Return	0.08	0.13
	(1.03)	(1.11)
Avg Volatility (log)	-0.06***	-0.06
	(-3.06)	(-0.44)
Avg Trading Volume (log)	0.11***	-0.04
	(10.34)	(-0.57)
Analyst Coverage (log)	0.03**	-0.01
	(2.57)	(-0.12)
Analyst Dispersion	0.00***	-0.00
	(3.66)	(-0.38)
Institutional Ownership	0.26***	0.07
	(8.76)	(0.39)
Stock Illiquidity	-3.27***	-3.55
	(-7.94)	(-0.94)
Bond Illiquidity	0.66***	0.10
	(56.56)	(1.43)
Debt Outstanding (log)	0.40***	0.16**
	(34.27)	(2.21)
Forex Derivative Hedging (%)	0.04***	-0.11**
	(7.23)	(-2.32)
Observations	52440	1011
Pseudo R^2	0.49	0.14

Panel B: Sample means of firm variables used in the propensity-score matching

	Before matching			*After matching*		
	Mean		(Diff)	Mean		(Diff)
	Treated	Control	T-stats	Treated	Control	T-stats
Sales (log)	7.75	6.24	164.70	7.50	6.86	2.71
Profitability	0.14	0.15	-6.92	0.14	0.14	0.15
Leverage	0.68	0.69	-6.23	0.68	0.70	-1.20
Mkt-to-Book	2.80	2.42	14.10	2.59	2.67	-0.36
Avg Volatility (log)	-4.00	-3.90	-21.40	-4.04	-4.00	-1.22
Avg Trading Volume (log)	-0.83	-2.06	121.35	-1.21	-1.66	2.60
Avg Return	0.01	0.01	0.19	0.02	0.01	1.26
Rating Scale	8.43	10.09	-67.62	8.21	9.51	-2.34
Analyst Coverage (log)	2.11	1.72	70.65	2.07	1.84	1.71
Analyst Dispersion	5.59	5.66	-0.29	5.64	6.33	-0.31
Institutional Ownership	4.27	4.23	16.85	4.25	4.28	-1.47
Stock Illiquidity	0.02	0.05	-86.75	0.02	0.03	-2.39
Bond Illiquidity	2.02	1.17	126.44	1.86	1.66	1.24
Debt Outstanding (log)	0.24	-0.36	80.87	0.13	-0.16	2.57
Forex Derivative Hedging (%)	2.26	1.72	40.51	1.67	1.80	-1.58

Panel C: Industry distribution of firms in the matched sample

FamaFrench 12 Industry Classifications	Treatment Sample (%)	Control Sample (%)
(1) Consumer Non-durables	5.59	6.03
(2) Consumer Durables	2.45	3.02
(3) Manufacturing	13.29	14.07
(4) Energy, Oil, Gas, and Coal Extraction	7.34	6.53
(5) Chemicals and Allied Products	4.90	6.53
(6) Business Equipment	6.29	4.52
(7) Telecommunciations	5.24	4.52
(8) Utilities	10.84	9.05
(9) Wholesale, Retail, and Services	12.59	8.54
(10) Healthcare	5.24	7.04
(11) Finance	13.99	17.09
(12) Others	12.24	13.07

Internet Appendix: Are credit ratings still relevant?

Sudheer Chava, Rohan Ganduri, and Chayawat Ornthanalai

This document contains discussions and additional results that were left out of the main paper due to space considerations. We will be happy to include any of these findings in the main paper.

Appendix IA.1 Descriptives of the credit rating change sample

Panel A of Table IA1 summarizes the number of upgrades and downgrades along with the size of their rating changes over each year. There are about 2.1 downgrades for every upgrade, which is more or less consistent with previous studies.[25] We observe clustering of upgrades and downgrades in certain years over the 15-year period, and we find that 42% of all downgrades occurred in 2001-2002 and 2007-2009, which correspond to the post-Internet bubble and the recent financial crisis periods, respectively. On the other hand, 39% of all upgrades occurred in pre-Internet bubble period, i.e. 1997-1998, and when the market volatility level is historically low, i.e. 2006-2007, as measured by the VIX index. The size of the rating change is the absolute value of the change in the rating scale. The average size of the rating change does not vary significantly over the years. There are 1416 downgrades and 689 upgrades during the period when the underlying firms have CDS contracts traded. On the other hand, there are 3249 downgrades and 1482 upgrades during the period when the underlying firms do not have CDS contracts traded. For downgrades (upgrades), the mean size of the absolute rating change for an issue without CDS trading is 1.69 (1.38), and for an issue with CDS trading, it is 1.55 (1.27). Table IA1 shows that the start dates of CDS trading in our sample begin in 2001, when we observe only 12 downgrades on firms that have CDS contracts traded. Nevertheless, the number of firms that have CDS contracts traded increases significantly in subsequent years. In fact, Panel A shows that the numbers of downgrades on firms with and without CDS contracts traded are roughly comparable after 2005.

In order to control for the differences between these two types of firms, we consider a subsample of firms for which CDS starts trading at some point during our sample period. We refer to this sample as the "Traded-CDS". Panel B of Table IA1 reports the sample size of traded-CDS sample. The average size of rating change for the sample is 1.45 before CDS trading starts and 1.49 after CDS trading starts.

Table IA2 presents the distribution of the absolute magnitude of rating changes for the pre- and post-CDS trading periods. Panel A reports the distribution year by year, while Panel B reports absolute rating changes for "within-letter-grade", "across-letter-grade", and "across-investment" rating changes. A rating change is defined as "within-letter-grade" if it is within the same alphabet letter (e.g., A+, A, A-). All other rating changes are classified as "across-letter-grade". Among the across-letter-grade changes, those that change between investment grade to speculative grade, and vice versa, are considered " across-investment" grade changes. Table B1 in the appendix summarizes rating categories that belong to the investment and speculative grades.

Appendix IA.2 Other robustness tests for stock price reactions to rating changes

The abnormal returns of firms around credit rating events could be affected due to factors which are unrelated to the rating event. In this case, the CARs would not average out to zero in the

[25] Our number is closer to that of Dichev and Piotroski (2001), who report twice as many downgrades as upgrades over their sample period of 1970 to 1987. In contrast, Jorion, Liu, and Shi (2005) report 4 downgrades for every upgrade from 1998 to 2002.

cross-section. This problem can be alleviated by using standardized CAR (SCAR) instead of CAR. We define SCAR as $SCAR_i(-1,+1) = \frac{CAR_i(-1,+1)}{\sigma(AR_i)\sqrt{3}}$, where $\sigma(AR_i)$ is the standard deviation of the one-period mean abnormal return, and the factor of $\sqrt{3}$ accounts for the length of the event window (-1,+1), which is equal to 3 days. We carry out all the univariate analysis, the regression analysis, and the matched sample analysis using SCAR instead of CAR as a measurement of abnormal returns and obtain the same conclusions.

In order to rule out the possibility that our results are due to outliers, we winsorize each of the CAR and SCAR specifications at the 1% level. We also test for the difference in the mean of stock price reactions between the pre- and post-CDS groups using bootstrapped standard errors. In both cases, we find that the results do not change qualitatively. In addition, we conduct various other subsample analyses based on credit rating agencies, industry type, across-investment-grade rating change, and we find that our results are robust.

We verify that our main conclusion holds for rating changes that are within-investment-grade, as well as those that are across investment grade. Using only traded-CDS firms, we find that stock price reactions to rating downgrades in the pre-CDS-trading period is -1.72% for “within investment grade” rating changes, while it is -9.13% for “across investment grade ” rating changes. However, in the post-CDS-trading period, we find that stock price reactions to rating downgrades is -0.84% and -2.86% for “within investment grade” and “across investment grade” rating changes, respectively. In both cases we find the difference in CAR(-1,1) to be positive and statistically different from zero. The difference in CARs between the pre-CDS-trading and post-CDS-trading periods for “within investment grade” rating change is 0.88% with a t-statistic of 1.82, while the for “across investment grade” rating change is 6.28% with a t-statistic of 3.60.

Apart from the instrumental variable analysis and the matched sample analysis described in Sections 4.4–4.5, we apply the “placebo test” test to further rule out a concern that our results are related to changes in certain market conditions over time — e.g., changes in volatility. To do this, we first generate random pseudo CDS introduction dates. Then we apply the standard event study methodology to these randomly generated pre- and post-CDS periods. We find that the difference in the stock price reactions between these pseudo pre- and post-CDS periods is not significantly different from 0. Overall, using a host of robustness tests, we confirm that the abnormal stock return around credit rating downgrades is muted after CDS contracts trade on the underlying firm’s debt.

Appendix IA.3 Bond price reactions to rating changes

We examine the impact of the CDS market on corporate bond pricing as a channel through which CDS trading attenuates firms’ equity price reactions to credit rating downgrades. The basic idea in the cost of capital calculation is that the market value of the firm’s assets must equal the market value of the firm’s debt plus the market value of the firm’s equity. Any impacts on the firm’s debt value can affect its equity return through changes in the firm’s total assets. We examine whether bond prices also react less to credit rating downgrade announcements when firms have CDS trading on their debt.

Similar to our analyses for stock returns, we consider a rating change event on a debt’s issuer as one observation. We calculate the daily bond price using the trade-weighted average of all the prices reported during that day (see also Bessembinder, Kahle, Maxwell, and Xu (2009)). In a number of cases, there are multiple bond issues per issuer. These multiple issues usually experience rating changes on the same day. In order to avoid double counting events, we study the return of a weighted bond portfolio (equal or value weighted) for each firm. We construct both the equal- and value-weighted portfolios using all the issues written on a firm, and we find that the results are not qualitatively affected by the weighting methods. To save space, we present only the results that are based on the value-weighted portfolios.

Unlike the stock sample analysis, bond trading is relatively thin. For instance, based on the filtered sample in 2006–2007, we find that each bond issue, on average, trades on only 30 days per year. Conditional on the day that we observe trades, there are approximately 3.48 trades per day. To compute abnormal bond returns, we follow the method advocated in Bessembinder, Kahle, Maxwell, and Xu (2009) by differencing the raw returns with the benchmark of indices. We match returns to six benchmark indices based on Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, and B), and the equivalent S&P and Fitch rating categories (See the mapping in Appendix Table B1). Matching further on additional dimensions yields an inadequately small sample because the majority of bonds do not trade daily. We construct daily bond return indices based on the above six rating categories. For each rating category, we calculate the daily index return using all of the bonds rated in that category. We exclude bonds that are re-rated on the day the index is constructed. Since few bonds trade on a daily basis, the composition of the index changes daily. As suggested by Bessembinder, Kahle, Maxwell, and Xu (2009), the bond index return is computed using the value-weighted average to reflect the daily change in index composition.

The cumulative bond return is first calculated at the issue level using transaction prices observed immidately before and after the event day. Because bonds do not often trade daily, the closest observations to the event day may be several days away. We pick the closest pre-event and post-event bond trades around the event day (Day 0) in the (-7,+7) event window. If we do not observe bond trades within (-7,+7) days relative to the event date, the rating change observation is excluded. On average, the closest transaction prices are observed on event-days -2.7 and +2.4 relative to the event date.[26] The cumulative abnormal return for the bond price is calculated by subtracting the cumulative bond return with the cumulative bond index return over the same window period. Finally, the bond market reaction to a rating change event for a firm is calculated as the value-weighted average returns of all of the issues traded around the event date.

Appendix Table IA7 displays the number of upgrades and downgrades and the sizes of rating changes per year in the bond sample. There are about twice the downgrades for every upgrade in the bond event-study sample, which is similar to the stock sample (Table IA7). Relative to the stock sample, we find significantly fewer rating events. This is because TRACE and NAICS databases had limited bond coverage during the early years. We rely on NAICS bond database before 2002, which reports only bond trades executed by national insurance companies. For TRACE, it was not until March 2003 that it began to cover all the bonds with an issue size of at least $100 million that were rated "A" or higher. Nevertheless, in subsequent years, the coverage has steadily increased. The Traded-CDS sample for bonds is constructed in the same manner as for the stocks. Panel B of Table IA7 shows a large reduction in the number of observations from the Full sample to the Traded-CDS sample. The number of unique firms in the Traded-CDS sample is only 123 (as opposed to 672 unique firms for the full sample) Therefore, we rely mainly on the Full sample when interpreting the results.

Table IA8 reports the mean bond cumulative abnormal returns (CAR) for the pre- and post-CDS trading periods. The results in Panel A are based on the full sample. Consistent with prior literature (Hand, Holthausen, and Leftwich (1992)), we find that bond prices react significantly to downgrades (-2.39%) but little to upgrades (0.0%). We find that average bond price reactions to rating upgrades in the post-CDS period is negative, but not significant. Panel A shows the mean of bond CARs to downgrades are negative and significant at the 1% level for both pre-CDS and post-CDS periods. However, the magnitude of bond price reaction is significantly weaker in the post-CDS period. The mean CARs for the pre- and post-CDS cases are -3.37% and -1.44%, respectively, and their difference is significant at the 1% level. To rule out concerns that our results are due to outliers, we verify that

[26] Sampling over smaller event windows such as (-3,+3) and (-5,+5) lead to a very small sample of unique firms. On the other hand, extending the sampling window – e.g., (-15,+15) would increase the bias due to confounding information arrivals (see Shivakumar, Urcan, Vasvari, and Zhang (2010), and Elkamhi, Jacobs, Langlois, and Ornthanalai (2011)).

the difference in the means of bond CARs to rating downgrades is statistically significant using the bootstrapped standard error. As for upgrades, the difference between bond price reactions in the pre- and post-CDS cases is not significant. This set of results is consistent with our findings on stock price reactions to rating change announcements.

Panel B of Table IA8 displays results for the Traded-CDS sample, which represents firms that have CDS traded at some point during 1996–2010. Again, we find that the overall bond price reaction to downgrades is negative (-1.91%) and significant at the 1% level. Consistent with our hypothesis, the magnitude of the bond price reaction is weaker in the post-CDS period (-1.61%) than in the pre-CDS period (-2.61%), although not significant. The fall in statistical power is clearly due to the small sample size. Also, most of the post-CDS downgrades for the bond sample occurs during the crisis, i.e. 2007-2009, which could systematically amplify the magnitude of bond price reaction to rating downgrade announcements.

Appendix IA.4 Primary market bond yields

This section tests whether CDS spreads are useful relative to credit ratings in explaining the primary market bond yields. Table IA6 reports the cross-sectional regression results where the dependent variables are corporate bond yields, in basis points, observed at their primary bond issuance. We report results for four regression specifications. We include rating-level, firm-level, and bond-issuance-level controls in the regressions. Where appropriate, the control variables are lagged by one period. Industry, year, and rating agency fixed-effects are also included. Appendix B describes the control variables. We use lagged CDS quotes that are traded immediately prior to the bond issuance in order to avoid the endogeneity concern that bond yields and CDS spreads are jointly determined.

In regression models (I) and (II), we compare the relative explanatory power of *Credit Rating* and *CDS Spread* to explain the cross section of primary market bond yields. *Credit Rating* is expressed on the cardinal scale (see Table B1 for mapping), and *CDS Spread* is expressed in basis points. The coefficient on *Credit Rating* in regression model (I) is 17.18 and significant at the one percent level, suggesting that credit ratings are useful for explaining the cross-section of newly issued bond yields. However, we find that once *CDS Spread* is introduced as a variable in the regression (see regression model (II)), the size of coefficient on *Credit Rating* decreases by a third to 6.18. We also find a substantial increase in adjusted R^2 when *CDS Spread* is added to the list of explantory variables —from 58.3 to 71.5 percent. We conclude that CDS spreads significantly help explain the cross-sectional variations in primary market bond yields in addition to credit ratings.

Because the *Credit Rating* variable is discrete while the *CDS Spread* is a continuous variable, we facilitate their comparison by expressing them as credit rating classes, which range from 1 to 6. The mapping between credit rating scales to credit rating classes is shown in Table B1. For CDS spreads, we use the CDS-implied rating classes calculated non-parametrically in Section 5.1. Regression models (III) and (IV) in Table IA6 report results where both CDS spreads and credit ratings are converted to the same unit of measurement, i.e., credit rating classes. We find that the results remain qualitatively similar when using rating classes to define credit ratings and CDS spreads. There is a substantial increase in adjusted R^2 when *CDS-implied rating classe* is added to the list of explantory variables – from 57.9 percent in regression model (III) to 71.1 percent in regression model (IV). Overall, we find that CDS spreads provide incremental information for the pricing of primary market bond issuance.

Appendix IA.5 CDS-implied equity risk premia

This Appendix section describes how we empirically estimate the equity risk premia implied from CDS spreads as shown in equation (18) of the main paper. For convenience, we replicate the equation below

$$ERP_{t+\tau}^{T} \equiv -\left(\frac{\log E_t^{\mathbb{P}}\left[S_{t+\tau}^{T}\right] - \log E_t^{\mathbb{Q}}\left[S_{t+\tau}^{T}\right]}{\sqrt{\int_t^{t+\tau} \sigma_{S,u}^2 du}}\right) \cdot \sqrt{\int_t^{t+\tau} \sigma_{E,u}^2 du}, \tag{19}$$

The equation above shows that calculating implied equity premium requires evaluating the $\mathbb{Q}$- and $\mathbb{P}$-measure expectations of future T-year CDS spreads. The expected risk-neutral CDS spreads can be represented using the firm's forward CDS spread, $\log E_t^{\mathbb{Q}}\left[S_{t+\tau}^{T}\right] = F_t^{\tau\times T}$, where $F_t^{\tau\times T}$ is the forward T-year CDS spread contracted at time t for delivery at time $t+\tau$.

As a result, we can write the CDS Sharpe ratio in equation (19) as

$$SR_{t+\tau} = \frac{\log E_t^{\mathbb{P}}\left[S_{t+\tau}^{T}\right] - F_t^{\tau\times T}}{\sqrt{\int_t^{t+\tau} \sigma_{S,u}^2 du}}. \tag{20}$$

Relying on the established approach in Cochrane and Piazzesi (2005) who estimated bond risk premia using the term structure of forward rates, Friewald, Wagner, and Zechner (2014) suggest that CDS Sharpe ratio in equation (20) can be estimated from the term structure of forward CDS spreads for contracts with maturities $T_k \in T = \{1, 3, 5, 7\}$,

$$\overline{SR}_{t+\tau} = \frac{1}{4}\sum_{T_k\in T} \frac{\log S_{t+\tau}^{T_k} - F_t^{\tau\times T_k}}{SD_{t+\tau}},$$

where $SD_{t+\tau}$ refers to the sample standard deviation of daily CDS spread returns between t and $t+\tau$. The above method yields time-series of CDS Sharpe ratio estimated from daily cross-maturity CDS spreads and CDS forward spreads. In order to extract the common component similar to that in Cochrane and Piazzesi (2005), we regress daily time-series of $\overline{SR}_{t+\tau}$ on $\mathbf{F}_t = \left(1, S_t^1, F_t^{3\times 1}, F_t^{5\times 1}, F_t^{7\times 1}\right)$, a vector of one-year CDS spread and one-year CDS forward spreads that start in 1, 3, 5, and 7 years. That is, we estimate

$$\overline{SR}_{t+\tau} = \gamma' \cdot \mathbf{F}_t + \varepsilon_{t+\tau}. \tag{21}$$

The fitted value of the estimated Sharpe ratio is then used for the implied equity premium calculation, which according to equation (18), is given by

$$\widehat{ERP}_{t+\tau} = -\widehat{\gamma} \cdot \mathbf{F}_t \widehat{\sigma}_{E,t,\tau}, \tag{22}$$

where $\widehat{\sigma}_{E,t,\tau}$ denotes the time-t conditional equity volatility estimated as the sample standard deviation of daily equity returns from $t-\tau$ to t.

For our empirical analysis, we estimate one-year CDS-implied equity risk premium in equation (22) on a daily basis for each firm in the sample. We use a one-year estimation window in the regression model (21) to obtain $\widehat{ERP}_{t+\tau}$ with τ equal to one year. In order for firms to be eligible for the $\widehat{ERP}_{t+\tau}$ calculation, it must have sufficient data on CDS quotes at maturities 1, 3, 5, 7, and 10 years.

Table IA9 reports results from constructing monthly portfolio sorts based on CDS-implied equity risk premia (ERP*)*. In Panel A, we report the mean characteristics of quintile sorted portfolios that are formed monthly based on ERP. The means of portfolio characteristics are calculated using equal weights. Because the start dates of CDS trading differ across firms, the number of firms available in monthly cross-sections also varies, but mostly increase from 2001 through 2010. On average, there are 72 firms available for quintile portfolio sorting each month. Panel A of Table IA9 shows no monotonic pattern in portfolio characteristics sorted based on CDS-implied equity premia. The equity risk premia estimated from CDS spreads are not related to firms' size or market-to-book values. We also do not find that ERP monotonically explains firms' cross-sections of credit ratings, as well as CDS spread levels.

Panel B of Table IA9 reports average one-year return of five portfolios sorted monthly based on ERP, credit ratings, and CDS spreads. We assign equal weight to firms in each porfoltio. We find a clear and distinct monotonic pattern in equity returns across the five portfolios. Firms with higher equity risk premia implied by their CDS spreads earn higher returns, consistent with the prediction of structural models, e.g. Merton (1974). The difference in one-year average returns between the highest (5) and lowest (1) ERP portfolios is economically large, with the magnitude of about 24% per year. The t-statistic associated with this magnitude is 13.0, suggesting an overwhelmingly strong statistical significance. Friewald, Wagner, and Zechner (2014) find the difference between the highest and lowest portfolios sorted by one-month ERP is about 1.51% per month after the risk-free rate (i.e., 18.12% per year). Thus, our results are roughly in line with theirs.

Panel B also shows that average one-year returns of portfolios sorted monthly based on credit ratings and CDS spreads do not monotonically explain the cross-section of equity returns. Sorting portfolios based on credit rating scales result in a 7.1% difference in average one-year returns between the worst-rated (5) and best-rated (1) firms. The finding is much weaker when we sort portfolios based on the level of CDS spreads. We do not find any significant difference in one-year portfolio returns between the highest (5) and lowest (1) CDS spread firms. Overall, Panel B shows that ERP estimated from CDS term structures are informative of equity returns, while the level of CDS spreads alone are not. Further, the findings suggest that ratings issued by credit rating agencies are not a good measure of default risk premium, and hence cannot explain cross-section of equity returns equally well relative to the ERP estimated from CDS spreads.

Table IA1: Distribution of bond rating changes

The sample consists of 4,665 downgrades and 2,171 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period) and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. Panel A reports year-by-year distribution of rating changes. Count represents the number of rating changes. Size represents the mean of the cardinal value of the new rating minus the cardinal value of the old rating. Bond ratings are converted to a cardinal scale measured on a 23-point scale (see Appendix A for the mapping). Panel B reports the number of rating changes and the average sizes of rating changes for the "Full Sample" and the "Traded-CDS". The full sample represents the entire sample period consisting of firms that have and do not have CDS traded on their debts. Traded-CDS sample consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010.

Panel A: Distribution of number and size of bond rating changes by year

	Downgrades				Upgrades			
Year	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
1996	16	1.31			31	1.23		
1997	149	1.39			206	1.35		
1998	251	1.65			195	1.52		
1999	310	1.63			147	1.23		
2000	428	1.73			128	1.34		
2001	556	1.92	12	1.25	99	1.42		
2002	510	1.74	72	1.25	66	1.45	4	1.00
2003	226	1.76	109	1.25	85	1.47	20	1.05
2004	131	1.63	108	1.31	97	1.33	73	1.25
2005	110	1.49	128	1.59	71	1.76	95	1.25
2006	98	1.23	170	1.60	95	1.22	132	1.17
2007	101	1.60	181	1.56	81	1.26	134	1.22
2008	112	1.56	290	1.62	58	1.24	77	1.31
2009	178	1.70	258	1.83	35	1.57	43	1.81
2010	73	1.42	88	1.27	88	1.38	111	1.28
Total	3249	1.69	1416	1.55	1482	1.38	689	1.27

Panel B: Distribution of number and size of bond rating changes by sub-sample

	Downgrades				Upgrades			
Sample	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
Full sample	3249	1.69	1416	1.55	1482	1.38	689	1.27
Traded-CDS sample	803	1.45	1029	1.49	300	1.22	574	1.29

Table IA2: Sample distribution by magnitude of rating changes

The sample consists of 4,665 downgrades and 2,171 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period) and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. In Panel A, *Freq* represents the number of rating changes. Bond ratings are converted to a cardinal scale measured on a 23-point scale. *Scale change* represents the absolute change, in cardinal value, of the new rating minus the old rating. *Pct* represents the percentage of rating changes observed in each scale change group. Panel B reports the distribution of rating changes for three rating-change classifications. A rating change is classified as "Within letter grade" if it is within the same letter group (e.g., A+, A, A-). All other rating change events are classified as "Across letter grade" as their change is from one letter group to a different letter group. We classify a rating change as "Across Inv Grade" if the change is from an investment grade to a speculative grade or vice-versa. Investment grade rating for S&P and Fitch corresponds to rating levels of BBB and above. Investment-grade rating for Moody's corresponds to rating levels of Baa and above.

Panel A: Sample distribution by absolute magnitude of rating changes

Scale change	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)
1	1945	59.86	979	69.14	1168	78.81	557	80.84
2	802	24.68	272	19.21	206	13.90	102	14.80
3	299	9.20	82	5.79	56	3.78	19	2.76
4	106	3.26	39	2.75	26	1.75	4	0.58
5	42	1.29	22	1.55	7	0.47	5	0.73
6	20	0.62	10	0.71	5	0.34		
7	15	0.46	7	0.49	5	0.34		
8	10	0.31	2	0.14	1	0.07	2	0.29
9	5	0.15			2	0.13		
10	3	0.09			1	0.07		
11	2	0.06	2	0.14	3	0.20		
12					1	0.07		
14			1	0.07	1	0.07		
Total	3249	100.00	1416	100.00	1482	100.00	689	100.00

Panel B: Sample distribution within and across rating

	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)	Freq	Pct(%)
Within letter grade	1714	52.75	655	46.26	592	39.95	258	37.45
Across letter grade	1535	47.25	761	53.74	890	60.05	431	62.55
Across Inv grade	367	11.30	206	14.55	167	11.27	79	11.47

Table IA3: Stock price reactions to bond rating changes: Robustness I

This table reports regression results of stock price reactions to bond rating changes. The sample consists of credit rating change events on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *market model*. Panel A consists of the full sample and includes Industry×Year fixed effects to control for time-varying industry-level fixed effects. Panel B consists of only non-financial firms. All the variables are defined in Appendix A. *dCDS* is an indicator variable equal to one when the firm has CDS contracts traded on its debt, and zero otherwise. Coefficients on other controls have been omitted to conserve space. Robust t-statistics are clustered at the firm-level and reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Time-varying industry-level FE

	Downgrades	***Upgrades***
	Full sample	**Full sample**
	(I)	(I)
dCDS	1.25*	0.14
	(1.80)	(0.53)
Rating controls	✓	✓
Firm controls	✓	✓
CDS-trading controls	✓	✓
Fixed effects	Ind×Year	Ind×Year
Observations	4176	1972
Adjusted R^2	0.126	0.009

Panel B: Non-financial firms

	Downgrades				***Upgrades***			
	Full sample			**Traded-CDS**	**Full sample**			**Traded-CDS**
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
dCDS	2.61***	1.80**	1.53**	2.62***	-0.34	-0.11	-0.04	-0.14
	(4.35)	(2.44)	(2.45)	(3.75)	(-1.40)	(-0.44)	(-0.14)	(-0.33)
Rating controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind	Ind	Ind & Year	Ind ×Year	Ind
Observations	3333	3333	3333	1559	1623	1623	1623	729
Adjusted R^2	0.126	0.129	0.136	0.082	0.001	-0.004	0.010	-0.004

Table IA4: Stock price reactions to bond rating changes: Robustness II

This table reports regression results of stock price reactions to bond rating changes. The sample consists of credit rating change events on taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. In Panel A the dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *Fama-French 3 factor model*. In Panel B the dependent variable is the cumulative abnormal return (CAR) calculated over the 3-day event window (-1,+1) using the *market model*. All the variables are defined in Appendix A. *dCDS* is an indicator variable equal to one when the firm has CDS contracts traded on its debt, and zero otherwise. In Panel B *dDowngrade* is an indicator variable equal to one if the rating change is a downgrade, and zero for an upgrade. We also interact all rating controls with *dDowngrade*. Coefficients on other controls have been omitted to conserve space. Robust t-statistics are clustered at the firm-level and reported in brackets below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Fama-French 3 factor adjusted CAR

	Downgrades				***Upgrades***			
	Full sample			**Traded-CDS**	**Full sample**			**Traded-CDS**
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
dCDS	1.86***	1.52**	1.12*	2.29***	-0.17	-0.06	0.04	0.05
	(3.09)	(2.18)	(1.69)	(3.36)	(-0.74)	(-0.22)	(0.15)	(0.12)
Rating controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind	Ind	Ind & Year	Ind ×Year	Ind
Observations	4176	4176	4176	1775	1972	1972	1972	834
Adjusted R^2	0.123	0.124	0.127	0.092	0.002	0.003	0.017	-0.001

Panel B: Pooled Downgrades & Upgrades

	Full sample			**Traded-CDS**
	(I)	(II)	(III)	(IV)
dCDS×dDowngrade	1.61***	1.65***	1.48**	1.38*
	(2.70)	(2.81)	(2.56)	(1.83)
dDowngrade	-3.23***	-3.30***	-3.09***	-3.13***
	(-8.51)	(-8.14)	(-7.16)	(-4.29)
dCDS	0.28	0.05	-0.18	0.88
	(0.76)	(0.13)	(-0.44)	(1.62)
Rating controls	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind ×Year	Ind
Observations	6148	6148	6148	2609
Adjusted R^2	0.133	0.134	0.138	0.091

Table IA5: Diff-in-diff downgrade CAR regression: 1–to–1 matching without replacement

This table reports diff-in-diff regression analysis of stock price response CAR(-1,1) to bond downgrades for the propensity-score matched sample. One non-traded-CDS (control) firm is matched to one traded-CDS (treated) firm without replacement. The caliper and common support conditions are not imposed for this 1:1 matching exercise. Panel A reports the main diff-in-diff regression results for the matched sample. Panel B reports matching diagnostics via a probit regression before and after matching. All the variables are defined in Appendix A. Coefficients on other controls have been omitted to conserve space. Robust t-statistics clustered at the firm-level and are reported in bracket below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: 1:1 Matched Sample

	Diff-in-diff		***Subsamples (diagnostics)***			
			Treatment	Control	Post-CDS	Pre-CDS
	(I)	(II)	(III)	(IV)	(V)	(VI)
dTreatment×dCDS	2.50***	2.42***				
	(2.64)	(2.63)				
dCDS	-0.79	-1.78	1.91**	-1.03		
	(-0.95)	(-1.59)	(2.45)	(-1.25)		
dTreatment	-0.09	-0.29			2.12**	0.17
	(-0.11)	(-0.39)			(2.29)	(0.19)
Rating controls	✓	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓
Fixed effects	Ind	Ind & Year	Ind	Ind	Ind	Ind
Observations	2883	2883	1797	1086	1753	1130
Adjusted R^2	0.097	0.099	0.087	0.109	0.105	0.103

Panel B: 1:1 Matching Diagnostics via Probit Regression

	Before matching	***After matching***		***Before matching***	***After matching***
Sales (log)	0.40***	0.48***	Analyst Coverage (log)	0.03**	0.29**
	-36.44	-5.43		-2.57	-2.51
Profitability	-0.53***	1.39	Analyst Dispersion	0.00***	0
	(-8.14)	-1.49		-3.66	-0.87
Leverage	0.26***	0.45	Institutional Ownership	0.26***	0.29
	-5.05	-0.68		-8.76	-0.87
Market-to-Book	-0.01***	0.02	Stock Illiquidity	-3.27***	-2.13*
	(-2.78)	-0.54		(-7.94)	(-1.79)
Rating Scale (log)	-0.26***	-0.84**	Bond Illiquidity	0.66***	1.14***
	(-9.10)	(-2.09)		-56.56	-7.01
Avg Return	0.08	1.08*	Debt Outstanding (log)	0.40***	0.72***
	-1.03	-1.72		-34.27	-4.66
Avg Volatility (log)	-0.06***	0.4	Forex Derivative Hedging (%)	0.04***	0.00
	(-3.06)	-1.45		-7.23	-0.02
Avg Trading Volume (log)	0.11***	-0.02			
	-10.34	(-0.15)			
Observations	52440	484			
Pseudo R^2	0.49	0.60			

Table IA6: Primary market bond yields regression

This table reports regression results for the determinants of primary market bond yields. The sample consists of coporate bonds issued by firms that have CDS contracts trading on their debt. The dependent variables are corporate bond yield spreads (in bps) observed at issuance. Regression models (I) and (II) examine the explanatory power of credit rating levels and lagged CDS spreads. *Credit Rating* is the rating level, in cardinal scale, issued by the credit rating agency. *CDS Spread* is the firm's 5-year CDS spread (in bps) last observed prior to the bond issuance date. In regression models (III) and (IV), credit rating and CDS-implied rating are expressed as rating class, i.e. between 1 to 6; see Table B1 for mapping. *CDS-implied rating class* is calculated using the nonparametric method described in Section 5.2. We include various issuance-level and firm-level controls in the regressions. *Subordinate* is an indicator variable equal to one if the issued bond is a subordinate debt, and zero otherwise. *Callable* is an indicator variable equal to one if the issued bond has a callable option. *Issue Size* is the log of the notational amount (in $) of the bonds issued. *Maturity* is the maturity of the issued bond. Firm-level characteristics are calculated using information in the quarter prior to bond issuance; see Appendix B for details. *Treasury Slope* is the difference between 10-year and 1-year treasury yields. All regressions include industry, year, and rating agency fixed-effects. Robust t-statistics are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

Dependent variable: Primary market bond yields (bps)				
	(I)	(II)	(III)	(IV)
Credit Rating (cardinal scale)	17.18***	6.18***		
	(9.84)	(4.57)		
CDS Spread (bps)		0.58***		
		(9.91)		
Credit Rating class			49.23***	12.76***
			(9.13)	(2.97)
CDS-implied Rating class				56.34***
				(15.51)
Issuance-level controls				
Subordinated	23.66**	23.87***	21.44**	25.61***
	(2.30)	(3.10)	(2.21)	(3.19)
Callable	-3.83	-0.42	-1.57	-1.23
	(-0.52)	(-0.07)	(-0.21)	(-0.20)
Issue Size (log)	51.16***	48.86***	49.99***	46.89***
	(5.40)	(4.89)	(5.37)	(5.27)
Maturity (yrs)	0.87***	1.09***	0.90***	1.17***
	(3.70)	(5.77)	(3.92)	(5.62)
Other controls				
Sales (log)	-19.57***	-21.89***	-19.13***	-21.04***
	(-4.24)	(-5.30)	(-4.06)	(-5.41)
Profitability	-17.88	-11.96	-21.07	-18.18*
	(-1.49)	(-1.05)	(-1.62)	(-1.75)
Long-Term Debt-to-Assets	8.89	-43.01	7.69	-43.84
	(0.27)	(-1.55)	(0.24)	(-1.61)
Leverage	0.83	-1.89	0.48	-2.59**
	(0.65)	(-1.57)	(0.36)	(-2.16)
Treasury Slope (10yr-1yr)	5.02	1.43	7.17	3.05
	(0.68)	(0.21)	(0.98)	(0.46)
Rating-type FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2208	2208	2208	2208
Adj. R^2	0.583	0.715	0.579	0.711

Table IA7: Distribution of bond rating changes: Bond market reaction sample

We report the distribution of bond rating change events used in the bond market reaction analysis. The full sample consists of 2,336 downgrades and 1,019 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. The sample is split between rating changes that occur in the presence of CDS trading (post-CDS period), and in the absence of CDS trading (pre-CDS period) on the underlying firm's debts. Panel A reports year-by-year distribution of rating changes. Count represents the number of rating changes. Size represents the mean of the cardinal value of the new rating minus the cardinal value of the old rating. Bond ratings are converted to a cardinal scale measured on a 23-point scale (see Table B1 for the mapping). Panel B reports the number of rating changes and the average sizes of rating changes for the "Full Sample" and the "Traded-CDS". The full sample represents the entire sample period consisting of firms that have and do not have CDS traded on their debts. Traded-CDS sample consists only of firms that have CDS trading at any point in our sample period, i.e from 1996 to 2010.

Panel A: Distribution of number and size of bond rating changes by year

Year	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
1996	3	1.00			2	1.00		
1997	8	1.25			16	1.31		
1998	22	1.50			23	1.35		
1999	35	1.43			21	1.14		
2000	71	2.15			17	1.82		
2001	140	2.31	11	1.18	29	1.97		
2002	208	1.96	47	1.26	16	1.19	3	1.00
2003	94	1.93	83	1.22	32	1.41	15	1.07
2004	48	1.56	92	1.33	40	1.40	38	1.16
2005	81	1.65	122	1.64	43	1.67	74	1.26
2006	71	1.38	164	1.80	82	1.48	133	1.11
2007	79	1.59	151	1.74	64	1.69	130	1.22
2008	95	1.48	240	1.66	32	2.69	70	1.69
2009	160	1.87	244	1.70	33	2.18	53	2.51
2010	36	1.44	31	1.23	16	1.25	37	1.59
Total	1151	1.81	1185	1.61	466	1.64	553	1.40

Panel B: Distribution of number and size of bond rating changes by sub-sample

Sample	Downgrades				Upgrades			
	Pre-CDS		Post-CDS		Pre-CDS		Post-CDS	
	Count	Size	Count	Size	Count	Size	Count	Size
Full sample	1151	1.81	1185	1.61	466	1.64	553	1.40
Traded-CDS sample	237	1.48	465	1.58	55	1.09	296	1.35

Table IA8: Bond price response to credit rating downgrades and upgrades

This table reports cumulative abnormal returns (CAR) of bond price to credit rating downgrades and upgrades.The full sample consists of 2,336 downgrades and 1,019 upgrades of taxable corporate bonds issued by U.S. firms from January 1996 to December 2010. Table IA7 in the appendix reports the distribution of bond rating changes used in this analysis. Panel A reports results for the full sample, while Panel B reports results for the traded-CDS sample. The traded-CDS sample (Panel B) consists only of firms that have CDS trading at any points in our sample period. In each panel, the sample is split between rating changes that occur in the presence of CDS trading (Post-CDS period) and in the absence of CDS trading (Pre-CDS period) on the underlying firm's debts. Cumulative abnormal bond return is defined as the firm's value-weighted bond portfolio's excess return against the bond return of a matching portfolio based on Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, and B). The event window is the shortest trading window within (-7,+7) calendar days relative to the rating change event day. T-statistics are displayed in square brackets. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Full sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-3.37***	1151	0.12	466
	(-10.25)		(1.11)	
Post-CDS	-1.44***	1185	-0.11	553
	(-4.44)		(-1.10)	
Difference (Pre–Post)	1.93***		-0.23	
	(4.18)		(-1.57)	
Total	-2.39***	2336	-0.00	1019
	(-10.32)		(-0.06)	

Panel B: Traded-CDS sample

	Downgrades		Upgrades	
	Mean CAR(%)	Count	Mean CAR(%)	Count
Pre-CDS	-2.61***	237	0.09	55
	(-4.01)		(0.26)	
Post-CDS	-1.61***	465	-0.25**	296
	(-3.46)		(-1.74)	
Difference (Pre–Post)	1.00		-0.34	
	(1.25)		(-0.93)	
Total	-1.94***	702	-0.20	351
	(-5.14)		(-1.49)	

Table IA9: CDS-implied equity risk premium and portfolio characteristics

This table reports means of portfolio characteristics and one-year average portfolio returns sorted by CDS-implied equity risk premia (ERP). The sample consists of U.S. firms that have CDS contracts with maturity of 1, 3, 5, 7, 10 years trading on their debts. We calculate daily CDS-implied ERP with one-year horizon for each reference entity using its CDS term structure. We follow the method in Friewald, Wagner, and Zechner (2014) for calculating ERP, which is motivated by Cochrane and Piazzesi (2005) who estimated bond risk premia using the term structure of forward rates. Section 7 describes the procedure for calculating ERP. In Panel A, we report the mean characteristics of quintile sort portfolios that are formed monthly based on based on CDS-implied ERP. The means of portfolio characteristics are calculated using equal weights and the sorting is done at the beginning of each month. Because the start dates of CDS trading differ across firms, the number of firms available in monthly cross-sections also varies, but mostly increase from 2001 through 2010. We require a minimum of 20 firms in the cross section to execute the portfolio sorts. *Size* is the log of firm's market capitalization. *Mkt-to-Book* is the ratio of a firm's market value of total assets to its book value of total assets. *Credit rating* is the average firm's credit ratings, in cardinal scale, given by the three agencies: Moody's, Fitch, and S&P. *CDS spread* is the 5-year CDS spread level of the firm. In Panel B, we report average one-year equity returns of portfolios sorted monthly based on ERP, credit ratings, and CDS spreads. The fifth (highest) quintile portfolio corresponds to firms with the highest ERP, lowest-rated firms, and largest CDS spreads. Newey-West t-statistics adjusted for 11 lags are reported in brackets below the average portfolio returns in Panels B–C. *, **, and *** indicate significance greater than 10%, 5%, and 1%, respectively.

Panel A: Portfolio characteristics sorted by CDS-implied ERP

	Average values				
	ERP	Size	Mkt-to-Book	Credit rating	CDS spread
1 (lowest ERP)	-0.005	15.753	2.486	9.105	0.015
2	0.005	21.289	2.931	7.913	0.006
3	0.009	22.842	2.806	8.151	0.007
4	0.016	18.925	2.635	8.739	0.011
5 (highest ERP)	0.034	12.095	2.392	10.016	0.025

Panel B: Average one-year returns of single-sorted portfolios

	Average one-year return		
	Sorted by ERP	Sorted by Credit ratings	Sorted by CDS spreads
1 (lowest)	-0.141***	-0.044***	-0.011*
	(-10.81)	(-3.80)	(-1.44)
2	-0.042***	-0.018*	-0.015**
	(-4.76)	(-1.53)	(-1.89)
3	-0.012*	-0.023**	-0.018**
	(-1.55)	(-1.97)	(-1.90)
4	0.020**	-0.018*	-0.032***
	(2.31)	(-1.44)	(-2.75)
5 (highest)	0.086***	0.012	-0.020
	(7.10)	(0.69)	(-1.12)
5−1	0.227***	0.056***	-0.009
	(13.16)	(2.64)	(-0.46)