Are Credit Ratings Still Relevant?

Sudheer Chava   Rohan Ganduri   Chayawat Ornthanalai*

ABSTRACT

We find that a firm's stock price reaction to its credit rating downgrade announcement is muted by 44–52% when credit default swaps (CDSs) trade on its debt. The impact of CDS trading is more pronounced for firms whose debt financing is more sensitive to credit ratings (e.g., those rated just above the speculative-grade boundary, those with a high number of rating-based covenants). Reductions in debt and investment, and the increase in financing costs are less severe for CDS firms after a credit rating downgrade. Our results suggest that CDSs mitigate the debt-financing frictions faced by downgraded firms.

JEL Classification: G18, G14, G12, G28, G33, G38

Keywords: Credit ratings; Credit default swaps; Financial regulations.

*Sudheer Chava can be reached at Scheller College of Business at the Georgia Institute of Technology, 800 W. Peachtree St NW, GA 30309-1148; *Phone:* 404-894-4371; *Email:* sudheer.chava@scheller.gatech.edu. Rohan Ganduri can be reached at Goizueta Business School at Emory University, 1300 Clifton Rd, GA 30322; *Phone:* 404-727-2539; *Email:* rohan.ganduri@emory.edu. Chayawat Ornthanalai can be reached at Rotman School of Management at the University of Toronto, 105 St.George St, Toronto, ON, Canada, M5S 3E6; *Phone:* 416-946-0669; *Email:* chay.ornthanalai@rotman.utoronto.ca. We are grateful to the Q-group for financial support. Ornthanalai acknowledges research funding support from the Social Science and Humanities Research Council (SSHRC). We would like to thank Pat Akey, Tarun Chordia, Jan Ericsson, Kris Jacobs, Robert Jarrow, Narayan Jayaraman, Narasimhan Jegadeesh, Madhu Kalimipalli, Gonzalo Maturana, Lars Norden, Stuart Turnbull, seminar participants at Scheller College of Business, Georgia Tech, Southern Methodist University, University of Alberta, Bank of Canada, University of Oklahoma, University of Maastricht, University of Rotterdam, European School of Management and Technology, Berlin, participants at 2012 European Finance Association Annual Meeting, 2013 Western Finance Association Annual Meetings, First IFSID Conference on Structured Products and Derivatives, and the 23rd Derivatives Conference at FDIC for helpful comments and suggestions.

I. Introduction

Credit rating agencies, which issue an assessment of a firm's credit worthiness, are considered an integral part of the financial landscape. The extant literature suggests that credit rating agencies exist for two broad reasons: First, they relieve information frictions between lenders and borrowers in the credit market by acting as certification providers (Bongaerts, Cremers, and Goetzmann (2012)). Second, as intermediaries, they act as delegated information acquirers and monitoring agents, thus avoiding duplicative costs.[1] These roles of credit rating agencies enable firms and creditors to enter into contracts that link a firm's cost of debt to credit ratings (Asquith, Beatty, and Weber (2005)), and also allow regulators to rely on them.[2]

When a firm's cost of debt financing is linked to its credit rating, a rating change can impact its cost of capital, its investment, and ultimately its expected return.[3] Further, Manso (2013) suggests that the contractual and regulatory dependence of the credit market on credit ratings can potentially create feedback effects, wherein rating downgrades trigger other events that worsen the downgraded firms' loss in access to and cost of financing. A downgrade, especially from an investment grade to a speculative grade, can lead to a reduction in the investor pool. Downgrades can also trigger debt covenants, which can increase the interest payment or lead to debt repurchases (see Kisgen (2007)). Underscoring the importance of credit ratings, the previous literature documents that the equity market reaction to credit rating downgrade announcements is significantly negative (e.g., Hand, Holthausen, and Leftwich, 1992; Dichev and Piotroski, 2001; Jorion, Liu, and Shi, 2005).

In this paper, we examine how the introduction of Credit Default Swaps (CDS)—an insurance contract against the default of an underlying firm's debt—affects the economic role of credit rating agencies. We show that when CDSs are trading on a firm, its equity market reaction to credit rating downgrades is muted by 44–52% relative to rating changes in the absence of CDS trading. We shed light on two important aspects that explain our results. First, we show that the regulatory and contractual dependence of the credit market on credit ratings magnifies the adverse effects of a credit rating downgrade on firms' access to and cost of debt financing. Second, our results suggest that CDS trading alleviates these debt-financing frictions, thus explaining the muted negative equity market reaction to credit rating downgrade announcements.

[1] See for examples, Akerlof (1970); Diamond (1984); Boot, Milbourn, and Schmeits (2006); Opp, Opp, and Harris (2013).

[2] Credit ratings are employed in bank capital regulation and in the investment of money market funds. Additionally, credit ratings are used to regulate the liquidity and investment of insurance companies.

[3] In perfect capital markets (á la Modigliani-Miller), financing is irrelevant for investment. However, in the presence of information frictions, credit rating changes can have a real impact on firms.

A priori, the effect of CDSs on a firm's sensitivity to credit rating downgrades is not obvious. Saretto and Tookes (2013) find that CDSs relieve financing frictions on the supply side by providing lenders the ability to hedge credit risk. This benefit allows banks the flexibility to maintain lending relationships with a firm that has a poor credit rating while also mitigating regulatory costs.[4] This suggests that CDSs can mitigate the downgraded firms' debt-financing frictions, thus leading to a muted equity market reaction. On the other hand, CDSs can create a misalignment of incentives between a creditor and a firm, wherein creditors can over-insure using CDSs, and thus have lower incentives to monitor, or push a firm into bankruptcy in order to trigger CDS payments (e.g., Bolton and Oehmke, 2011; Subrahmanyam, Tang, and Wang, 2014). If creditors' incentive to over-insure dominates (i.e., the empty creditor problem), then a rating downgrade for CDS firms can elicit a stronger negative equity market reaction because these firms would face a greater default risk.

We test the effect of CDS introduction on the market reaction to credit rating downgrades by regressing the cumulative abnormal returns (CAR) in the 3-day window around the rating downgrade announcement on an indicator variable that signifies the presence (or absence) of CDS trading. We include *Prev-Rating*$\times$*Rating-change* fixed effects in all our regression specifications, where *Prev-Rating* is the credit rating of the firm before the downgrade and *Rating-change* is the number of downgraded notches. This allows us to estimate the difference in market reactions between CDS and non-CDS firms that are identically rated and experience the same rating change magnitude. Additionally, we control for industry-, year-month, and rating-agency fixed effects, along with the time-varying firm-level and CDS-trading controls. In this specification, the magnitude of stock market reaction to credit downgrades for CDS firms relative to non-CDS firms is lower by 44-52%. However, the introduction of CDSs is unlikely to be random across firms. In order to reduce the bias from potential omitted variables that drive the introduction of CDS, we exclude firms that never had CDS trading during our sample period. Firms in this subsample had CDS introduced at some point of time during our sample period and are more likely to be similar on observable and unobservable characteristics. For this subsample, we find that CDS trading is associated with a muted negative market reaction to rating downgrades by 67–75%.

Although we estimate the effect of CDS trading within firms that have identical rating-change events and control for time- (year-month) fixed effects, a time-varying omitted variable could still bias our results. To mitigate this concern, we focus on credit rating downgrades that occur within short time windows around the initiation of CDS trading on each

[4] Basel II and III allow banks to use CDS contracts to mitigate the credit risk exposure of their financial claims in order to lower their regulatory capital requirements, which are typically tied to the credit ratings of their financial claims.

firm (e.g., ±1, ±2, ±3 years). This allows us to compare the stock market reactions to rating downgrade events that are closer to one another in time, but occur just before and after the introduction of CDS trading. Our results are robust and stronger in this setting. We also estimate the baseline regression model within the short balanced-time windows around CDS introductions using a matched sample of CDS and non-CDS firms. This allows us to compare CDS versus non-CDS firms that are similar on multiple observable factors, especially on those that can be affected by time-varying confounding shocks. The results again show that CDS trading is associated with the muted market reaction to credit rating downgrades.

We further show that our results are robust to potential confounding time-varying omitted variables that affect the likelihood of CDS introduction and the market reaction to credit rating downgrades, by estimating a two-stage least squares/instrument variable (2SLS/IV) regression. We use two instruments for the probability of CDS introduction. The first instrument is the average foreign exchange derivatives (forex) traded for hedging purposes by a downgraded firm's lending banks, which mainly captures the cross-sectional variation in the likelihood of CDS introduction (see Saretto and Tookes (2013) and Subrahmanyam et al. (2014)). The second instrument is the growth of the aggregate CDS notional amount traded globally, which captures the time-series variation in the likelihood of CDS introduction for firms. Our results remain qualitatively unchanged in the 2SLS/IV analysis, and importantly, the point estimates on the instrumented CDS variable are comparable to those from OLS estimates.

In order to understand the economic channels through which CDS trading dampens the negative market reaction to rating downgrade announcements, we examine when and where this effect of CDS trading is most prominent. Greater understanding of these channels can also shed more light on why the equity market reacts negatively to rating downgrade announcements in the first place.

We find that the market reaction to credit rating downgrade announcements is much stronger among (a) firms that are rated just above the investment–speculative grade (IG-SG) boundary, (b) firms that have a relatively high number of rating-based performance pricing (PP) covenants, and (c) firms that have a relatively large number of outstanding bank loans. These findings suggest that the stock market reaction to rating downgrades is stronger when the downgraded firms' debt financing is more sensitive to credit ratings. For instance, a downgrade from an investment to a speculative grade would significantly reduce the pool of creditors due to the sharp increase in the regulatory costs of lending to a speculative-grade company. Creditors also often tie loan covenants to credit ratings to reflect their monitoring need as well as the regulatory costs of lending to lower-rated firms. Firms to which banks have extended more loans are more likely to be sensitive to credit rating downgrades because their lenders are subject to the capital requirement that depends on the credit ratings of their borrowers. CDS trading can alleviate these debt-financing frictions by enabling the suppliers of capital to transfer costly credit risk to investors who are subject to lower rating-based regulatory costs while maintaining lending relationships and specializing in debt origination. Consistent with this, we find that these rating-downgrade observations, in which firms' debt financing is more sensitive to credit ratings, are precisely where CDS trading significantly mutes the stock market reaction to credit rating downgrades. Further, we find that the effect of CDS trading in muting the market reaction to rating downgrades is greater during periods when the supply of credit is tight. Taken together, these results suggest that CDS trading helps relieve debt-financing frictions that downgraded firms face due to the regulatory and contractual dependence of the credit market on credit ratings.[5]

We next show that the *ex post* evidence on the downgraded firms' debt-financing decisions is consistent with the financing-frictions channel. We find that firms significantly decrease their net debt issuance and increase their net equity issuance after they have been downgraded. The overall reduction in net debt issuance relative to net equity issuance is 3.72% in the year following a rating downgrade compared to the year just before. However, for CDS firms, the overall reduction in net debt versus equity issuance is 2.28%, which is about 40% lower relative to non-CDS firms. We re-emphasize that all our analyses include *Prev-rating*×*Rating-change* fixed effects. This allows for the results to be interpreted as the difference in financing decisions between CDS versus non-CDS firms that experience identical credit rating changes. We further examine the drivers of the change in net debt issuance after a rating downgrade by decomposing it into: the issuance of new debt and the repayment of existing debt. We find that the result is driven by the greater repayment of existing debt by non-CDS firms relative to CDS firms after their credit rating downgrades. Debt repayment after a downgrade is more likely driven by rating-based covenants that either trigger a higher coupon payment or call for an accelerated principal repayment. Interest rates and the schedule of debt repayment are typically determined at issuance, and thus, without rating-based triggers, it is less likely that firms would increase their existing debt repayment immediately after the downgrade.

We compare the increase in financing costs between CDS and non-CDS firms after their credit rating downgrades. We find that the at-issuance loan spreads of non-CDS firms increase by 22.3–29.3% in the year after they have been downgraded. However, for CDS firms, the increase in the at-issuance loan spreads is roughly cut by half (or lower by 12.7–16%). These

[5]Another possibility is that CDS trading may provide information about the firm's credit quality that is not already present in stock and bond prices, thus potentially reducing the informativeness of credit rating downgrade announcements. We present some evidence for the information channel in the Internet Appendix.

results are estimated with *Prev-rating*×*Rating-change* fixed effects, which help control for the average expected rating-based regulatory costs incurred by creditors who lend to firms that experience identical credit rating changes. Assuming that most of these costs are passed on to the borrowing firm, our results suggest that the rating-based regulatory costs associated with lending to a CDS firm is roughly half that of a similarly rated non-CDS firm. Consistent with the higher costs borne by firms after a credit rating downgrade, we find that non-CDS firms reduce investment by 1.2–2.2% per quarter in the year after they have been downgraded compared to the year just before. However, for CDS firms that experience an identical credit rating downgrade, we do not find any reduction in their investment.

The reliance of the credit market on credit ratings has been shown to create an *ex ante* incentive for firms to alter their financing decisions in order to avoid being downgraded (e.g., Kisgen, 2006; Kisgen and Strahan, 2010). One criterion on which credit ratings agencies base their assessment of a firm's credit quality is a firm's Debt/EBITDA ratio. The thresholds (min and max) of this ratio are somewhat arbitrary and based on simple intervals such as 2.0 and 2.5 (Begley (2015)). We use Begley's (2015) definition of rating-based salient thresholds based on the Debt/EBITDA ratio to classify firms according to whether they have high (or low) incentives to manage debt capital. We find that firms that have Debt/EBITDA ratios close to the salient thresholds, as outlined by credit rating agencies for downgrades, improve their Debt/EBITDA ratios by reducing their net debt issuance in the order of 1.92–2.02% per quarter, relative to firms that are far from these salient thresholds. However, the decrease in net debt issuance is dampened by 0.65–0.71% per quarter for CDS firms that are close to rating-based salient thresholds. These estimates are economically large, which implies that CDS trading lowers the sensitivity of firms' net debt issuance to credit ratings by about 2.8% per year. We note that this final analysis is not conditional on a rating event. Therefore, the analysis allows us to draw more general conclusions between CDS firms and non-CDS firms, about the reliance of debt-financing decisions on firms' credit ratings. Additionally, we show that the distribution of firms in our sample, in relation to these Debt/EBITDA thresholds, are independent of whether firms have CDS trading on their debt. Therefore, the results from our final test could be interpreted as causal evidence that the reliance of firms' debt-financing decision on credit ratings is weakened in the presence of CDS trading.

Our paper contributes primarily to two strands of literature. The first is the literature on credit ratings, which documents abnormal stock and bond market returns to credit rating downgrades (See for examples, Holthausen and Leftwich (1986), Hand et al. (1992), Goh and Ederington (1993), Dichev and Piotroski (2001), and Jorion et al. (2005).) Most of these studies highlight the role of credit ratings in providing information on the credit quality of firms. For instance, Goh and Ederington (1993) document that a rating downgrade due to the deterioration of a firm's financial prospects produces a negative abnormal stock return, while downgrades due to an increase in leverage do not. Jorion et al. (2005) show that the exemption of credit ratings from Regulation Fair Disclosure (Reg FD) made rating changes more informative. Our results add to this literature by indicating that a substantial portion of the equity market reaction to credit rating downgrades is due to the regulatory and contractual dependence of credit markets on credit ratings.

Second, our paper contributes to the literature on the economic role of CDSs. In theory, a CDS contract can be replicated using a risk-free bond and a short position in the corporate bond, thus rendering CDS contracts redundant securities. However, higher illiquidity and trading costs in the bond market make the CDS market a preferred venue for trading credit risks (see Oehmke and Zawadowski (2015b), Oehmke and Zawadowski (2015a)). Saretto and Tookes (2013) show that CDS firms can maintain higher leverage ratios and can borrow at longer maturities. Our results suggest that CDSs alleviate the financing frictions that downgraded firms face due to the regulatory and contractual reliance of their debt financing on credit ratings. Consequently, we show that the presence of the CDS market can have a real impact on firms' financing and investment.

The rest of this paper proceeds as follows. Section II discusses identification challenges and our empirical specifications. Section III presents our main results. Section IV provides further evidence that CDS trading relieves financing-related frictions. Section V concludes.

II. Identification Challenges and Empirical Specifications

A. *Identification Challenges*

Empirical identification of the effect of CDS trading is challenging in our context, since the introduction of CDS trading is unlikely to be random across firms. We start by estimating the regression model in Equation (1) below, and then discuss how it mitigates the selection effect associated with CDS introduction:

$$CAR_{i,t} = \alpha + \beta \times dCDS_{i,t} + f(X_{i,t}) + \Gamma_{R,\Delta N} + \eta_{indus} + \nu_{agency} + \tau_{time} + \varepsilon_{i,t}, \qquad (1)$$

where $CAR_{i,t}$ is the 3-day cumulative abnormal return centered on the date of a rating downgrade announcement for firm i on day t. The main independent variable of interest is an indicator $dCDS_{i,t}$, which is equal to 1 if the firm has CDS contracts traded at the time of the rating change announcement, and 0 otherwise. A positive and statistically significant estimate of β would suggest that the market reaction to credit rating downgrades is less negative (i.e., muted) when the firm has CDS trading on its debt. We include $f(X_{i,t})$, which is a large set of firm-specific observables that may drive the differential market reaction between CDS firms and non-CDS firms in response to a rating downgrade.

Despite controlling for various observable characteristics, if the introduction of CDS trading is correlated with unobserved factors that also affect the market reaction to a rating change announcement, then the estimated coefficient of interest β will be biased. Moreover, the direction of this bias is not necessarily obvious. Saretto and Tookes (2013) find that CDS firms generally tend to be larger and better rated. If a firm's general improvement in credit quality leads to the introduction of CDS trading and leads to a less negative market reaction to a rating downgrade, then the bias will be positive. On the other hand, Oehmke and Zawadowski (2015a) argue that firms that face greater information asymmetry (as measured by analyst forecast dispersion) are more likely to have CDS trading on its debt. The resolution of this information asymmetry through a credit rating downgrade may lead to a more negative equity market reaction to a rating-change announcement. In this latter case, the bias for the estimated β will be negative.

We use various fixed effects in our baseline specification in Equation (1) to mitigate certain potential endogeneity concerns. We include *Prev-Rating*×*Rating-change* fixed effects represented by $\Gamma_{R,\Delta N}$ in Equation (1). This helps control for potential time-invariant unobserved rating-related factors that drive both a rating change and a CDS introduction. *Prev-Rating* is the credit rating of the firm before the downgrade, and *Rating-change* is the number of notches in the rating change announcement. The rating level and the number of notch changes are expressed in a cardinal scale from 1 (AAA/Aaa) to 23 (D). Intuitively, markets should react similarly to firms that have the same credit rating (*Prev-Rating*) and experience the same change in credit ratings (*Rating-change*). In this setting, β captures the average difference in the market reaction to rating changes between CDS firms and non-CDS firms that are identically rated and also experience the same rating-change magnitude.

The sensitivity of the overall market reaction to credit rating downgrades can vary with time. We therefore control for time fixed effects (τ_{time}) at the year-month level in Equation (1). These *Year-month* fixed effects help control for potential unobserved time-varying market-wide factors that affect the average market reaction to rating-change announcements and the initiation of CDS trading. In addition, we control for industry fixed effects (η_{indus}) using the Fama-French 12-industry classification, and control for rating-agency fixed effects (ν_{agency}) associated with the three credit rating agencies: S&P, Moodys', and Fitch. The Fama-French 12-industry classification controls for the time-invariant average sensitivity of each industry to rating change announcements. The rating-agency fixed effects control for the time-invariant average market reaction to rating changes by each credit rating agency.

Additionally, to bolster our empirical identification, we estimate the regression model in Equation (1) on subsamples of rating-downgrade observations that are within short balanced time windows (e.g., $\pm 1, \pm 2$ years) centered around the initiation of CDS trading on each firm. This approach allows us to compare the stock market reactions to rating downgrade events that are closer to one another in time, but occur just before and after the introduction of CDS trading. Thus, we are more likely to capture the effect of CDS introduction alone, while also mitigating the impact of potential time-varying omitted variables that could affect the firm's stock price reaction to rating downgrades. We apply these balanced time windows approach to estimate the effect of the *dCDS* variable in the OLS analysis, the propensity-score matched sample analysis, as well as the IV analysis.

Under the specification in Equation (1) with *Prev-Rating*×*Rating-change* fixed effects, an omitted variable that can bias the coefficient on *dCDS* must be time varying within firms that have the same credit rating, and experience the same change in credit rating (i.e. an identical rating-change event). Moreover, in the context of our analysis within the short time windows, such a time-varying omitted variable must precisely vary with the staggered CDS introduction for firms across time and also affect the market reaction to rating changes between CDS and non-CDS firms. To address such an omitted-variable concern, we employ two instruments for *dCDS* in a 2SLS/IV regression. The first instrument is the average foreign exchange derivatives (forex) traded for hedging purposes by a downgraded firm's lending banks. This instrument is described in detail in Saretto and Tookes (2013) and Subrahmanyam et al. (2014). Among banks' various derivatives activities, their forex position is more likely to reflect their hedging needs for macro risk, and thus is unlikely to be directly related to the credit rating change of the firms they lend to (*exclusion restriction*). However, on the other hand, a bank's hedging activity in the forex market likely reflects their hedging culture and thus makes them more likely to initiate CDS trading on the firms they lend to (*relevance condition*).

Our second instrument for CDS trading is the log aggregate CDS notional amount traded globally. This instrument is constructed from surveys of the International Swaps and Derivatives Association (ISDA), and is available semiannually. While our first instrument mainly captures cross-sectional variation in the likelihood of CDS introduction on firms, our second instrument captures time-series variation in the likelihood of CDS introduction on firms. Our second instrument is motivated by the exponential growth (by a factor of 100) of the CDS market after its inception. We argue that the aggregate growth of the CDS market is likely due to an overall unmet demand for trading credit risk (see ICE Report (2010)), rather than due to the change in the credit quality of any given firm or the change in the average credit quality of all the firms (*exclusion restriction*). Additionally, we show that the growth in the aggregate CDS notional amount significantly increases the probability of CDS trading on firms (*relevance condition*). Figure I plots the log aggregate CDS notional amount in the economy, the log notional amount of U.S. bonds outstanding, and the average credit rating levels of high-quality (AAA-A), medium-quality (BBB), and low-quality (BB & lower) U.S. firms in the Compustat database. The aggregate CDS notional amount in 2001 was $631.5 billion before it peaked at $62.17 trillion at the end of 2007— a growth by a factor close to 100 in 7 years. The aggregate CDS notional amount dropped to one-thirds in the next three years to $25.55 trillion in 2010. However, these changes in the CDS market seem unrelated to the *changes* in the average credit quality of firms (see Figure I).

One limitation of this instrument is that it does not vary in the cross section. In order to ensure that we are not capturing a simple time trend, we conduct our analysis while restricting our sample to short time windows around the CDS introduction period for each firm, and add a set of macroeconomic variables to the analysis. Additionally, we conduct placebo tests by assigning counterfactual CDS introduction dates for non-CDS firms using a propensity score matching procedure. We describe these tests in Section III.D.

B. Data and Descriptive Statistics

We use CMA Datavision (CMA), a CDS database that is widely used among financial market participants, to identify firms for which we observe CDS quotes on their debt. CMA contains consensus data that are sourced from 30 buy-side firms, including major global investment banks, hedge funds, and asset managers.[6] We further ensure the accuracy of CDS coverage 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.

We obtain bond ratings data from the Mergent Fixed Income Securities Database (FISD), which provides comprehensive issue-level data on corporate debt securities. We consider credit ratings issued by the top three nationally recognized statistical rating organizations (NRSROs): S&P, Moody's, and Fitch. We restrict our sample to U.S. domestic corporate debentures of nonfinancial firms, and we exclude Yankee bonds, bonds issued via private placements, preferred stocks, mortgage-backed bonds, trust preferred capital, convertible bonds, and bonds with credit enhancements. Also, we consider only those 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 divided evenly between S&P and Moody's. We consider one rating change for an issuer as one observation. When rating

[6] 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 they find that the CMA database quotes lead the price discovery process.

changes on multiple bond issues for an issuer occur on the same day, we use the issue that has the greatest absolute rating scale change.

We focus on the 3,310 credit rating downgrades of 644 unique firms observed January 1996 to December 2010[7]. Among these firms, 283 have CDS contracts introduced at some point during the sample period. We refer to these firms as *traded-CDS* firms. There are 1,534 rating downgrade observations in the traded-CDS firm sample. Similarly, we refer to *non-traded-CDS* firms as those firms that do not have CDS trading at all during our sample period. We conduct our main identification tests mainly using traded-CDS firms in order to mitigate the potential concern of omitted factors that could drive the difference in the market reaction to credit rating downgrades in the presence and absence of CDS trading. Subsequently, we also use non-traded-CDS firms to construct the control group in the matched sample analysis, and to conduct placebo tests in the 2SLS/IV analysis.

III. Main Results

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.[8] We calculate the cumulative abnormal return (CAR) in the 3-day window centered around the day of the credit rating change as $CAR_i(-1,1) = \sum_{t=-1}^{+1} AR_{it}$. Before we discuss the results, we emphasize that our conclusions are robust to other measures of abnormal returns. Specifically, we show that our results are qualitatively similar when we measure abnormal returns using the Fama-French 3-factor model or using standardized abnormal returns (i.e., abnormal returns divided by their standard deviation). These results are presented in Table IA-6.

A. *Baseline regression results*

Table I reports the cross-sectional regression results that examine the magnitude of CARs around credit rating downgrades. We start with only fixed effects in Column (1), add rating and firm-level controls in Column (2), and then add CDS-trading controls in Column (3). We describe all control variables in detail in Appendix A. Rating-level controls include the log number of days since the rating was last revised and an indicator variable for rating

[7] We also conduct our analysis for credit rating upgrade announcements. As in prior studies, we do not find a significant market reaction to credit rating upgrades, and we find no impact of CDS trading for rating upgrades.

[8] 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 does not affect our conclusions.

downgrades concurrent with earnings announcements. Firm-level controls are collectively motivated by previous studies (e.g. Jorion et al. (2005)). CDS-trading controls are motivated by Oehmke and Zawadowski (2015a), who find that the CDS market is a preferred trading venue for credit risk due to its greater liquidity compared to the bond market. Their study suggests that the demand for CDS trading that arises due to the hedging motive is related to bond and stock illiquidity, while the demand for CDS trading that arises due to the speculative motive is related to institutional ownership and analysts' forecasts dispersion.[9]

In Table I we estimate our baseline specification given by Equation 1 . The coefficient estimate of *dCDS* is between 1.91–2.15% which indicates the extent of the muted market reaction to credit rating downgrades after CDS contracts begin trading on a firm's debt. For a relative comparison, the last row of this table shows that the univariate mean of CARs to credit rating downgrades in the *absence* of CDS trading is −2.85%. This indicates that the muting of the market reaction to credit rating downgrades in the presence of CDS trading on traded-CDS firms ranges from 67–75%. The coefficient on *dCDS* is relatively stable when including or excluding control variables. In fact, when we add the full set of controls in Column (3), the coefficient on *dCDS* increases modestly, indicating that the bias in its estimation from excluding these controls is negative and small. Also, none of the control variables loads up significantly, except *Avg Return*, which is the average daily return in the month before the downgrade. In Table IA-5, we illustrate that most of the variation in CARs is absorbed by *Prev-rating*×*Rating-change* fixed effects. This indicates that the market indeed reacts similarly to identically rated firms that experience the same credit rating change, thus underscoring the importance of including *Prev-rating*×*Rating-change* fixed effects to absorb the effect of unobserved factors on the market reaction to rating changes. So, an unobservable omitted variable that is as economically important as our included control variables and correlated with CDS trading, is less likely to drive the market reaction to rating changes within the *Prev-rating*×*Rating-change* bins.

B. Are the results simply capturing time-trends?

In Table I, we estimate the effect of introduction of CDS trading within firms that have identical rating-change events and control for time- (year-month) fixed effects. But, it is still possible that a time-varying omitted variable within the *Prev-rating*×*Rating-change* bins could bias our results. To mitigate this concern, we focus on credit rating downgrades within short fixed time windows centered around the introduction of CDS trading for firms that have

[9] Summary statistics of these control variables are presented in Table IA-4. Consistent with Saretto and Tookes (2013) and Oehmke and Zawadowski (2015a), we find that CDS firms are generally larger, better rated, and have higher analyst forecast dispersions.

CDS introduced during our sample period. By focusing on a narrow time-window around the introduction of CDS, we can compare the stock market reactions to rating downgrades that are announced more closer in time to one another, but just before and after the introduction of CDS. Such a comparison is more likely to capture the effect of CDS introduction alone. Moreover, if the CDS introduction for firms is staggered across time, then it less likely for a systematic time-varying factor within the *Prev-rating*×*Rating-change* bins to affect our results. We consider five time windows, namely, ±1 year to ±5 years. Tests using shorter time windows are less likely to be affected by a confounding time trend and the effect of CDS trading can be interpreted more precisely. On the other hand, longer time windows include more rating changes, boosting the statistical power of the tests.

Table II shows results for these five balanced time windows. The coefficients on *dCDS* are positive and significant and the relative effect of CDS trading on the market reaction to credit rating downgrades mirrors results reported in Table I. This suggests that the effect of CDS trading is unlikely to be driven by time-varying factors within firms that have identical rating-change events. As a robustness check, we re-estimate the regression specifications in Table II from 2001 (after the Reg FD was implemented) to 2007 (when the sub-prime crisis starts), and our estimates for the *dCDS* variable are largely unaffected (see IA-7.)[10]

C. Matched-sample analysis

We also perform a matched sample analysis to further ensure the robustness of our main finding. We match non-traded-CDS firms that are downgraded during our sample period to traded-CDS firms in the quarter of their CDS introduction using the propensity score obtained from a logit model. We use various observable factors to estimate the probability that a firm has CDS trading. The CDS introduction date of each traded-CDS firm ("Treated") is assigned to its matched non-traded-CDS firm ("Control"), which serves as the control firm's counterfactual CDS introduction date. We match each treated firm to five control firms. Using this procedure, we are attempting to compare a CDS firm against non-CDS firms that are similarly matched on multiple observable dimensions, and especially on those observable dimensions that can be affected by time-varying confounding shocks around the introduction of CDS trading.[11] Additionally, matching can also account for the effect of nonlinearities in the covariates, thereby avoiding functional form restrictions imposed by linear regression. However, the similarity between treated and control firms in the matched sample can be

[10] Jorion et al. (2005) find that CARs to rating downgrades are stronger after the Reg FD implementation.

[11] This is equivalent to controlling for factors such as $Observable\ factor_{i,t} \times Unobservable\ shock_t$ in the regression analysis, which is useful especially when the unobservable macro factor does not enter the regression model itself, but rather does so through its interaction with an observable firm-specific factor.

achieved only on observable dimensions.[12] Section B.B.3 in the Internet Appendix provides details of the matching procedure. To be conservative, we include all the matching covariates as controls in our matched sample CAR regressions to control for any imperfect matches.

Panel A of Table III reports results for the treated sample (traded-CDS firms). The coefficient estimates of *dCDS* are significant within shorter time windows around the introduction of CDS and for all downgrade observations, and their magnitudes are close to those reported in Table II. Panel B shows estimates that use only non-traded-CDS firms in the control sample. The coefficient on *dCDS* is statistically insignificant and negative in most of the specifications in this placebo test. It appears that CARs to credit rating downgrades are not muted when firms do not actually have CDS trading, even though they share observable characteristics similar to traded-CDS firms at the time of their CDS introduction.

Panel C reports results from the difference-in-difference (DID) regression with both treated and control firms. The variable of interest is the interacted term *dTreated*×*dCDS*, which represents the overall effect of CDS trading on CARs to rating downgrades after accounting for the response of the control firms. Moreover, if our matching procedure is adequate in terms of randomizing the CDS introduction among the treated and control firms, then the coefficient on the interacted term *dTreated*×*dCDS* could be interpreted as an estimate of the average treatment effect of introduction of CDS trading on the stock market's reaction to rating downgrades. We find that the coefficient on the interacted term is positive and significant, and similar to the estimated coefficients on *dCDS* in Table II using the short balanced time windows. This further confirms the robustness of our main finding that the market reaction to credit rating downgrades is muted in the presence of CDS trading.

D. *Instrumental variable analysis*

Recall that most of our firm-specific time-varying controls are statistically insignificant in explaining the market reaction to rating downgrades after including the *Prev-rating*×*Rating-change* fixed effects. Despite this, and our previous tests, we cannot completely rule out the possibility that an unobservable *firm-specific* factor, that drives both CDS introduction and the market reaction to rating changes, could still bias our results. We tackle this potential endogeneity concern using an instrument variable analysis as discussed in detail in Section II.A. We use two instruments for this analysis: log growth rate of the aggregate CDS notional amount traded globally, and the usage of foreign exchange derivatives for hedging purposes by the downgraded firm's lead banks.

[12] Importantly, achieving this similarity on dimensions between treated and control firms is more important for those dimensions that also affect the market reaction to rating downgrades, especially after including *Prev-rating*×*Rating-change* fixed effects.

The use of aggregate CDS notional growth rate is motivated by the exponential rise of the CDS market during our sample period. Figure I plots the log aggregate CDS notional amount traded in the economy. We argue that the aggregate growth of the CDS notional amount traded globally is likely due to an unmet demand for trading in credit risk (ICE report (2010)) as opposed to the *change* in the credit rating of any particular firm or due to the change in the average credit rating of all the firms. In support of the latter argument, Figure I also plots the average credit rating levels, and seems to indicate that the growth of the CDS market was unrelated to the changes in the average credit rating of firms. Nevertheless, this instrument captures only the time-series variation in the probability of CDS trading. It does not vary in the cross section and as a result, we can not include time fixed effects in this analysis. To ensure we are not simply capturing a time-varying trend in the market reaction to rating changes through this instrument, we estimate the impact of CDS trading using the short time window around the introduction of CDS trading on each firm, similar to those in Table II. Additionally, we add a set of macroeconomic controls that control for time-varying credit-market conditions and the volatility of the equity market.

We estimate the regression model using 2SLS/IV regression. In the first stage, we estimate the linear probability model for the likelihood of CDS trading on the IV and other controls. Appendix Table IA-9 reports results from the first-stage IV regression, in which we find that doubling the total CDS notional amount outstanding increases the probability of CDS trading for a firm by 22.7% to 30.6%. The F-statistic for the excluded instrument in all the specifications is greater than the threshold of 10, indicating that it is a strong instrument (Bound, Jaeger, and Baker, 1995; Staiger and Stock, 1997).

Panel A of Table IV reports the results for the second stage. We find that coefficients on the instrumented *dCDS* are positive and statistically significant, indicating that the market reaction to credit rating downgrades is muted in the presence of CDS trading by 70–85%.[13] These coefficient estimates are comparable to the OLS estimates reported in Table II suggesting a lower bias in those OLS estimates. In Panel B of Table IV we run placebo tests that support the validity of our instrument. Here, we run the 2SLS/IV regressions on the control (non-traded-CDS) firms from the propensity-score matched sample described in Section III.C. The instrumented *CDS* variable is statistically insignificant for the control sample. This finding indicates that the aggregate CDS notional amount affects the stock market reaction to credit rating downgrades *through* CDS-trading. Additionally, the statistically insignificant coefficient on the instrumented *dCDS* in Panel B indicates that the

[13]The instrumented *dCDS* variable is not statistically significant for the $[-1, +1]$ window. This is likely due to the availability of the instrument at a semiannual frequency, which may not allow for sufficient time-series variation over a ± 1 year window.

instrument is not simply capturing a time trend. In an alternate placebo test, we regress rating downgrade CARs directly on the instrument for the traded-CDS sample and the non-traded-CDS sample separately. Results reported in Table IA-10 show that the instrument loads significantly only in the traded-CDS sample and not in the non-traded-CDS sample, further suggesting that the instrument has explanatory power only through CDS trading.

We show that our results are also robust to using another instrument that has previously been employed in the literature to instrument for CDS trading. This instrument is the amount of foreign exchange derivatives that are traded for hedging purposes by banks that have a lending relationship with the downgraded firm. In our context, we argue that a bank's forex position is unlikely to directly affect the changes in credit rating of firms. At the same time, it reflects the bank's hedging culture, thus making it more likely to initiate CDS trading on the firms they lend to. Saretto and Tookes (2013), and Subrahmanyam et al. (2014) give a detailed account of the construction and implementation of this IV. Our results remain qualitatively unchanged when we use this instrument as shown in Table IA-11.[14]

E. Heterogeneous effects of CDS trading on CARs to rating downgrades

In this section, we study the heterogeneous effect of CDS trading on CARs to credit rating downgrades in order to understand the channels that explain our results. Specifically, we design our tests by performing sample cuts along the dimensions where credit rating downgrades are likely to matter more. To achieve greater variation on the multiple dimensions of sample cuts, we include both the traded-CDS and non-traded-CDS firms, and also consider the entire sample period as opposed to the short balanced windows around CDS introduction. Additionally, this combined sample allows us to draw more general inferences about the effects of CDS introduction for an average firm. Nevertheless, the main results presented here also hold for the smaller sample of traded-CDS firms reported in Table IA-14.

We first verify our main finding that CDS trading mutes the equity price reaction to credit rating downgrades using this larger cross section of traded-CDS and non-trade-CDS firms (see Table IA-12). We find that the average treatment effect of CDS trading in this larger sample indicates that the stock market reaction to credit rating downgrades is significantly muted by 44–52% in the presence of CDS trading.[15]

[14]It is possible that a bank's forex derivatives usage may indicate its financial sophistication. If a bank's sophistication and its ability to hedge are directly related to the quality of the firms they lend to, then this would violate the exclusion restriction. We thank an anonymous referee for pointing out this limitation.

[15]The coefficient estimates of the *dCDS* variable are between 1.95 and 2.28, which are consistent with our results shown in Table I. However, in the absence of CDS trading in this sample, the mean of CARs to credit rating downgrades is −4.41, which is greater in magnitude than the mean shown in Table I due to the inclusion of non-traded-CDS firms.

Next, we study the heterogeneous effect of CDS trading by estimating the augmented baseline regression model in Equation (1) as follows:

$$CAR_{i,t} = \sum_{j=1}^{N} \mathbb{1}(\omega_j)[\beta_j \times dCDS_{i,t} + f(X_{i,t}) + g(Y_t)] + \Gamma_{R,\Delta N} + \eta_{indus} + \nu_{agency} + \varepsilon_{i,t}, \quad (2)$$

where N denotes the number of different subsamples given by the indicator functions $\mathbb{1}(\omega_j)$ with $j = 1, \ldots, N$. We exclude time fixed effects in this analysis, as some of our sample cuts to study the heterogeneous effect of CDS trading are across time. The regression model in Equation (2) is similar to estimating the baseline specification in Equation (1) separately for each j subsample, except without interactions between their error terms. In this specification, β_j measures the impact of the *dCDS* variable on rating downgrade observations in group j. The advantage of estimating the model in Equation (2), as opposed to running N separate regressions, is that we can easily compare the coefficients β_j on *dCDS* across the subsamples.

E.1. Exploiting the variation in regulatory dependence on credit ratings

A credit rating downgrade, especially from investment grade to speculative grade, can lead to a reduction in the pool of investors. This is because certain banks, pension funds, and insurance funds are either prohibited or disincentivized by higher capital charges from lending to speculative-grade firms (Kisgen (2007)). This, in turn, increases the cost of borrowing for downgraded firms as their investors demand higher yields for their return due to a smaller investor pool for risk sharing, higher regulatory costs, or loss of bond liquidity. This regulatory dependence on credit ratings should make firms that are closer to the boundary of investment-speculative grades (IG-SG) more sensitive to credit rating downgrades.

Motivated by the rating-based regulatory frictions on bond investments, we divide the sample into three groups based on the credit rating level before the firm is downgraded. The first group consists of high-quality investment-grade (IG) firms (AAA-A), the second group consists of medium-quality investment-grade firms (BBB), and the third group consists of low-quality speculative-grade (SG) firms (BB and below). The results shown in Panel A of Table V indicate that the effect of CDS trading is strongest on firms in the second group (i.e., firms with medium-quality credit). A comparison between the mean CAR of this group (-3.39%) and the coefficient estimate on *dCDS (Medium: BBB)* (3.92%) suggests that CDS trading completely dampens the market reaction to rating downgrades for IG firms that are rated just above the IG-SG boundary. Recall that firms in this group are more likely to be exposed to greater rating-based regulatory market frictions. This suggests that CDS trading dampens CARs to rating downgrades by relieving the financing frictions associated with the regulatory dependence of downgraded firms' debt financing on credit ratings.

We provide a summary of credit rating downgrade observations for each rating group in

Table IA-13 of the Internet Appendix. Interestingly, we find that firms rated in the medium credit-quality group (BB) are more likely to have CDS trading on their debt. Approximately 41% of rating downgrade observations in the medium credit-quality group occur in the presence of CDS trading, while the proportions are 34% and 26% for the high and low credit-quality groups, respectively. As argued in Kisgen (2007) and Kisgen and Strahan (2010), the financing frictions associated with the regulatory dependence of firms' debt financing on credit ratings are likely to be greater for firms rated just above the IG-SG boundary. Our finding that firms which are rated just above the IG-SG boundary are more likely to have CDS traded is consistent with the CDS-trading demand that manifests to relieve these regulation-based financing frictions.

E.2. Exploiting the variation in contractual dependence on credit ratings

Covenants are used in debt contracts to mitigate market frictions, reduce the agency costs of asset substitution, and resolve asymmetric information between a lender and a borrower. [16] For instance, performance pricing (PP) covenants are widely used in bank loans. In bank loan agreements, PP covenants are triggers that raise the loan interest rate or force an early repayment of the principal. These PP covenants can be based on the credit ratings of the firm's senior or subordinated bonds and commercial paper, or based on accounting ratios such as leverage, EBITDA, and current ratio.

We obtain the data on PP covenants from LPC's Dealscan database (see Chava and Roberts (2008)). We identify all the active loan facilities for firms in our sample on the rating downgrade announcement day. Then, we calculate their number of PP covenants and classify them based on whether they are credit rating-based or accounting ratio-based. These classifications need not be mutually exclusive, since both types of covenants can be present in each loan facility. Section B.B.4 in the Internet Appendix provides examples of rating-based and accounting-based covenants. We divide the sample into two groups, conditional on having an outstanding loan facility and a PP covenant: firms with a high (above-the-median) number of rating-based PP covenants and firms with a low number (below-the-median) of rating-based PP covenants. Importantly, we sort the sample based on rating-based PP covenants *within* each credit rating level at the time they are downgraded. This approach mitigates the concern that firms that have lower credit quality are more likely to a have higher number of PP covenants to satisfy their lenders' need for greater monitoring.

Table V, Panel B, Column (1) reports the results of estimating the regression model

[16] See Asquith et al. (2005) for the mitigation of market frictions, Bhanot and Mello (2006); Manso, Strulovici, and Tchistyi (2010) for the reduction in agency costs of asset substitution, and Garleanu and Zwiebel (2009); Demiroglu and James (2010) for the decrease in asymmetric information.

in Equation (2) on the sample that is grouped based on the number of rating-based PP covenants. We first compare CARs to rating downgrades in the absence of CDS trading. The bottom rows of Column (1) present the results. We find that the equity price of firms in the above-the-median (high) group reacts more negatively to credit rating downgrades (about -5.70%) relative to the equity price of firms in the below-the-median (low) group (which is about -3.57%). We find that the effect of CDS trading on CARs is only statistically significant for observations in the above-the-median (high) group. For this group, the coefficient estimate on *dCDS (high)* is 4.19%, which implies a 74% reduction relative to the magnitude of CARs to rating downgrades in the absence of CDS trading (-5.70%). These results show that firms that have more number of debt contracts tied to credit ratings have a more severe negative market reaction when they are downgraded. However, this market reaction is muted when the firm has a traded CDS.

Table V, Panel B, Column (2) presents estimation results with the sample sorted into two groups based on the number of accounting-based PP covenants written on the firm's debt contracts: high (above-the-median) and low (below-the-median). However, in this case, we find that the effect of CDS trading on CARs to credit rating downgrades do not differ across groups; see the row $\Delta dCDS(High - Low)$. This serves as a good placebo test, because, as shown in Column (2), if the effect of CDS introduction is through mitigating the contractual dependence of a firm's debt financing on credit ratings, then we should not expect to find a differential effect of CDS in relation to the number of accounting-based PP covenants.[17]

Finally, Table V, Panel B, Column (3) reports the estimation results for the sample sorted into two groups based on the total number of outstanding bank loan facilities This sample split is motivated by the fact that banks are subject to capital requirements, which are typically based on the credit ratings of their corporate claims.[18] Banks therefore have incentives to tie their loan interest rates to credit ratings. This dependence of banks' capital requirements on credit ratings, in turn, generates a contractual dependence on credit ratings for the firms that borrow from them. The bottom two rows of Column (3) show that in the absence of CDS trading, CAR to rating downgrades is more severe for the group with above-the-median (high) number of active loan facilities, i.e., -5.88% relative to -3.01% for the below-the-median group. However, when these firms have CDS contracts traded, the equity market reaction to their credit rating downgrades is dampened by about 40% as implied by the estimate of 2.32 on *dCDS (High)*.

[17]This argument implicitly assumes that the presence of a rating-based covenant and an accounting-based covenant are not strongly correlated. In our sample, the correlation between having an above-the-median number of both rating-based PP covenants and accounting-based PP covenants is -0.21.

[18]For instance, the risk weights in Basel II are 20% for AAA to AA-; 50% for A+ to A-; 100% for BBB+ to BB-; and 150% for below BB-rated firms.

Minton, Stulz, and Williamson (2009) find that banks are, in general, active players in the CDS market, because they act as market makers as well as hedgers of their loan portfolio risk. This suggests that banks can specialize in originating and underwriting loans while laying-off of their loans' credit risk after origination through CDS, especially when the cost of keeping these loans on their balance sheet is high due to regulatory capital charges. Overall, our findings are consistent with the notion that CDS relieves debt-financing frictions associated with the contractual dependence of debt markets on credit ratings.

E.3. Exploiting the variation in credit supply

Stiglitz and Weiss (1981) show that when the supply of credit is tight and lenders face increasing information asymmetry, borrowers are more likely to be rationed out. As a result, debt financing frictions should be more severe during periods of tighter credit market conditions. We show that the effect of CDS trading on CARs to credit rating downgrades is greater *when* the supply of credit is more constrained. Specifically, we exploit the variation in credit market conditions across time.

We divide observations into two groups based on the tightness of credit market conditions at the time of each rating downgrade. We use two measures: the average Baa–Aaa credit spread and the bank senior loan officer (SLO) survey. Both data sets are obtained from the Federal Reserve. For the SLO survey, we quantify the credit market tightness as the number of banks that report tightening standards, minus the number of banks that report easing standards, divided by the total number of reports (Chava, Gallmeyer, and Park (2015)). In both measures, their higher values would indicate tighter credit market conditions. We divide the observations of rating downgrades into groups that correspond to periods with above-the-median (high) and below-the-median (low) Baa-Aaa credit spread levels as well as SLO-survey levels. Table V, Panel C reports results from this sample split.

Panel C shows that the equity market reaction to rating downgrades is more severe when credit is tight. The bottom two rows of Columns (1) and (2) show that during periods when the credit conditions are tight, and in the absence of CDS trading, the magnitude of CARs to rating downgrades is approximately twice as large as when credit conditions are loose. However, for firms with CDS trading, we find that the equity market reaction to rating downgrades is muted by 54–57%, as evidenced by the positive and significant coefficients on *dCDS (High)* in both columns. On the other hand, during periods of looser credit market conditions, there is no significant difference in CARs to rating downgrades in the presence nor in the absence of CDS trading. This is evident from the statistically insignificant and small coefficients on *dCDS (Low)*.

IV. Impact of CDS on firms' debt-financing frictions

Evidence from Section III.E suggests that debt-financing frictions is likely to be the main channel through which CDS trading dampens the stock market reaction to rating downgrade announcements. This section provides further tests of this hypothesis.

A. *CDS trading and the financing decision of downgraded firms*

Previous studies show that credit ratings affect a firm's capital structure as there are costs associated with worse credit rating levels. Some of these costs are higher capital structure adjustment costs (Leary and Roberts (2005)), greater monitoring costs due to increasing information asymmetry on the firm quality (Faulkender and Petersen (2006)), and higher regulation-related costs (Kisgen (2006, 2009); Kisgen and Strahan (2010)).

Firms target some minimum credit rating levels, with firms lowering their leverage after downgrades, but not changing their leverage after upgrades (Kisgen (2009)). In a similar spirit, we examine changes in net debt and equity between CDS and non-CDS firms after they have been downgraded. Panel A of Table VI reports regression results in which the dependent variables are quarterly changes in net debt and equity issuance (net of new issuance and reduction) as a fraction of lagged total assets over ± 4 quarters around credit rating downgrade, excluding the quarter in which the downgrade is announced. The sample consists of 2,143 unique firm-downgrade events, each represented by a window of eight quarterly observations.[19] If a firm-quarter observation overlaps across N rating events, we weight that firm-quarter observation by $1/N$ to ensure that the effect of each rating downgrade event on the changes in net debt and equity is given equal treatment. On average, the firm's net debt issuance decreases while its net equity issuance increases in the four quarters after the rating downgrade. The coefficient estimates of *dPostDNG* in Columns (3) and (6), where we include the full set of controls, indicate that the change in net debt issuance relative to lagged total assets is -0.52% per quarter. The change in net equity issuance relative to lagged total assets is 0.41% per quarter. This implies an average decrease of 3.70% per year in net debt issuance relative to net equity issuance, in line with Kisgen (2009).

Importantly, Table VI, Panel A shows that the decrease in net debt issuance is significantly smaller for firms with CDS trading, as evidenced by the positive and significant coefficient on *dPostDNG*$\times$*dCDS* in Columns (1)–(3). On the other hand, Columns (4)–(6) show that the increase in net equity issuance is not significantly different between CDS and non-CDS firms. The row labeled "(a) + (b)" reports the sum of coefficients from *dPostDNG*

[19] There are fewer downgrades compared to Table I, Panel A, because there are multiple rating downgrade announcements on a firm in the same quarter, often corresponding to downgrades by different rating agencies.

and $dPostDNG \times dCDS$, which represents the overall change in net debt (or equity) issuance of CDS firms after they have been downgraded. Columns (3) and (6) show that CDS firms decrease their net debt issuance by about -0.63%, while increasing their net equity issuance by about 1.64% in the year after the downgrade. These estimates imply a decrease in net debt issuance relative to net equity issuance of 2.28% in the year after a CDS firm has been downgraded, which is about 40% less relative that for a non-CDS firm. The downgraded firm either reduces its total debt owed to lenders by repaying existing debt, or issues less new debt after it has been downgraded, or both. However, these two sources are likely driven by different factors; therefore, analyzing them separately can shed light on the mechanism by which the presence of a traded CDS leads to the results documented in Table VI, Panel A.

The repayment of existing debt after the firm has been downgraded is more likely to be triggered by rating-based covenants embedded in debt contracts. Such covenants could raise the downgraded firm's debt interest rates as a function of a firm's credit rating, which causes the firm to reduce its use of existing debt voluntarily.[20] Additionally, when these rating-based covenants are triggered, they can force the downgraded firm into early repayment of the principal by explicitly calling for a debt repurchase. In the absence of any rating-based triggers on debt interest rates or debt repurchase, it is less likely that firms would increase their existing debt repayment immediately after they have been downgraded, because their interest rates and the schedule of principal repayment would have been determined at issuance. In contrast, reduction in new debt issuances are more likely driven by a lender's decision to ration credit, along with a firm's decision to voluntarily avoid issuing new debt at higher interest rates. The information asymmetries that underlie credit rationing may be exacerbated after a rating downgrade (Stiglitz and Weiss (1981)).

We use a linear probability model to estimate the likelihood of a large reduction (and a large new issuance) in debt and equity after a firm has been downgraded. Based on Kisgen (2009), we define large debt and equity issuances (reductions) in a quarter as those issuances (reductions) that are greater (less) than 1.25% of the total assets (or 5% in annualized terms). The negative and statistically significant estimate of $dPostDNG \times dCDS$ in Column (1) of Table VI, Panel B, shows that the differential effect of credit rating downgrades on the change in net debt issuance between CDS and non-CDS firms is largely driven by the reduction of existing debt. This result is consistent with the argument that CDSs relieve debt-financing costs associated with rating-based covenants in debt contracts that are triggered after the firm is downgraded. Results in Panel B show that there is no difference in the likelihood of a large equity issuance or reduction between CDS and non-CDS firms after they have been downgraded. Broadly, this suggests that the impact of CDS trading on firms' financing

[20] Kisgen (2009) argues that firms voluntarily reduce debt after a downgrade to achieve better credit ratings.

occurs mainly through the debt-financing channel.

To further illustrate that CDS trading mitigates rating-based costs that arise after firms have been downgraded, we estimate the probability of large debt reductions on a sample that is sorted based on firms' contractual dependence on credit ratings. The results shown in Table IA-15 demonstrate that the impact of CDS trading is driven by downgrades on firms that either have an above-the-median (high) number of rating-based PP covenants or have an above-the-median (high) number of active loan facilities. These findings are consistent with Table V, Panel B, which shows that CDS trading dampens CARs to rating downgrades for firms that have relatively high contractual dependence on credit ratings.

Overall, the evidence provided in this section point to the existence of rating-based costs that are triggered after credit rating downgrades and indicates that CDS trading mitigates these costs. While the results do not provide a causal interpretation, it seems less likely that an alternate channel can explain all these results. For instance, an alternate channel must explain how CDS and non-CDS firms within the same rating class and experiencing the same rating change have different propensities to reduce debt, but not equity, after a rating downgrade event. Interest rates and principal repayment schedules are typically determined at issuance. In the absence of rating-based triggers on debt contracts, debt reduction for CDS and non-CDS firms should be equally unlikely, contrary to what we document.

B. Quantifying the impact of CDS trading on the financing cost of downgraded firms

Lenders who are subject to rating-based regulatory costs may pass these costs to downgraded borrowers with poorer credit ratings in the form of a price effect or a quantity effect, or both. The price effect will lead to higher debt costs causing firms to reduce its use of debt capital. The quantity effect will result in firms being rationed out in the debt market. As we do not directly observe credit denials by lenders, we focus on the price effect associated with poorer credit ratings. We use the price of issued loans to quantify the costs borne by firms after credit rating downgrades, and test whether CDS trading can relieve these costs.

We estimate a weighted linear regression model (similar to that used in Table VI) for at-issuance loan spreads for firms in the ± 1 year window around its rating downgrade event. We observe 1,419 loan issuances around credit rating downgrades, with a median loan size of \$500 million. The dependent variable is the log of all-in-drawn spread, which is the sum of the spread of the loan facility over LIBOR and any annual fees paid to the lender group. We use indicator variables to control for loan characteristics such as the loan type (e.g., revolver loan, term loan), the presence of performance pricing covenants, and the loan purpose.

Panel A of Table VII shows that loan spreads at issuance for non-CDS firms increase by 22.3–29.3% in the 1-year period after their credit rating downgrades. However, the increase in loan spreads for CDS firms is 12.7–16.1% lower in comparison to non-CDS firms. These results are estimated with *Prev-rating*×*Rating-change* fixed effects, which help control for the average expected rating-based regulatory costs incurred by creditors who lend to firms that experience identical credit rating changes. Assuming that most of these costs are passed on to the borrowing firm, our results suggest that the rating-based regulatory costs associated with lending to a CDS firm is roughly half that of a similarly rated non-CDS firm.

Overall, the results in Panel A of Table VII are consistent with banks being more efficient liquidity providers to firms that experience negative shocks to their cash flows (Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006)). However, this liquidity provision can be costly when a bank's borrowers are downgraded, since banks are subject to capital charges based on the credit ratings of their financial claims. CDSs enable banks to lay-off this costly credit risk after loan origination. Our results indicate that the presence of CDS trading can relieve some of the costs associated with providing credit to downgraded firms. Consistent with this argument, Table IA-16 shows that the presence of CDS trading dampens the increase in the loan spreads of downgraded firms precisely when these CDS firms have relatively high numbers of rating-based covenants and active bank loan facilities.

C. Real effects of CDS trading on downgraded firms

The evidence in Table VI is consistent with rating-based costs affecting the firm's capital structure decision after a credit rating downgrade. Importantly, we find that these costs are higher for non-CDS firms compared to CDS firms. Such costs could manifest as higher debt interest rate payments, which in turn could lead firms to reduce their use of debt capital. These costs are a drain on the firm's cash flows and thus could affect the downgraded firm's investment activity. We test this conjecture in Panel B of Table VII by comparing the firm's quarterly capital expenditure (CAPEX) as a fraction of its lagged total sales before and after a rating downgrade. We focus on the four quarters before and the four quarters around the rating downgrade event, and exclude the quarter in which the firm is downgraded.

Panel B of Table VII shows that the firm's CAPEX relative to its lagged sales decreases by 1.2–2.2% per quarter in the year after a credit rating downgrade. However, the statistically insignificant coefficients in the "(a)+(b)" row indicate that CAPEX for CDS firms does not change after a rating downgrade. These results are consistent with CDS firms incurring lower rating-based costs after a rating downgrade. Moreover, these results suggest that financing-related frictions associated with the regulatory and contractual dependence of the credit market on credit ratings have a real effect on the economy by reducing firms' investment levels by about 5–9% in the year after the firms have been downgraded. However, this effect appears to be less severe when firms have CDS trading on their debt. Further, in line with lower future investment activity, we find that non-CDS firms have persistent negative long-run stock returns after they have been downgraded, unlike CDS firms (see Table IA-17).

D. CDS trading and the reliance of firms on credit ratings: Ex ante evidence

The results in this section so far, suggest that CDS trading alleviates financing-related frictions after a credit rating downgrade. We next test whether the ex post effects of downgrades create an ex ante incentive for firms to avoid being downgraded, and whether CDS trading weakens this incentive.

A firm's Debt/EBITDA ratio is a key criterion on which credit rating agencies base their assessment of a firm's credit quality. Rating agencies provide guidance on the typical range of Debt/EBITDA ratios (Begley (2015)). The thresholds (min and max) for a given range of Debt/EBITDA ratios are based on intervals such as 2.0 and 2.5 and are somewhat arbitrary. If there are benefits from avoiding a credit rating downgrade, we expect that firms whose Debt/EBITDA ratios are close to these salient thresholds will seek to improve their Debt/EBITDA ratios by reducing their debt. We test whether firms' financing decisions are sensitive to the rating-based salient thresholds of Debt/EBITDA ratios and whether this sensitivity differs between CDS versus non-CDS firms. In contrast to the empirical framework so far, results in Table VIII are not conditional on a rating event, allowing us to draw conclusions about the relevance of credit ratings on CDS versus non-CDS firms in a more general setting.

We use rating-based salient thresholds of Debt/EBITDA (see Begley (2015)) to classify firms according to their high (or low) incentives to manage their debt issuance. Intuitively, a high-incentive zone is a small range of Debt/EBITDA ratios around, and containing, a rating-based salient threshold. A low-incentive zone is a range of Debt/EBITDA ratios that do not contain any rating-based salient thresholds and do not overlap with any high-incentive zones. In Columns (1)–(4), we include *Industry*$\times$*Rating* fixed effects, while in Column (5) we include *Firm* and *Rating* fixed effects. We find that the net debt issuance, as a fraction of lagged total assets, is 1.92-2.02% lower per quarter for firms in the high-incentive zones compared to those in the low-incentive zones. However, the sensitivity of net debt issuance for CDS firms in the high-incentive zones is 0.65-0.71% lower per quarter, despite the fact that CDS firms and non-CDS firms have a roughly equal probability of being in the high-incentive (8.88% vs 9.08%) or low-incentive zones (31.42% vs 30.9%). As shown in Begley (2015), it is unlikely that drivers of debt issuance (e.g., changes in investment opportunities, liquidity shocks, default risk) systematically depend on the distance of firms' Debt/EBITDA ratios from rating-based salient thresholds. This indicates that, the distribution of firms relative to these arbitrary Debt/EBITDA thresholds are independent of whether firms have CDS trading on their debt and the results in Table VIII could be interpreted as causal evidence of the reliance of firms' debt-financing decision on credit ratings. We also do not find any evidence that the Debt/EBITDA thresholds affect quarterly changes in a firm's equity to lagged total assets (Table IA-18), which suggests that firms' reliance on credit ratings when making their financing decisions mainly occurs through the debt-financing channel.

Overall, our results show that the reliance of the credit market on credit ratings creates an ex ante incentive for firms to alter their financing decisions in order to avoid being downgraded. However, this incentive is less binding in the presence of CDS trading.

V. Conclusion

We demonstrate that after the introduction of CDS trading on a firm's debt, the equity market exhibits a muted negative reaction to the announcement of the firm's credit rating downgrade. The effect of CDS trading on the sensitivity of stock market reactions to downgrades is driven by (a) firms that are rated near the boundary between investment grade and speculative grade or (b) firms that have a high number of rating-based performance pricing covenants and (c) a large number of active loan facilities. After a rating downgrade, CDS firms do not reduce their debt as significantly as non-CDS firms, and the increase in the cost of debt financing is lower for CDS firms. In line with these findings, CDS firms do not reduce investment as much as non-CDS firms after a credit rating downgrade. Broadly, these results suggest that CDS trading mitigates the financing-related frictions that downgraded firms encounter due to the regulatory and contractual dependence of the credit market on credit ratings, leading to a muted market reaction to rating downgrades.

Our paper highlights an important economic role for the CDS market; however, CDS contracts and credit ratings are not equivalent, and credit rating agencies still play an important role in financial markets. The CDS market complements credit ratings by providing a market-based indicator of default risk. However, it is critical to note that a significant number of firms do not have CDS trading on their debt. The presence of CDS trading on a firms' debt also can potentially give rise to an empty creditor problem. In addition, just as we observe the regulatory and contractual dependence on credit ratings, a similar feedback effect may ensue and generate negative consequences for the affected firms if a large number of contracts are written on CDS spreads or if capital charges are tied to CDS contracts.

REFERENCES

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Akerlof, George A, 1970, The market for" lemons": Quality uncertainty and the market mechanism, *The quarterly journal of economics* 488–500.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31 – 56.

Asquith, Paul, Anne Beatty, and Joseph Weber, 2005, Performance pricing in bank debt contracts, *Journal of Accounting and Economics* 40, 101–128.

Begley, Taylor A, 2015, The real costs of corporate credit ratings, *Working paper* .

Bhanot, K., and A. Mello, 2006, Should corporate debt include a rating trigger?, *Journal of Financial Economics* 79, 69–98.

Bolton, Patrick, and Martin Oehmke, 2011, Credit default swaps and the empty creditor problem, *Review of Financial Studies* 24, 2617–2655.

Bongaerts, Dion, Martijn Cremers, and William N. Goetzmann, 2012, Tiebreaker: Certification and multiple credit ratings, *The Journal of Finance* 67, 113–152.

Boot, Arnoud WA, Todd T Milbourn, and Anjolein Schmeits, 2006, Credit ratings as coordination mechanisms, *Review of Financial Studies* 19, 81–118.

Bound, John, David A Jaeger, and Regina M Baker, 1995, Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak, *Journal of the American statistical association* 90, 443–450.

Breger, L., L. Goldberg, and O. Cheyette, 2003, Market implied ratings, *www.barra.com* .

Chava, Sudheer, Michael Gallmeyer, and Heungju Park, 2015, Credit conditions and stock return predictability, *Journal of Monetary Economics* 74, 117 – 132.

Chava, Sudheer, and Michael R. Roberts, 2008, How does financing impact investment? the role of debt covenants, *The Journal of Finance* 63, 2085–2121.

Dehejia, R.H., and S. Wahba, 2002, Propensity score-matching methods for nonexperimental causal studies, *Review of Economics and Statistics* 84, 151–161.

Demiroglu, Cem, and Christopher M James, 2010, The information content of bank loan covenants, *Review of financial Studies* 23, 3700–3737.

Diamond, Douglas W, 1984, Financial intermediation and delegated monitoring, *The Review of Economic Studies* 51, 393–414.

Dichev, I.D., and J.D. Piotroski, 2001, The long-run stock returns following bond ratings changes, *Journal of Finance* 56, 173–203.

Faulkender, Michael, and Mitchell A Petersen, 2006, Does the source of capital affect capital structure?, *Review of financial studies* 19, 45–79.

Garleanu, Nicolae, and Jeffrey Zwiebel, 2009, Design and renegotiation of debt covenants, *Review of Financial Studies* 22, 749–781.

Gatev, Evan, and Philip E Strahan, 2006, Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market, *The Journal of Finance* 61, 867–892.

Goh, J.C., and L.H. Ederington, 1993, Is a bond rating downgrade bad news, good news, or no news for stockholders?, *Journal of Finance* 48, 2001–2008.

Hand, J.R.M., R.W. Holthausen, and R.W. Leftwich, 1992, The effect of bond rating agency announcements on bond and stock prices, *Journal of Finance* 47, 733–752.

Holthausen, R.W., and R.W. Leftwich, 1986, The effect of bond rating changes on common stock prices, *Journal of Financial Economics* 17, 57–89.

ICE, 2010, Global credit derivatives markets overview: Evolution, standardization and clearing, Technical report.

Jorion, P., Z. Liu, and C. Shi, 2005, Informational effects of regulation FD: evidence from rating agencies, *Journal of Financial Economics* 76, 309–330.

Jorion, P., and G. Zhang, 2007, Information effects of bond rating changes: The role of the rating prior to the announcement, *The Journal of Fixed Income* 16, 45–59.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein, 2002, Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *The Journal of Finance* 57, 33–73.

Kisgen, Darren J, 2007, The influence of credit ratings on corporate capital structure decisions, *Journal of Applied Corporate Finance* 19, 65.

Kisgen, Darren J., 2009, Do firms target credit ratings or leverage levels?, *Journal of Financial and Quantitative Analysis* 44, 1323–1344.

Kisgen, Darren J., and Philip E. Strahan, 2010, Do regulations based on credit ratings affect a firm's cost of capital?, *Review of Financial Studies* 23, 4321–4347.

Kisgen, D.J., 2006, Credit ratings and capital structure, *The Journal of Finance* 61, 1035–1072.

Kou, J., and S. Varotto, 2008, Timeliness of spread implied ratings, *European Financial Management* 14, 503–527.

Leary, Mark T, and Michael R Roberts, 2005, Do firms rebalance their capital structures?, *The journal of finance* 60, 2575–2619.

Manso, Gustavo, 2013, Feedback effects of credit ratings, *Journal of Financial Economics* 109, 535 – 548.

Manso, Gustavo, Bruno Strulovici, and Alexei Tchistyi, 2010, Performance-sensitive debt, *Review of Financial Studies* 23, 1819–1854.

Mayordomo, Sergio, Juan Ignacio Pena, and Eduardo S. Schwartz, 2010, Are all credit default swap databases equal?, *NBER working paper series* .

Merton, R, 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Minton, Bernadette A., Rene Stulz, and Rohan Williamson, 2009, How much do banks use credit derivatives to hedge loans?, *Journal of Financial Services Research* 35, 1–31.

Oehmke, Martin, and Adam Zawadowski, 2015a, The anatomy of the cds market, *Review of Financial Studies* forthcoming.

Oehmke, Martin, and Adam Zawadowski, 2015b, Synthetic or real? the equilibrium effects of credit default swaps on bond markets, *Review of Financial Studies* forthcoming.

Opp, Christian C, Marcus M Opp, and Milton Harris, 2013, Rating agencies in the face of regulation, *Journal of Financial Economics* 108, 46–61.

Qiu, Jiaping, and Fan Yu, 2012, Endogenous liquidity in credit derivatives, *Journal of Financial Economics* 103, 611 – 631.

Saretto, Alessio, and Heather E. Tookes, 2013, Corporate leverage, debt maturity, and credit supply: The role of credit default swaps, *Review of Financial Studies* 26, 1190–1247.

Staiger, Douglas, and James H Stock, 1997, Instrumental variables regression with weak instruments, *Econometrica* 65, 557–586.

Stiglitz, Joseph E, and Andrew Weiss, 1981, Credit rationing in markets with imperfect information, *The American economic review* 71, 393–410.

Subrahmanyam, Marti G., Dragon Yongjun Tang, and Sarah Qian Wang, 2014, Does the tail wag the dog?: The effect of credit default swaps on credit risk*, *Review of Financial Studies* .

Appendix Appendix A. Variable Definitions

Rating-level variables

- *dCDS* is an indicator variable equal to 1 if the rating change takes place when the CDS trades on the underlying firm, and 0 otherwise.
- *dTradedCDS* is an indicator variable equal to 1 if the firm belongs to the Traded-CDS sample, and 0 otherwise. This variable only appears when we run regressions using the combined sample of traded-CDS and non-traded-CDS firms.
- *dPostDNG* is an indicator variable equal to 1 in a pre-specified period after the firm has been downgraded, and 0 otherwise.
- *dHiZone* is an indicator variable equal to 1 if firm's Debt/EBITDA ratio falls within salient thresholds provided by credit rating agencies, and 0 otherwise. These thresholds of Debt/EBITDA ratio are criteria on which credit rating agencies base their assessment of a firm's credit quality. See Begley (2015) for details.
- *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.

Firm-level variables: Lagged firm fundamentals

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

Firm-level variables: Lagged 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's (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:

$$\sqrt{1000000 * |\text{Ret}_t| / (\text{Volume} \times \text{Price}_t)}.$$

- *Bond Illiquidity* is the number of outstanding bond issues in a given month (see Oehmke and Zawadowski (2015a)).
- *Bond Hedging Demand* It is the residual from regressing total amount of bond debt outstanding on the number of bond issues. This variable measures the amount of bond debt outstanding for a firm that is linearly unrelated to the number of its bond issues.

Macro variables

- *Baa-Aaa Spread* is the Moody's $Baa - Aaa$ corporate bond yield spread obtained from the Federal Reserve at the monthly-level.
- *SLO Survey* is a quarterly measure of credit supply derived from the bank senior loan officer (SLO) survey obtained from the Federal Reserve. We consider the question in the survey pertaining to the credit standards for approving commercial and industrial (C&I) loans. The survey data is converted to a quantifiable measure as the number of banks reporting tightening standards minus the number of banks reporting easing standards divided by the total number of reporting banks.
- *VIX* is the monthly average of the option-implied volatility index obtained from the CBOE.

Figure I. Aggregate CDS Notional Amount

We plot the log aggregate CDS notional amount, and the log aggregate outstanding U.S. bond debt (in USD bllions) from 2001–2010 against the left y-axis of this figure. We obtain the aggregate CDS notional amount traded in the economy (US and Global) from the International Swaps and Derivatives Association (ISDA). The amount of US bond outstanding is obtained from the Securities Industry and Financial Markets Association (SIFMA). On the right y-axis, we plot the average credit rating levels (in cardinal scale) for low-quality (BB & lower), medium-quality (BBB), and high-quality (AAA–A) firms in the Compustat universe. The average credit rating for each group is calculated using firms' long-term debt ratings.

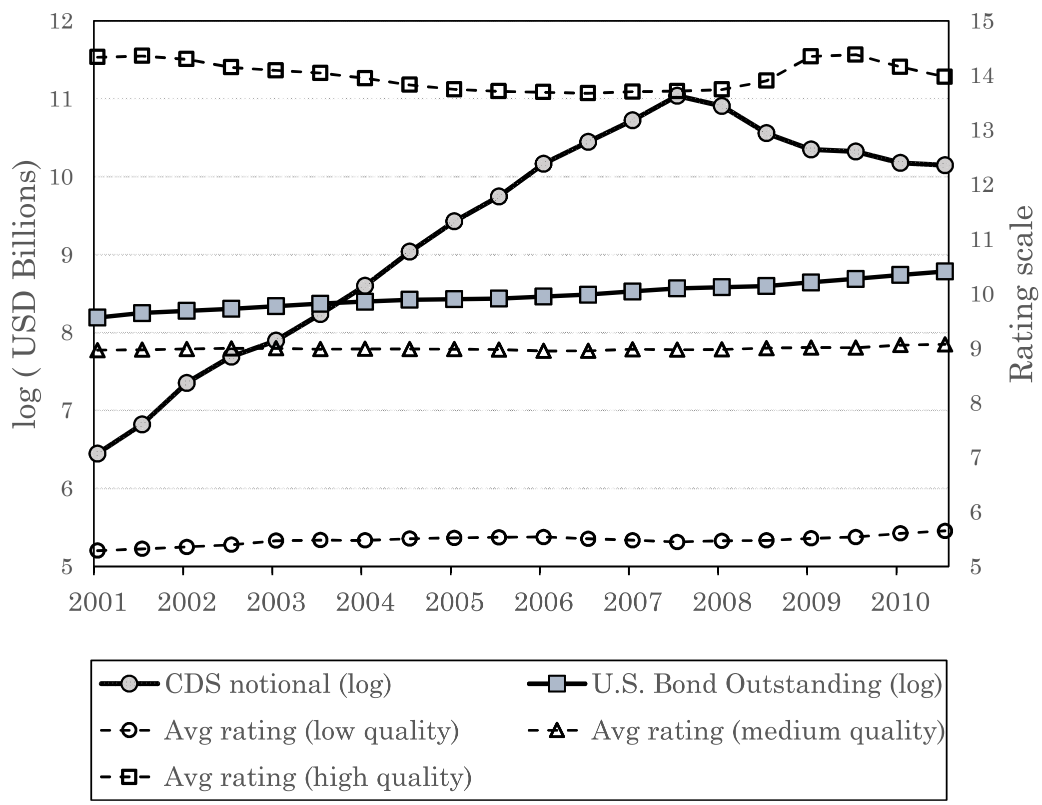

Table I. CARs to credit rating downgrades

The dependent variable is the cumulative adjusted stock return (CAR) calculated over the 3-day window around the date of rating downgrade announcement. The sample consists of rating downgrades on non-financial U.S. firms that had CDS contracts introduced during our sample period (traded-CDS firms). *dCDS* is an indicator equal to 1 if the firm has CDS contracts traded at the time of rating downgrade, 0 otherwise. Control variables are defined in Appendix A. The last row reports the univariate mean of CARs to rating downgrades in the absence of CDS trading. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR	(1)	(2)	(3)
dCDS	2.14***	1.91**	2.15**
	(3.48)	(2.03)	(2.21)
Rating-level controls			
Days Since Last Rating (log)		−0.02	−0.06
		(−0.09)	(−0.23)
Earnings Ann Related		−1.29	−1.18
		(−1.03)	(−0.94)
Firm-level controls			
Sales (log)		−0.55	−0.45
		(−1.24)	(−0.95)
Profitability		1.37	1.13
		(1.15)	(0.88)
Leverage		2.63	3.27
		(1.04)	(1.26)
Mkt-to-Book		−0.01	−0.03
		(−0.08)	(−0.24)
Avg Volatility (log)		−0.60	−0.56
		(−0.59)	(−0.53)
Avg Trading Volume (log)		−0.12	−0.24
		(−0.28)	(−0.54)
Avg Return		5.97**	5.98**
		(2.03)	(2.04)
CDS-trading controls			
Analyst Coverage (log)			0.64
			(1.17)
Analyst Dispersion			0.00
			(0.80)
Institutional Ownership			−0.48
			(−0.61)
Stock Illiquidity			−4.09
			(−0.33)
Bond Illiquidity			−0.49
			(−1.04)
Bond Hedging Demand (log)			−0.32
			(−0.63)
Industry FE	✓	✓	✓
Rating-agency FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
Year-month FE		✓	✓
N	1527	1527	1527
Adj. R^2	0.063	0.090	0.089
Avg CDS=0 CAR (%)	−2.85	−2.85	−2.85

Table II. CARs to rating downgrades: Balanced window around CDS introductions

The dependent variable is the 3-day cumulative adjusted stock return (CAR) around the date of rating downgrade announcement. The sample consists of rating downgrades on non-financial U.S. firms that had CDS contracts introduced during our sample period (traded-CDS firms). Each column reports a regression result on a subsample of rating downgrade observations that occur within the window [−Y,+Y] around the initiation of CDS trading on each firm, where Y is in year(s). Control variables are defined in Appendix A. The last row reports the univariate mean of CARs to credit rating downgrades in the absence of CDS trading. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within the specified window around CDS introductions				
	[−1, +1]	[−2, +2]	[−3, +3]	[−4, +4]	[−5, +5]
Depvar: CAR	(1)	(2)	(3)	(4)	(5)
dCDS	3.43**	3.17**	3.01***	2.71**	2.42**
	(2.23)	(2.49)	(2.62)	(2.49)	(2.29)
Rating-level controls					
Days Since Last Rating (log)	0.26	0.46	0.20	0.04	−0.14
	(0.55)	(1.29)	(0.70)	(0.16)	(−0.52)
Earnings Ann Related	1.45	−0.93	−0.17	−0.46	−0.62
	(0.69)	(−0.52)	(−0.12)	(−0.33)	(−0.46)
Firm-level controls					
Sales (log)	−1.08	0.07	−0.14	−0.55	−0.57
	(−1.24)	(0.09)	(−0.23)	(−1.03)	(−1.15)
Profitability	1.10	1.60	1.08	1.52	0.96
	(0.59)	(1.00)	(0.76)	(1.09)	(0.69)
Leverage	0.48	2.41	2.87	4.44	3.94
	(0.09)	(0.55)	(0.72)	(1.34)	(1.35)
Mkt-to-Book	−0.18	−0.19	0.03	−0.16	−0.04
	(−0.80)	(−0.81)	(0.20)	(−1.22)	(−0.32)
Avg Volatility (log)	−0.65	2.78**	0.83	−0.19	−0.63
	(−0.47)	(1.98)	(0.77)	(−0.16)	(−0.58)
Avg Trading Volume (log)	0.73	−0.62	−0.21	−0.07	−0.06
	(0.88)	(−0.89)	(−0.37)	(−0.13)	(−0.14)
Avg Return	3.10	1.34	3.55	5.57*	5.13*
	(0.56)	(0.36)	(1.22)	(1.84)	(1.69)
CDS-trading controls					
Analyst Coverage (log)	0.33	−0.44	0.05	0.50	0.67
	(0.44)	(−0.61)	(0.08)	(0.99)	(1.20)
Analyst Dispersion	−0.00	0.01	0.01*	0.01	0.01
	(−0.50)	(1.05)	(1.67)	(1.59)	(1.60)
Institutional Ownership	1.41	−0.55	−0.96	−0.84	−0.73
	(0.85)	(−0.54)	(−1.04)	(−1.04)	(−0.87)
Stock Illiquidity	−30.53	−21.55	−10.86	−6.67	5.14
	(−0.69)	(−0.80)	(−0.60)	(−0.41)	(0.44)
Bond Illiquidity	−1.67*	−1.31**	−1.31**	−0.81	−0.53
	(−1.83)	(−2.01)	(−2.32)	(−1.46)	(−1.05)
Bond Hedging Demand (log)	−2.03*	−1.18	−0.87	−0.56	−0.42
	(−1.81)	(−1.52)	(−1.30)	(−0.92)	(−0.73)
Industry FE	✓	✓	✓	✓	✓
Rating-agency FE	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓
N	422	668	898	1142	1334
Adj. R^2	0.127	0.134	0.138	0.153	0.101
Mean CDS=0 CAR (%)	−2.54	−3.10	−2.82	−2.96	−2.87

Table III. CARs to credit rating downgrades: Matched sample analysis

The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. We match treated firms with control firms based on their propensity score of having CDS trading. Panel A reports results for firms in the treatment group (traded-CDS firms). Panel B reports results for firms in the control group (non-traded-CDS firms). Panel C reports difference-in-difference regression results for the matched treatment-control sample. *dCDS* is an indicator equal to 1 if the firm has CDS contracts traded at the time of rating downgrade, and 0 otherwise. *dTreated* is an indicator equal to 1 if the firm is in the treatment group, and 0 otherwise. In each column, we estimate the regression model on a subsample of rating downgrade observations that occur within the window [−Y,+Y] around the initiation of CDS trading, where Y is in year(s). All fixed-effects and control variables are included in each regression specification. All control variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. The last row of Panels A and B reports the univariate mean of CARs to rating downgrades in the absence of CDS trading. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within the specified window around CDS introduction					
	[−1, +1]	[−2, +2]	[−3, +3]	[−4, +4]	[−5, +5]	All
Depvar: CAR	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Treated (traded-CDS) firms in the matched sample						
dCDS	3.25**	3.11**	2.89**	2.63**	2.37**	2.17**
	(2.19)	(2.47)	(2.54)	(2.43)	(2.28)	(2.28)
N	421	667	897	1141	1333	1520
Adj. R^2	0.122	0.136	0.141	0.140	0.099	0.081
Mean CDS=0 CAR (%)	−2.39	−3.00	−2.75	−2.90	−2.81	−2.77
Panel B: Control (non-traded-CDS) firms in the matched sample						
dCDS	0.22	−0.06	−0.08	−0.33	−0.23	0.03
	(0.44)	(−0.12)	(−0.15)	(−0.64)	(−0.41)	(0.07)
N	1039	1721	2305	2752	3073	3591
Adj. R^2	0.486	0.463	0.462	0.437	0.437	0.431
Mean CDS=0 CAR (%)	−3.77	−3.64	−3.37	−3.33	−3.27	−3.35
Panel C: Difference-in-Difference regression on the matched sample						
dTreated×dCDS	2.85**	2.43**	2.27**	3.27***	3.18***	2.96***
	(2.42)	(2.40)	(2.52)	(3.31)	(3.43)	(3.39)
dCDS	0.51	0.16	0.01	−0.39	−0.28	0.07
	(0.90)	(0.27)	(0.02)	(−0.66)	(−0.46)	(0.13)
dTreated	0.82	2.21	1.43	−0.06	−0.06	−0.10
	(0.65)	(1.65)	(1.41)	(−0.07)	(−0.08)	(−0.13)
N	1460	2388	3202	3893	4406	5111
Adj. R^2	0.389	0.346	0.353	0.317	0.308	0.310
Industry FE	✓	✓	✓	✓	✓	✓
Rating-agency FE	✓	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
Rating-level controls	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓

Table IV. Instrumented CDS: 2SLS/IV Regression

The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. We estimate a two-stage-least-squares (2SLS) model with an instrumental variable (IV) for *dCDS*. In the first stage, we instrument the *dCDS* variable using the aggregate log CDS notional amount traded globally. See Section III.D for more details. The first-stage regression results are reported in the Internet Appendix Table IA-9. Panel A reports results for traded-CDS firms which have CDS contracts introduced at some point during the sample period. Panel B presents a placebo test. Here, we report 2SLS/IV results on a sample of control firms (i.e., non-traded-CDS firms) that are in the matched sample. In each column, we estimate the regression model on a subsample of rating downgrade observations that occur within a fixed window [−Y,+Y] around the CDS introduction of each firm, where Y is in year(s). Each column also reports the univariate mean of CARs to credit rating downgrades in the absence of CDS trading for its sample (see "Mean CDS=0 CAR %"). All control variables are defined in Appendix A. The first-stage coefficient estimate of the *dCDS* variable on the instrument, as well the F-statistic test for the exclusion of the instrument are reported at the bottom of each column. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within the specified window around CDS introductions					
	$[-1,+1]$	$[-2,+2]$	$[-3,+3]$	$[-4,+4]$	$[-5,+5]$	All
Depvar: CAR	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Traded-CDS firms						
Instrumented dCDS	0.69	4.44**	3.58*	3.84***	3.76***	3.88***
	(0.52)	(2.23)	(1.85)	(2.64)	(2.69)	(2.74)
N	437	657	823	991	1134	1261
Adj. R^2	0.102	0.136	0.100	0.140	0.088	0.084
Avg CDS=0 CAR (%)	−2.71	−3.56	−3.24	−3.37	−3.38	−3.69
1^{st} Stg Coeff	0.274	0.256	0.221	0.220	0.210	0.210
F-stat (excl)	42.12	99.47	144.88	253.68	267.94	295.49
Panel B: Placebo test on control firms (non-traded-CDS firms) in the matched sample						
Instrumented dCDS	0.82	0.52	0.28	0.68	0.56	0.40
	(0.87)	(0.59)	(0.07)	(0.25)	(0.23)	(0.19)
N	1049	1585	2037	2261	2462	2817
Adj. R^2	0.331	0.367	0.358	0.349	0.355	0.360
Mean CDS=0 CAR (%)	−3.76	−3.75	−3.62	−3.72	−3.67	−3.85
1^{st} Stg Coeff	0.122	0.127	0.159	0.186	0.196	0.211
F-stat (excl)	13.29	23.54	73.62	171.08	249.94	378.82
Industry FE	✓	✓	✓	✓	✓	✓
Rating-agency FE	✓	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓	✓
Macro controls	✓	✓	✓	✓	✓	✓
Rating-level controls	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓

Table V. Heterogeneous effects of CDS trading on CARs to downgrades

This table presents regression results examining the heterogeneous effects of CDS trading on firms' stock price reaction to their bond rating downgrades. The sample consists of traded-CDS and non-traded-CDS firms. The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. In each panel, we sort observations into different groups as indicated by the "Grouping variable." We then estimate the following regression model:

$$CAR_{i,t} = \sum_{j=1}^{N} \mathbb{1}(\omega_j)[\beta_j \times dCDS_{i,t} + f(X_{i,t}) + g(Y_t)] + \Gamma_{R,\Delta N} + \eta_{indus} + \nu_{agency} + \varepsilon_{i,t},$$

where $\mathbb{1}(\omega_j)$ is an indicator function that is equal to 1 if the observation belongs to group j, and 0 otherwise. See Section III.E for more details. All specifications include *Industry FE, Rating-type FE, Prev-rating×Rating-change FE, Rating-level controls, Firm-level controls, CDS-trading controls, and Macro controls.* These control variables are defined in Appendix A. In each panel, we report the coefficient estimate of $dCDS$ that is associated with each group j, as well as difference in their estimates between groups ($\Delta dCDS$). For a quick reference, bottom rows of Panels A-C report univariate means of CARs to rating downgrades calculated using observations from each group in the absence of CDS trading.

In Panel A, we sort observations into three groups based on the credit rating level before the firm is downgraded. In Panel B, we sort observations into two groups based on the contractual dependence of firms' debt financing on credit ratings that we observe in their bank loans before their downgrades. Columns (1) and (2) report results where observations are sorted based on the number of rating-based performance pricing (PP) covenants and accounting-based PP covenants, respectively. Column (3) reports results sorted based on the number of active loan facilities.

Panel C reports results where we sort observations based on the credit market's tightness before the firm is downgraded. In Column (1), we sort observations in based on the credit market's Baa-Aaa spread, while in Column (2), they are sorted based on the measure of credit supply derived from the bank senior loan officer survey. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Table IA-13 in the Internet Appendix summarizes the number of observations and the sample mean of sorting variables that correspond to each of the grouping shown in Panels A to C.

Panel A: Heterogeneous effects of CDS trading across credit rating categories

	Grouping variable:
Depvar: CAR	Previous rating before the downgrade
dCDS (High: AAA–A)	1.06
	(1.57)
dCDS (Medium: BBB)	4.17***
	(3.09)
dCDS (Low: BB & lower)	1.56
	(0.90)
Δ dCDS (Medium − High)	3.10**
	(2.19)
Δ dCDS (Medium − Low)	2.61
	(1.06)
N	3310
Adj. R^2	0.198
Mean CDS=0 CAR (%) (High)	−0.82
Mean CDS=0 CAR (%) (Medium)	−3.39
Mean CDS=0 CAR (%) (Low)	−7.15

Table V. Heterogeneous effects of CDS trading on CARs to downgrades (continued)

Panel B: Heterogeneous effects of CDS when firms have contractual dependence on ratings

	Grouping variable:		
	Rating PP covenants	Accounting PP covenants	Active loan facilities
Depvar: CAR	(1)	(2)	(3)
dCDS (High)	4.19***	2.47	2.32***
	(4.30)	(1.60)	(2.67)
dCDS (Low)	0.85	2.14***	1.29
	(0.74)	(2.69)	(1.21)
Δ dCDS (High − Low)	3.34**	0.33	1.03
	(2.18)	(0.18)	(1.45)
N	2423	2423	3310
Adj. R^2	0.183	0.180	0.196
Mean CDS=0 CAR (%) (High)	−5.70	−5.17	−5.88
Mean CDS=0 CAR (%) (Low)	−3.57	−3.85	−3.01

Panel C: Heterogeneous effects of CDS when the credit market is tight

	Grouping variable:	
	Baa-Aaa credit spread	Senior loan officer survey
Depvar: CAR	(1)	(2)
dCDS (High)	3.00***	2.44***
	(3.60)	(3.29)
dCDS (Low)	0.76	−0.05
	(0.79)	(−0.05)
Δ dCDS (High − Low)	2.24*	2.49**
	(1.88)	(2.11)
N	3310	3310
Adj. R^2	0.193	0.194
Mean CDS=0 CAR (%) (High)	−5.61	−5.13
Mean CDS=0 CAR (%) (Low)	−3.68	−2.27

Table VI. CDS trading and firm's financing decisions: Post-downgrade

This table presents results examining the firms' financing decision after they have been downgraded. The sample consists of traded-CDS and non-traded-CDS firms. Panel A reports regression results for the firm's quarterly change in debt and equity issuance (net of new issuance and reduction of existing amount) over the four quarters before to the four quarters after the firm is downgraded. The quarter of the rating downgrade announcement is excluded. Panel B estimates the linear probability model for the large reduction (and new issuance) of debt and equity around the rating downgrade event. The dependent variables are shown above each column. *dPostDNG* is an indicator equal to 1 for the four quarters after the firm is downgraded, or 0 otherwise. *dTradedCDS* is an indicator equal to 1 if the firm is a traded-CDS firm, or 0 otherwise. All other control variables are defined in Appendix A. Robust t-statistics clustered at the firm level are reported in parentheses. The row labeled "(a) +(b)" reports the sum of coefficients from rows (a) and (b).

Panel A: Debt and equity issuance of downgraded firms

		Depvar: ΔDebt/Total assets			Depvar: ΔEquity/Total assets		
		(1)	(2)	(3)	(4)	(5)	(6)
dPostDNG	(a)	−0.805***	−0.697***	−0.516***	0.355***	0.422***	0.408***
		(−5.38)	(−4.61)	(−3.43)	(3.42)	(4.02)	(3.83)
dPostDNG×dCDS	(b)	0.468**	0.393*	0.358*	0.068	0.016	0.003
		(2.32)	(1.94)	(1.89)	(0.44)	(0.10)	(0.02)
dCDS		−0.835***	−0.605***	−0.522***	−0.250**	−0.227*	−0.152
		(−4.97)	(−3.31)	(−2.81)	(−2.04)	(−1.78)	(−1.18)
dTradedCDS		0.367**	0.364**	0.465***	0.133	0.076	0.073
		(2.44)	(2.28)	(2.91)	(1.19)	(0.63)	(0.57)
(a) + (b)		−0.336**	−0.304**	−0.158	0.424***	0.438***	0.411***
		(−2.35)	(−2.11)	(−1.09)	(3.74)	(3.86)	(3.60)
Industry FE		✓	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE		✓	✓	✓	✓	✓	✓
CDS-trading controls			✓	✓		✓	✓
Firm-level controls				✓			✓
N		12515	12515	12515	12622	12622	12622
Adj. R^2		0.012	0.020	0.038	0.047	0.057	0.074

Panel B: Linear probability model for a large reduction (or issuance) of debt and equity

		Depvar: Indicator variable = 1 (0 otherwise) if observing:			
		Large Debt Red.	Large Debt Issu.	Large Equity Red.	Large Equity Issu.
		(1)	(2)	(3)	(4)
dPostDNG	(a)	0.059***	−0.073***	−0.037***	0.053***
		(4.99)	(−5.71)	(−3.48)	(4.67)
dPostDNG×dCDS	(b)	−0.036*	0.027	−0.001	0.000
		(−1.88)	(1.42)	(−0.07)	(0.00)
dCDS		0.014	−0.070***	0.007	0.035*
		(0.83)	(−3.71)	(0.46)	(1.77)
dTradedCDS		0.004	0.008	0.006	−0.003
		(0.24)	(0.47)	(0.40)	(−0.15)
(a) + (b)		0.023	−0.045***	−0.038***	0.053***
		(1.41)	(−2.98)	(−2.77)	(3.37)
Industry FE		✓	✓	✓	✓
Prev-rating×Rating-change FE		✓	✓	✓	✓
CDS-trading controls		✓	✓	✓	✓
Firm-level controls		✓	✓	✓	✓
N		12515	12515	12622	12622
Adj. R^2		0.035	0.043	0.092	0.104

Table VII. CDS trading, financing cost, and investment level: Post-downgrade

We examine firms' financing cost and investment level over the four quarters before to the four quarters after they are downgraded. The sample consists of traded-CDS and non-traded-CDS firms. The dependent variable in Panel A is the log of loan spreads issued by the firm before and after the rating downgrade event. We use the all-in-drawn spread obtained from Dealscan, which is the sum of the spread of the facility over LIBOR and any annual fees paid to the lender group. We control for various loan characteristics in Panel A; see text for details. In Panel B, the dependent variable is firm's capital expenditure (CAPEX) as a fraction of lagged sales. *dPostDNG* is an indicator equal to 1 for the four quarters after the firm is downgraded, and 0 otherwise. All other variables are defined in Appendix A. Robust t-statistic clustered at the firm level is reported in parentheses below each estimate. The row labeled "(a) +(b)" reports the sum of coefficients from rows (a) and (b). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Financing cost of downgraded firms

		Depvar: log(All-in-drawn Spread)		
		(1)	(2)	(3)
dPostDNG	(a)	0.293***	0.278***	0.223***
		(8.19)	(7.71)	(6.72)
dPostDNG×dCDS	(b)	−0.160**	−0.161**	−0.127**
		(−2.36)	(−2.37)	(−2.08)
dCDS		0.107	0.103	0.098*
		(1.64)	(1.59)	(1.71)
dTradedCDS		−0.160***	−0.134**	−0.119**
		(−3.12)	(−2.41)	(−2.31)
(a) + (b)		0.133**	0.117**	0.095*
		2.36	2.09	1.90
Deal purpose FE		✓	✓	✓
Industry FE		✓	✓	✓
Prev-rating×Rating-change FE		✓	✓	✓
CDS-trading controls			✓	✓
Firm-level controls				✓
N		4003	4003	4003
Adj. R^2		0.692	0.699	0.745

Panel B: Investment level of downgraded firms

		Depvar: CAPEX/Sales		
		(1)	(2)	(3)
dPostDNG	(a)	−2.177***	−1.800**	−1.189
		(−2.83)	(−2.30)	(−1.63)
dPostDNG×dCDS	(b)	1.992**	1.683**	1.566*
		(2.42)	(2.05)	(1.94)
dCDS		−1.584**	−1.359*	−0.845
		(−2.27)	(−1.71)	(−1.04)
dTradedCDS		−0.866	−1.673**	−0.467
		(−1.26)	(−2.02)	(−0.57)
(a) + (b)		−0.184	−0.116	0.377
		(−0.48)	(−0.30)	(0.95)
Industry FE		✓	✓	✓
Prev-rating×Rating-change FE		✓	✓	✓
CDS-trading controls			✓	✓
Firm-level controls				✓
N		12274	12274	12274
Adj. R^2		0.052	0.055	0.065

Table VIII. CDS trading and firms' reliance on credit ratings

This table reports firm-quarter panel-regression results examining firms' ex ante incentives to reduce their net debt issuance in accordance with a criteria on which credit rating agencies base their assessment of a firm's credit quality. The sample consists of traded-CDS and non-traded-CDS firms. The dependent variable is the quarterly change in a firm's debt (net of issuance and reduction) over its lagged total asset. Based on Begley (2015), we define rating-based salient thresholds as regions of Debt/EBIDTA in which firms are incentivized to manage their debt issuance in order to avoid being downgraded. High-Incentive zones and Low-Incentive zones correspond to non-overlapping regions around rating-based salient thresholds representing when firms have high and low incectives to manage their debt, respectively. The indicator variable *dHiZone* is equal to 1 if the firm-quarter observation is in the High-Incentive zone, or 0 otherwise. *dCDS* is an indicator variable equal to 1 if the firm has CDS contracts traded on its debt, or 0 otherwise. Firm-level and CDS-trading control variables are defined in Appendix A. The row labeled "(a) +(b)" reports the sum of the coefficients denoted by (a) and (b). Rating fixed-effects correspond to the average rating level of each firm-quarter observation in cardinal scale. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Depvar: Δ Debt/Total assets				
		(1)	(2)	(3)	(4)	(5)
dHiZone	(a)	−1.30***	−2.15***	−2.10***	−2.02***	−1.92***
		(−8.66)	(−11.19)	(−10.93)	(−10.52)	(−9.23)
dHiZone×dCDS	(b)	0.80***	0.78***	0.74***	0.71***	0.65**
		(3.51)	(3.36)	(3.17)	(3.02)	(2.50)
dCDS		−0.85***	−0.57***	−0.58***	−0.25	−0.15
		(−5.76)	(−3.79)	(−3.68)	(−1.34)	(−0.72)
(a) + (b)		−0.50***	−1.37***	−1.36***	−1.30***	−1.27***
		−2.96	−6.87	−6.74	−6.42	−5.87
Industry×Rating FE		✓	✓	✓	✓	
Firm-level controls			✓	✓	✓	✓
CDS-trading controls				✓	✓	✓
Year-Qtr FE					✓	✓
Firm FE						✓
Rating FE						✓
N		16441	16441	16441	16441	16417
Adj. R^2		0.012	0.031	0.032	0.037	0.062

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. In Section A, we describe the sample of credit rating changes used in the paper. Section B provides a additional tests in support of the main finding in our paper. In Section C, we examine the role of CDS market in facilitating price discovery in the stock market.

A: Sample Description

- Table IA-1 lists the numbering and classification of credit rating codes.
- Table IA-2 shows the distribution of credit rating downgrades in the sample by year.
- Table IA-3 shows the distribution of credit rating downgrades sorted by firms' credit rating levels before they are downgraded.
- Table IA-4 shows the mean and median of variables used in the CAR regression for CDS and non-CDS firms.

B: Market Reaction to Credit Rating Downgrades: Supplementary results

- Table IA-5 shows the efficacy of including *Pre-rating*×*Rating-Change* fixed effects in the main result in Table I.
- Table IA-6 shows the main result in Table I is robust to using the Fama-French 3-factor adjusted CARs, and standardized CARs.
- Table IA-7 replicates the main CARs regression results over the 2001–2007 period.
- Table IA-8 presents diagnostics of the propensity-score matched sample.
- Table IA-9 presents the first-stage IV regression results for the 2SLS/IV regression analysis where we instrument the probability that a firm has CDS trading introduced using the log growth of CDS notational amount traded globally.
- Table IA-10 presents a placebo test for the instrumental variable (IV) analysis by regressing CARs on the IV separately for the traded-CDS firm sample and the non-traded-CDS firm sample. The instrument that we use is the log growth of CDS notational amount traded globally.
- Table IA-11 presents the 2SLS/IV regression results where the instrument is the amount of forex derivatives usage for hedging by the firm's lending banks.
- Table IA-12 presents the baseline regression results on the combined sample of traded-CDS firms and non-traded-CDS firms.
- Table IA-13 shows sample distributions of observations used to generate results in each Panel of Table V — Heterogeneous effects of CDS trading.
- Table IA-14 shows that our results on the heterogeneous effects of CDS trading are qualitatively similar when estimated using only traded-CDS firms.

C: CDS trading and firms' financing-related frictions: Additional results

- Table IA-15 shows that the impact of CDS trading on the downgraded firms' large debt reduction is concentrated among firms with high contractual and regulatory dependence on credit ratings.
- Table IA-16 shows that impact of CDS trading on the downgraded firms' financing cost is concentrated among firms with high contractual and regulatory dependence on credit ratings.
- Table IA-17 shows the impact of CDS trading on long-run stock returns after credit rating downgrades.
- Table IA-18 estimates the firm-quarter panel regression similar to Table VIII in the main paper but with the change in net equity issuance over lagged total assets as the dependent variable. The results show that credit ratings do not affect the firms' equity-financing decision.

D: Information discovery in CDS spreads before credit rating downgrades

- Figure IA-1 shows CDS-implied ratings before the firm is downgraded.
- Table IA-19 shows the information flow between the CDS and stock markets before the firm is downgraded.
- Table IA-20 examines the heterogeneous effect of CDS trading on CARs to credit rating downgrades based on observations sorted by the level of CDS-trading activities before the firm is downgraded.

Appendix A. Sample Description

This section discusses the sample distribution of credit rating changes. Table IA-1 shows the mapping between rating cardinal scales to different rating categories for the three credit rating agencies: S&P, Moody's, and Fitch.

The sample consists of rating-downgrade observations on non-financial U.S. firms from 1996 to 2010. Firms in this sample can be classified as either a *traded-CDS* firm or a *non-traded-CDS* firm. We define traded-CDS firms as those that had CDS contracts introduced during our sample period. On the other hand, non-traded-CDS firms are those that did not experience CDS trading at any point during our sample period. While rating downgrade observations for a traded-CDS firm are observed in both the presence (CDS=1) and the absence (CDS=0) of CDS trading, rating downgrade observations for a non-traded-CDS firm are observed only in the absence of CDS trading (CDS=0).

We use the traded-CDS firm sample to document our main empirical finding that the equity price reaction to credit rating downgrades is muted in the presence of CDS trading. This sample is designed to help mitigate differences between firms that are chosen to have CDS trading introduced and those that are not. We later use non-traded-CDS firms as our control group in the matched sample analysis, and in the placebo test of our instrumental variable analysis. Subsequently, we use the combined sample of traded-CDS and non-traded-CDS firms in the analyses which examine the economic channels through which CDS-trading introduction impacts the equity price reaction to rating downgrades. This larger cross-sectional sample of traded-CDS and non-traded-CDS firms allows for a greater heterogeneous variations in rating downgrade observations. Further, it allows us to draw a more general conclusion on the effect of CDS-trading introduction for an average firm.

Table IA-2 summarizes the number of downgrades along with the size of their rating changes for CDS firms (CDS=1) and non-CDS firms (CDS=0) over each year. We report results separately for: (1) the traded- and non-traded-CDS firm sample; and (2) the traded-CDS firm sample. We observe clustering of downgrades in certain years over the 15-year period. We find that 42% of all downgrades occurred in 2001–2002 and 2007–2009, which correspond to the post-Internet bubble and the recent sub-prime crisis periods, respectively. The size of the rating change announcement is the absolute value ofchange in the cardinal rating scale. The average size of the rating change does not vary significantly over the years, and are comparable in magnitude between the two samples. Table IA-2 shows that the starting year of CDS trading in our sample is 2001 when we observe 12 downgrades on firms with CDS trading. The proportion of firms that have CDS contracts traded increases significantly in subsequent years. In fact, the traded-CDS firm sample shows that by 2008, all firms in this sample have CDS trading introduced. These findings indicate that CDSs introductions during our sample period occur between 2001 to 2007.

Table IA-3 presents the distribution of bond rating downgrades conditional on the firm's cardinal rating scale before it was downgraded (i.e., previous rating). We separately report the results for the combined traded- and non-traded-CDS firm sample, and for the traded-CDS sample. We group previous ratings into three categories: investment grade (IG), bordering investment-speculative grade (IG-SG), and speculative grade (SG). Table IA-1 shows the mapping between cardinal scales to different rating categories. Looking at both samples, the percentage of CDS trading (%CDS=1) concentrates around credit rating downgrades on firms that are near the border of investment-speculative grade.

Appendix B. Market Reaction to Rating Downgrades: Additional results

Appendix B.1. *The efficacy of controlling for Prev-rating×Rating-Change fixed effects*

This section discusses the effectiveness of including *Prev-rating*×*Rating-Change* fixed effects when studying the stock market reaction to credit rating downgrades. The intuition of including these fixed effects is that if credit ratings sufficiently describe a firm's credit quality, then the stock market should react similarly to credit rating downgrades that are announced on a CDS firm and a non-CDS firm within the same credit rating level, and experience the same credit rating change magnitude. The rating level (*Prev-rating*) and the number of rating-notch changes (*Rating-Change*) are expressed in cardinal scale, which is from 1 (AAA/Aaa) to 23 (D). Table IA-1 in this Internet Appendix presents the mapping.

Table IA-5 reports the regression results for CARs to credit rating downgrades similar to that in Table I of the main paper. Here, we estimate the baseline regression model using the full set of controls. We apply different sets of fixed effects to each regression specification. Column (1) reports results with no fixed effects. Column (2) reports results with only the *Year-month* fixed effects. Columns (3) and (4) report results where only the *Rating-agency* fixed effects and the *Industry*-fixed effects included, respectively. Finally, Column (5) reports results where only the *Prev-rating*×*Rating-Change* fixed effects are included.

The results in Table IA-5 clearly show that among the various sets of fixed effects that we consider, *Prev-rating*×*Rating-Change* fixed effects explain the most cross-sectional variations in CARs to credit rating downgrades. Unlike the results in Columns (1)–(4), we find that most of the control variables in Column (5) loose their statistical significance in explaining CARs to credit rating downgrades. This indicates that *Prev-rating*×*Rating-Change* fixed effects can explain a substantial amount of cross-sectional differences in the equity price reaction to credit rating downgrades. In fact, Column (5) shows that *Avg Return*, which is the one-month cumulative return of the firm before it is downgraded, is the only statistically significant control variable.

This indicates that when the unobserved heterogeneity associated with rating-change characteristics has been absorbed by *Prev-rating*×*Rating-Change* fixed effects, the economic importance of the *dCDS* variable magnifies.

Appendix B.2. *Robustness to other measures of stock price reactions*

In the main paper, the cumulative abnormal stock return to rating downgrade announcements (CAR) is calculated using the market model. We verify that our results are robust to the use of an alternative benchmark model for calculating CAR. We use the Fama-French 3-factor model to calculate CAR and verify that the main finding of this paper is qualitatively unchanged. Panel A of Table IA-6 reports the results where we estimate the baseline regression model similar to that in Table I.

The magnitude of abnormal return around credit rating change events could be affected by the current volatility level of the firm. To address this, we measure abnormal stock return to rating downgrades 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 daily abnormal return calculated over the $[-90,-5]$ period before the rating-change announcement. We multiply $\sigma(AR_i)$ by a factor of $\sqrt{3}$ to accounts for the 3-day period corresponding to the event window $(-1,+1)$. Panel B of of Table IA-6 reports the regression results. Similar to the baseline regression results that we report in Table I of the main paper, we find that CDS trading mutes the stock market reaction to rating downgrades by about 60–75%. This is calculated by comparing the estimate of *dCDS* to the mean of standardized CARs in the absence of CDS shown in the bottom row.

Appendix B.3. Matching procedure for traded-CDS and non-traded-CDS firms

We estimate firms' propensity of having CDS trading introduced using a logit model on a panel of firm-quarter observations. The dependent variable in the model, *dCDS*, is an indicator variable equal to 1 if there is a CDS trading for that firm in that quarter, and 0 otherwise. We include all *firm-level* and *CDS-trading* control variables from our baseline regression in Table I. These explanatory variables are lagged by one quarter. Appendix Table IA-8 provides their details. Additionally, we include *industry*, *year-quarter* fixed effects, and *rating-group* fixed effects in the logit model, where we consider three rating groups: high credit rating (AAA–A), medium credit rating (BBB), and low credit rating (BB & lower). These fixed effects capture time-invariant unobservable characteristics at the industry and rating level that drive the introduction of CDS trading on firms. Thus, the predicted propensity score allows us to match observations based on some of these unobservable characteristics as well.

We require that firms entering the matching sample have complete time-series information on their observable variables from 2001 onwards, which is when we first observe CDS trading in the sample. This requirement leaves us with 315 traded-CDS firms and 370 non-traded-CDS firms. We refer to this set of firms as the "before-matching" sample. The fitted probability from the logit model, which is the propensity score for CDS trading, is used to match traded-CDS firms to non-traded-CDS firms.

For each traded-CDS firm, we use its estimated propensity score in the quarter when CDS starts trading to identify a non-traded-CDS firm with the closest propensity score in the same quarter, industry, and rating group. We implement the common support condition in the matching procedure by dropping traded-CDS firms (treated) whose propensity score is greater than the maximum or lower than the minimum propensity score of non-traded-CDS firms (control). This ensures that there is sufficient overlap in characteristics between traded-CDS and non-traded-CDS firms. 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 pairs (see Dehejia and Wahba (2002)). Upon matching, each non-traded-CDS firm is assigned a counterfactual CDS introduction date that is equal to its matched traded-CDS firm's CDS introduction date. The matching is carried out with replacement. However, we impose that a non-traded-CDS firm cannot serve as a match for different traded-CDS firms more than five times. This implies that a matched non-traded-CDS firm can have at most five unique counterfactual CDS introduction dates. The matching exercise leaves us with 309 unique traded-CDS firms (treated) each matched to five eligible non-traded-CDS firms (controls). There are 312 unique non-traded-CDS firms in the control sample.

The column labeled "After matching" in Panel A of Table IA-8 reports logit model results for the matched observations. We find that differences between CDS and non-CDS firms on certain observable characteristics (e.g., firm size and leverage) still remain. To control for these differences, we include all the matching covariates in our matching regressions. In Table IA-8, Panel B, of this Internet Appendix, we report the industry distribution of firms in the treatment and control samples. We find that industry distributions of the two samples are similar and that the control group is not overweighted by any particular industry relative to the treated group.

Appendix B.4. Examples of performance pricing (PP) covenants

We present below three examples of PP covenants linked to the loan facility as reported in the Performance Pricing table of the Dealscan database.

- **Rating-based only PP covenants.** Pricing is tied to co.'s sr. unsec'd LTD rating by S&P and Moody's. If split-rated, the lower rating applies. If split-rated by more than one level, the rating above the lower level applies. Pricing for 19154: LIBOR + bp: A- >=< BBB+ : 37.5; BBB + >=< BBB: 50; BBB >=< BBB-: 62.5; BBB- >=< BB: 71.25; BB >=<BB-: 100; BB->= : 137.5
- **Rating- and accounting-based PP covenants.** Pricing is as indicated thru FQE 3/31/95; tied to ratio thereafter. Ratio = EBITDA less capex to interest expense. LIBOR margin and LC fee reduce to 62.5 bps if the sr. debt rating > or = BBB-/Baa3, but < BBB/Baa2; LIBOR margin and LC fee reduce to 50 bps if the rating > or = BBB/Baa2.
- **Accounting-based only PP covenants.** Pricing as indicated thru 12/31/94 and tied to the funded debt to capital ratio and the interest coverage ratio (ICR); as indicated when ICR > or = 6.5:1; LIB and CD margins increase by 12.5 bps when ICR > or = 4.5:1, but < 6.5:1; 25 bps when the ratio > or = 3.5, but < 4.5:1; 37.5 bps when the ratio < 3.5:1.

Appendix C. Information discovery in CDS spreads before credit rating downgrades

Besides the demand to hedge and trade credit risk, Oehmke and Zawadowski (2015a) show that trading in the CDS market is associated with speculative motives. Similar to credit ratings, CDS spreads reflect the credit risk of their underlying firms. In this case, CDS-trading activities, particularly before the firm is downgraded, may provide information about the firm's credit risk that is beyond what investors already observe in the stock and bond markets. As a result, the equity market reaction to rating downgrades is muted because the rating-change announcement is less informative about the downgraded firm's credit risk in the presence of CDS trading. In this Section of the Internet Appendix, we for the evidence of this *information* hypothesis.

Section C.1 presents results showing that CDS-implied ratings start adjusting ahead of the firm's rating downgrade announcement. Section C.2 shows that CDS spreads lead stock returns in the 90-day period before the firm is downgraded. In Section C.3, we test examine whether CDS-activities before the firm is downgraded affect the firm's stock market reaction to credit rating downgrade announcements.

Appendix C.1. CDS-implied ratings

We construct CDS-implied credit ratings following the approach in Breger, Goldberg, and Cheyette (2003) and Kou and Varotto (2008). Figure IA-1 plots the results. 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. These boundaries are estimated daily using all CDS spreads traded on the firm.

More specifically, missclassification occurs when the CDS spread of a higher-rated firm is greater 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:

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

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 (IA.1). 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. The mapping between rating codes and rating classes is shown in the Appendix Table IA-1. 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, and 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.

In Figure IA-1, we plot the 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; see Table IA-1 for the mapping. 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.

We find that CDS-implied ratings started increasing at least 180 days prior to a downgrade announcement. This suggests that the CDS market responds to the firm's deteriorating credit quality several months ahead of credit rating downgrade announcements. Figure IA-1 also 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, consistent with the prevailing consensus, as well as our results, showing that rating upgrades have little pricing relevance.

Appendix C.2. Information flow between the CDS and stock markets

This section provides evidence on information being impounded from the CDS to equity markets before rating downgrade events. We follow the empirical framework in Acharya and Johnson (2007) by looking at the lead-lag relationship between CDS and stock returns. We first construct the unanticipated component in CDS spreads by removing components in CDS changes that are predictable using lagged CDS returns, contemporaneous stock return, and lagged stock returns.

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

$$\begin{aligned}\text{Stock return}_{i,t} = a + &\sum_{k=1}^{5}\left(b_k + b_k^d \text{ dPreDNG}_{i,t}\right) \times u_{i,t-k} \\ &+ \sum_{k=1}^{5}\left(c_k + c_k^d \text{ dPreDNG}_{i,t}\right) \times \text{Stock return}_{i,t-k} + \varepsilon_{i,t}, \quad \text{(IA.2)}\end{aligned}$$

where $u_{i,t-k}$ is the CDS innovation or unanticipated component on day $t-k$. The CDS innovation, $u_{i,t}$, is estimated by running a firm-by-firm time-series regression to remove the components in CDS changes that are predictable using lagged CDS returns, contemporaneous stock return, and lagged stock returns.

We include lagged stock returns in the above regression model to ensure that any relationships between past CDS innovations and future stock returns are not artifacts of stock return autocorrelations. We introduce a new variable in the regression specification into equation (IA.2). $PreDNG_t$ is an indicator variable equal to 1 on day t if it is within $[-90, -2]$ days of credit rating downgrades, and 0 otherwise. This variable is designed to capture information flow from the CDS to equity markets that occurs before rating downgrade announcements.[1] For our analysis, we use CDS spreads with 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 IA-19 reports the results. In columns (1) and (2), we report results estimated using all eligible observations consisting of 345 unique firms. Column (1) reports the baseline regression results without $PreDNG_t$. 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 a day-to-day basis. We find that its estimate of -0.74% is significant at the 10% confidence level. The negative sign is consistent with Merton (1974), who shows that as default risk increases, equity price falls. However, the magnitude of 0.74% seems economically small. On the other hand, we find that past stock returns significantly predict future stock returns with a coefficient of -7.23%. This strong negative auto-correlation is consistent with the well-established mean-reversion characteristic of stock returns.

[1] We obtain similar conclusions when replicating the results with rating condition dummies defined over the following event windows $[-60, -2]$, $[-60, +30]$, and $[-30, +30]$ relative to rating change events.

The regression model for column (2) in Table IA-19 focuses on the pre-downgrade period. In this case, $\sum_{k=1}^{5} b_k^d$ quantifies the information flow from the CDS to equity markets before credit rating downgrades. We find that it is negative and statistically significant, indicating an approximate 4.3% transmission of information from CDS innovation to future stock returns. We also find that the information flow measure $\left(\sum_{k=1}^{5} b_k\right)$ is no longer significant, suggesting that outside the period surrounding credit rating downgrades, the CDS market is not informative of future stock returns. Interestingly, column (2) shows that past stock returns are not significantly predictive of future stock returns during the rating-downgrade period. This is seen from the statistically insignificant estimates on $\sum_{k=1}^{5} c_k^d$.

Appendix C.3. Testing the informativeness of credit ratings vis-à-vis CDS spreads

We test whether CDS-trading activities before firms are downgraded can explain the magnitude of their equity price reactions to rating downgrade announcements. We proxy for the informativeness of CDS-trading activities using three measures: (i) the cumulative log CDS spread change; (ii) the volatility of log CDS spread change; and (iii) the number of CDS dealer quotes. These measures are calculate using daily 5-year CDS spreads over the 90-day period before each rating downgrade announcement. The first and second measures convey the CDS market's expectation and uncertainty, respectively, of the change in a firm's credit quality before the rating downgrade announcement. The third measure is a proxy for CDS market's liquidity in the CDS market. This liquidity measure was also used Qiu and Yu (2012) to show that greater liquidity in the CDS market is associated with greater informed trading and information flow from the CDS market to the equity market ahead of an impending bad news about a firm.

Panel A of Table IA-20 reports regression results on samples that are grouped according to the three CDS-trading measures that we described above. For each measure, we divide observations *within* each rating category into above-the-median (high) group and below-the-median (low) group. Columns (1)–(2) show that the equity market reaction to credit rating downgrades does not differ based on the cumulative CDS spread changes and the volatility of CDS spread changes before the firm is downgraded, even though the differences in CDS-trading activities between the high and low groups in Columns (1)–(2) are large.

Panel B of Table IA-20 presents summary statistics of the variables that we use as proxies for the informativeness of CDS-trading activities in each group. For instance, the mean of cumulative CDS spread change before downgrades in the high group is 54.37%, while for the low group, it is −15%, indicating that CDS spreads do not always move in the expected positive direction that reflects an increasing default risk of the downgraded firm. Despite the stark difference in how CDS spreads change before the firm is downgraded, Column (1) of Panel A shows that the effect of CDS trading is about the same between these two groups. Similarly, the average volatility of CDS spread changes in the above-th-median (high) group (4.87%) is more than twice that of the (below-the-median) low group (2.07%). However, Column (2) shows that the effect of CDS trading does not differ when we split rating downgrade observations in the sample along this dimension.

Finally, Column (5) in Panel A examines the impact of CDS trading on CARs to rating downgrades that are preceded by above-the-median (high) and below-the-median (low) number of CDS dealer quotes — a proxy for CDS liquidity. We find some evidence that CARs to rating downgrades are more muted when there is greater liquidity in the CDS market before the firm is downgraded. The difference in CARs between the high and low groups is significant at the 10% level. Importantly, while higher number of CDS dealer quotes could imply greater informed trading in the CDS market, it is also associated with greater demand for purchasing credit protection ahead of an impending bad news (Qiu and Yu (2012)). Taken together, the evidence in Table IA-20 is weakly supportive of the information hypothesis and thus cannot be ruled out.

Table IA-1. 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 et al. (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 IA-2. The distribution of bond rating downgrades by year

We report the year-by-year distribution of rating-downgrade observations that we study. We report results for two samples. We study 3,310 credit rating downgrades on taxable corporate bonds issued by non-financial U.S. firms from January 1996 to December 2010. The sample in Panel A consists of *traded-CDS* and *non-traded-CDS* firms. Whereas, Panel B summarizes rating downgrade observations on a subsample of traded-CDS firms only. We define traded-CDS firms as those that had CDS trading introduced during our sample period, and non-traded-CDS firms as those that did not have CDS trading introduced during our sample period. The sample is split between rating changes that occur in the presence of CDS trading (CDS= 1) and in the absence of CDS trading (CDS = 0) on the underlying firm's debts. We report the year-by-year distribution of credit rating downgrades. *Count* represents the number of rating downgrades. *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 IA-1 for the mapping).

	Panel A: Traded-CDS and non-Traded-CDS sample				Panel B: Traded-CDS sample			
Year	CDS= 0		CDS= 1		CDS= 0		CDS= 1	
	Count	Size	Count	Size	Count	Size	Count	Size
1996	14	1.36			7	1.14		
1997	109	1.38			36	1.31		
1998	160	1.61			50	1.42		
1999	221	1.58			73	1.23		
2000	310	1.59			103	1.44		
2001	438	1.85	12	1.25	156	1.51	9	1.33
2002	369	1.72	55	1.31	162	1.50	42	1.33
2003	165	1.88	101	1.26	55	1.55	78	1.24
2004	87	1.56	92	1.32	22	1.55	74	1.26
2005	69	1.45	113	1.47	5	1.60	89	1.44
2006	78	1.22	162	1.59	5	1.00	139	1.53
2007	63	1.54	152	1.59	5	1.40	129	1.56
2008	48	1.38	174	1.37			143	1.36
2009	61	1.48	158	1.55			116	1.49
2010	39	1.41	60	1.20			36	1.17
Total	2231	1.64	1079	1.44	649	1.45	885	1.41

Table IA-3. The distribution of bond rating downgrades across credit rating levels

We report results for two samples. We study 3,310 credit rating downgrades on taxable corporate bonds issued by non-financial U.S. firms from January 1996 to December 2010. The sample in Panel A consists of *traded-CDS* and *non-traded-CDS* firms. Whereas, Panel B summarizes rating downgrade observations on a subsample of traded-CDS firms only. We define traded-CDS firms as those that had CDS trading introduced during our sample period, and non-traded-CDS firms as those that did not have CDS trading introduced during our sample period. The sample is split between rating changes that occur in the presence of CDS trading (CDS= 1) and in the absence of CDS trading (CDS = 0) on the underlying firm's debts. We report distribution of rating downgrades with respect to the firm's cardinal rating scale before it was downgraded (i.e., previous rating). Count represents the number of rating downgrades. Bond ratings are converted to a cardinal scale measured on a 23-point scale (see Appendix IA-1 for the mapping).

	Panel A: Traded-CDS and non-Traded-CDS sample			Panel B: Traded-CDS sample		
Previous rating	CDS=0 Count	CDS=1 Count	%CDS=1	CDS=0 Count	CDS=1 Count	%CDS=1
	(1)	(2)	(3)	(4)	(5)	(6)
Investment grade: AAA to A						
1	8	7	46.67%	6	0	0.00%
2	7	3	30.00%	0	0	n.a.
3	33	17	34.00%	16	10	38.46%
4	66	22	25.00%	39	15	27.78%
5	114	64	35.96%	57	46	44.66%
6	158	89	36.03%	77	71	47.97%
7	203	96	32.11%	99	79	44.38%
Bordering Investment–Speculative grade: BBB						
8	204	142	41.04%	90	105	53.85%
9	220	161	42.26%	85	128	60.09%
10	208	132	38.82%	60	105	63.64%
Speculative grade: BB to C						
11	110	78	41.49%	24	66	73.33%
12	126	61	32.62%	38	53	58.24%
13	114	61	34.86%	22	56	71.79%
14	143	40	21.86%	24	33	57.89%
15	127	30	19.11%	18	27	60.00%
16	143	32	18.29%	10	25	71.43%
17	96	22	18.64%	11	20	64.52%
18	62	13	17.33%	2	11	84.62%
19	44	7	13.73%	1	5	83.33%
20	24	2	7.69%	0	0	n.a.
21	21		0.00%	0	0	n.a.
Total	2231	1079	32.60%	679	855	55.74%

Table IA-4. Mean and median of observable factors for CDS and non-CDS observations

This table presents the mean and median of the observable factors for CDS and non-CDS observations. Median values are presented in square brackets. *, **, and *** indicate statistical significance of the t-statistic that tests the difference between the means of CDS and non-CDS firms at the 10%, 5%, and 1% levels, respectively.

	CDS=1	CDS=0	Diff
Rating-related factors			
Rating	9.517	10.722	-1.205***
	[9.000]	[10.000]	[-1.000]
Abs Rating Change	1.442	1.642	-0.200***
	[1.000]	[1.000]	[0.000]
Earnings Ann Related (%)	0.089	0.064	0.025**
	[0.000]	[0.000]	[0.000]
Days since rating change	48.367	47.625	0.742
	[60.000]	[60.000]	[0.000]
Firm-related factors			
Sales ($ Bil)	4.876	1.693	3.183***
	[2.312]	[0.624]	[1.688]
Profitability	0.075	-0.015	0.090***
	[0.068]	[0.058]	[0.011]
Leverage	0.688	0.715	-0.027***
	[0.678]	[0.698]	[-0.020]
Mkt-to-Book	2.177	1.749	0.428***
	[1.491]	[1.145]	[0.346]
Avg Volatility	0.031	0.044	-0.013***
	[0.022]	[0.032]	[-0.010]
Avg Trading Volume	1.251	0.568	0.683***
	[0.587]	[0.128]	[0.460]
Avg Return	-0.020	-0.053	0.033***
	[-0.005]	[-0.025]	[0.020]
CDS trading-related factors			
Analyst Coverage (#)	9.146	6.892	2.254***
	[9.000]	[5.000]	[4.000]
Analyst Dispersion	3.835	2.064	1.771
	[4.308]	[2.542]	[1.766]
Institutional Ownership (%)	0.764	0.618	0.146***
	[0.779]	[0.631]	[0.148]
Stock Illiquidity	0.027	0.111	-0.084***
	[0.015]	[0.047]	[-0.032]
Bond Illiquidity	10.353	7.467	2.886***
	[8.000]	[5.000]	[3.000]
Bond Hedging Demand ($ Mil)	4.895	2.044	2.851***
	[3.075]	[0.925]	[2.150]
Contract-related factors			
Loan Facilities	20.031	19.145	0.885
	[12.000]	[8.000]	[4.000]
Performance Pricing (PP) Covenants	9.608	6.391	3.217***
	[6.000]	[3.000]	[3.000]
Rating-based PP Covenants	7.977	4.368	3.609***
	[4.000]	[0.000]	[4.000]

Table IA-5. CARs to credit rating downgrades: Variations absorbed by fixed-effects

The dependent variable is the cumulative adjusted stock return (CAR) calculated over the 3-day window around rating downgrade announcement days using the market model. The regression results are estimated on sample of traded-CDS firms from January 1996 to December 2010. *dCDS* is an indicator variable equal to 1 if the firm has CDS contracts traded on its debt, and 0 otherwise. Control variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Depvar: CAR	(1)	(2)	(3)	(4)	(5)
dCDS	2.15***	2.09**	2.16***	2.04***	2.54***
	(3.14)	(2.26)	(3.13)	(3.08)	(3.43)
Rating-level controls					
Days Since Last Rating (log)	0.05	−0.02	0.06	−0.04	−0.05
	(0.20)	(−0.08)	(0.27)	(−0.15)	(−0.20)
Earnings Ann Related	−0.98	−1.05	−0.93	−1.01	−0.97
	(−0.86)	(−0.85)	(−0.81)	(−0.91)	(−0.84)
Firm-level controls					
Sales (log)	0.12	0.07	0.12	0.29	−0.24
	(0.39)	(0.20)	(0.38)	(0.67)	(−0.72)
Profitability	1.44	1.57	1.43	1.21	0.90
	(1.28)	(1.18)	(1.28)	(1.07)	(0.84)
Leverage	−0.27	0.11	−0.32	0.97	1.70
	(−0.13)	(0.05)	(−0.16)	(0.43)	(0.79)
Mkt-to-Book	0.18**	0.18**	0.19**	0.15*	0.03
	(2.42)	(2.09)	(2.48)	(1.75)	(0.34)
Avg Volatility (log)	−0.58	−0.33	−0.58	−0.66	−0.76
	(−0.86)	(−0.28)	(−0.88)	(−0.99)	(−1.21)
Avg Trading Volume (log)	−0.57	−0.77**	−0.58	−0.47	−0.22
	(−1.57)	(−2.06)	(−1.59)	(−1.12)	(−0.52)
Avg Return	8.55***	6.30*	8.60***	8.39***	8.49***
	(3.04)	(1.93)	(3.04)	(3.13)	(3.38)
Analyst Coverage (log)	0.43	0.62	0.42	0.28	0.43
	(0.65)	(1.15)	(0.63)	(0.40)	(0.83)
CDS-trading controls					
Analyst Dispersion	0.00	0.00	0.00	0.00	0.00
	(0.79)	(0.64)	(0.77)	(0.96)	(0.80)
Institutional Ownership	−0.32	0.04	−0.33	−1.10*	0.06
	(−0.56)	(0.07)	(−0.57)	(−1.67)	(0.11)
Stock Illiquidity	−9.83	−17.56	−10.02	−11.43	4.15
	(−0.74)	(−1.40)	(−0.75)	(−0.87)	(0.30)
Bond Illiquidity	−0.44	−0.49	−0.42	−0.59	−0.45
	(−0.97)	(−1.08)	(−0.93)	(−1.28)	(−0.95)
Bond Hedging Demand (log)	−0.61	−0.55	−0.59	−0.41	−0.59
	(−1.40)	(−1.21)	(−1.37)	(−0.91)	(−1.33)
Year-month FE		✓			
Rating-agency FE			✓		
Industry FE				✓	
Prev-rating×Rating-change FE					✓
N	1527	1527	1527	1527	1527
Adj. R^2	0.053	0.056	0.053	0.062	0.081
Mean CDS=0 CAR (%)	−2.85	−2.85	−2.85	−2.85	−2.85

Table IA-6. CARs around credit rating downgrades: Alternative CAR benchmarks

This table presents regression results of firms' stock price reaction to their bond rating downgrades on firms that had CDS trading introduced during our sample period (traded-CDS firms). The dependent variable CAR is calculated over the 3-day window around rating change announcement days using the market model. The sample consists of rating changes by S&P, Moodys, and Fitch from 1996–2010. *dCDS* is an indicator variable equal to 1 if the firm has CDS contracts traded on its debt, and 0 otherwise. Control variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama-French 3-factor adjusted CARs

Depvar: FF-adjusted CAR	(1)	(2)	(3)
dCDS	1.94***	1.81*	2.06**
	(3.19)	(1.84)	(2.01)
Industry FE	✓	✓	✓
Rating-agency FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
Firm-month FE	✓	✓	✓
Rating-level controls		✓	✓
Firm-level controls		✓	✓
CDS-trading controls			✓
N	1527	1527	1527
Adj. R^2	0.064	0.090	0.089
Mean CDS=0 CAR (%)	−2.75	−2.75	−2.75

Panel B: Standardized CARs

Depvar: Standardized CAR	(1)	(2)	(3)
dCDS	0.30**	0.43*	0.44*
	(2.14)	(1.84)	(1.79)
Industry FE	✓	✓	✓
Rating-agency FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
Firm-month FE	✓	✓	✓
Rating-level controls		✓	✓
Firm-level controls		✓	✓
CDS-trading controls			✓
N	1527	1527	1527
Adj. R^2	0.029	0.059	0.057
Mean CDS=0 Standardized CAR (%)	−0.50	−0.50	−0.50

Table IA-7. CARs around rating downgrades: 2001–2007

This table presents regression results of firms' stock price reaction to their bond rating downgrades similar to Table II in the main paper, but with the shorter sample period over 2001–2007. The sample period starts in 2001, which is after the implementation of Regulation Fair Disclosure (Reg FD), and ends in 2007 at the start of the sub-prime crisis. The dependent variable is cumulative adjusted stock return (CAR) calculated over the 3-day window around rating change announcement days using the market model. *dCDS* is an indicator variable equal to 1 if the firm has CDS contracts traded on its debt, and 0 otherwise. In each panel, Columns (1)–(4) report results obtained using yearly balanced time-windows [−Y,+Y] around the initiation of CDS trading of each firm, where Y is in year(s). In Column (5), we report results without restricting observations to a specific time-window around CDS introductions. All fixed-effects and control variables are included. Control variables are identical to those shown in Table I and are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within the specified window around CDS introductions				
	[−1, +1]	[−2, +2]	[−3, +3]	[−4, +4]	All
Depvar: CAR	(1)	(2)	(3)	(4)	(5)
dCDS	3.65**	3.24**	3.10***	2.67**	2.49**
	(2.37)	(2.57)	(2.69)	(2.43)	(2.38)
Firm-level controls	✓	✓	✓	✓	✓
Rating-level control	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Rating-agency FE	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓
N	413	626	791	888	963
Adj. R^2	0.123	0.146	0.137	0.133	0.174
Avg CDS=0 CAR	−2.74	−3.53	−3.24	−3.37	−3.70

Table IA-8. The propensity score matched sample

This table presents the matched sample diagnostics. All variables are defined in Appendix A. Panel A shows the probit model used in the propensity score matching. 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 on a sample of traded-CDS firms and their propensity-score matched non-traded-CDS firms. Firms that had CDS contracts introduced during our sample period (1996-2010) are identified as the treatment group, i.e. traded-CDS firms. Firms in the control group that we use in the matching are those that did not have CDS contracts introduced during our sample period , i.e. non-traded-CDS firms. *, **, and *** indicate statistical confidence greater than 10%, 5%, and 1%, respectively. Panel B reports industry distributions (Fama-French 12 classification) for the treatment firms and the matched control firms.

Panel A: Propensity score matched sample

	Before matching	After matching
Sales (log)	0.77***	0.98***
	(20.20)	(5.46)
Profitability	-0.51**	0.20
	(-2.23)	(0.16)
Leverage	1.66***	1.27*
	(9.31)	(1.68)
Market-to-Book	-0.02**	0.00
	(-2.35)	(0.06)
Rating Scale (log)	-0.09	-0.23*
	(-0.47)	(-1.80)
Avg Return	-0.50*	1.32
	(-1.73)	(1.00)
Avg Volatility (log)	0.06	0.56
	(0.76)	(1.63)
Avg Trading Volume (log)	0.18***	0.09
	(4.82)	(0.52)
Analyst Coverage (log)	0.15***	0.26
	(3.29)	(1.36)
Analyst Dispersion	0.00**	-0.00
	(2.06)	(-0.32)
Institutional Ownership	0.13	0.37
	(1.45)	(1.10)
Stock Illiquidity	-2.61**	-4.51
	(-2.45)	(-0.64)
Bond Illiquidity	1.05***	1.06***
	(27.70)	(6.31)
Bond Debt Outstanding (log)	0.88***	1.19***
	(22.13)	(7.01)
Industry FE	✓	✓
Year–Qtr FE	✓	✓
Rating Quality FE	✓	✓
N	15613	986
Pseudo R^2	0.50	0.49

Panel B: Industry distribution of firms in the matched sample

FamaFrench 12 Industry Classifications	Treatment Sample (%)	Control Sample (%)
(1) Consumer Non-durables	7.12	7.53
(2) Consumer Durables	2.91	2.69
(3) Manufacturing	14.89	19.35
(4) Energy, Oil, Gas, and Coal Extraction	7.44	9.14
(5) Chemicals and Allied Products	6.15	5.38
(6) Business Equipment	7.44	9.68
(7) Telecommunciations	6.47	6.45
(8) Utilities	11.97	11.29
(9) Wholesale, Retail, and Services	13.92	8.06
(10) Healthcare	6.47	4.30
(12) Others	15.21	16.13

Table IA-9. **First-stage regression using aggregate CDS notional as instrument**

This table presents the first-stage regression results for the IV/2SLS regression in Table IV. We instrument the *dCDS* indicator variable with the aggregate log CDS notional amount traded in the economy. Columns (1)–(5) report results for rating downgrade observations that occur within a fixed window [−Y,+Y] around the CDS introduction of each firm, where Y is in year(s). Column (6) reports results for all firms in the Traded-CDS sample. All control variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within yearly windows around CDS introduction					
	(−1, +1)	(−2, +2)	(−3, +3)	(−4, +4)	(−5, +5)	All
Depvar: dCDS	(1)	(2)	(3)	(4)	(5)	(6)
CDS Notional (log)	0.27***	0.26***	0.22***	0.22***	0.21***	0.21***
	(6.49)	(9.97)	(12.04)	(15.93)	(16.37)	(17.19)
Rating-level controls						
Earnings Ann Related	−0.03	−0.01	0.01	0.01	0.00	−0.01
	(−0.54)	(−0.16)	(0.36)	(0.20)	(0.14)	(−0.32)
Days Since Last Rating (log)	0.01	0.00	−0.00	−0.00	−0.00	0.00
	(0.70)	(0.21)	(−0.06)	(−0.19)	(−0.21)	(0.01)
Firm-level controls						
Sales (log)	0.07*	0.06**	0.05*	0.04*	0.04	0.03
	(1.68)	(2.04)	(1.84)	(1.70)	(1.58)	(1.64)
Profitability	0.06	0.10*	0.12**	0.09*	0.08	0.08*
	(0.68)	(1.77)	(2.42)	(1.90)	(1.56)	(1.68)
Leverage	0.31	0.28*	0.28*	0.21	0.15	0.12
	(1.33)	(1.71)	(1.91)	(1.64)	(1.28)	(1.13)
Mkt-to-Book	−0.01	−0.02	−0.02**	−0.01*	−0.01	−0.01
	(−0.56)	(−1.41)	(−2.35)	(−1.97)	(−1.37)	(−1.08)
Avg Volatility (log)	0.12**	0.00	−0.04	−0.03	−0.01	−0.01
	(2.24)	(0.02)	(−1.29)	(−1.02)	(−0.37)	(−0.42)
Avg Trading Volume (log)	−0.01	0.02	0.03	0.02	0.01	0.00
	(−0.28)	(0.74)	(1.06)	(0.96)	(0.26)	(0.16)
Avg Return	0.44**	0.26***	0.22***	0.16**	0.11*	0.07
	(2.47)	(2.66)	(2.81)	(2.41)	(1.93)	(1.34)
CDS-trading controls						
Analyst Coverage (log)	−0.01	−0.04	−0.03	−0.03	−0.02	−0.02
	(−0.31)	(−1.10)	(−1.05)	(−1.56)	(−0.99)	(−1.04)
Analyst Dispersion	0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.40)	(−0.65)	(−1.35)	(−0.87)	(−0.49)	(−0.62)
Institutional Ownership	0.08	0.03	0.02	0.04	0.04	0.04
	(1.29)	(0.89)	(0.55)	(1.05)	(1.08)	(1.12)
Stock Illiquidity	−3.70***	−2.04**	−0.85	−0.52	−0.33	0.02
	(−2.67)	(−2.05)	(−0.99)	(−0.83)	(−0.89)	(0.05)
Bond Illiquidity	0.16***	0.12***	0.10***	0.10***	0.10***	0.10***
	(3.81)	(4.49)	(3.95)	(4.00)	(4.01)	(3.99)
Bond Hedging Demand (log)	0.05	0.06*	0.04	0.03	0.04*	0.04*
	(1.10)	(1.67)	(1.35)	(1.35)	(1.70)	(1.79)
Macro controls						
SLO Survey	−0.79***	−0.65***	−0.60***	−0.48***	−0.47***	−0.42***
	(−4.48)	(−4.94)	(−5.37)	(−5.51)	(−6.08)	(−6.34)
Baa-Aaa spread	−0.09	−0.06	−0.03	0.04	0.07*	0.03
	(−0.76)	(−0.80)	(−0.48)	(0.97)	(1.71)	(0.70)
VIX	0.02***	0.02***	0.01***	0.01***	0.01***	0.01***
	(3.06)	(3.80)	(4.08)	(3.33)	(2.94)	(2.86)
Industry FE	✓	✓	✓	✓	✓	✓
Rating-type FE	✓	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓	✓
N	437	657	823	991	1134	1261
Adj. R^2	0.477	0.588	0.628	0.646	0.651	0.665
F-stat (excl)	42.12	99.47	144.88	253.68	267.94	295.49

Table IA-10. Instrumented CDS: Placebo Tests

This table presents a placebo test for the instrumental variable that we use in the IV/2SLS regression analysis; see Table IV. The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. We report regression results where the independent variable of interests is the aggregate log CDS notional traded in the economy, which is the instrumental variable that we use. Column (1) reports results for the *Traded-CDS* sample, which consists of firms that had CDS trading introduced during the sample period. Column (2) reports results for the *non-Traded-CDS* sample, which consists of firms that did not have CDS trading introduced during the sample period. All specifications include *Industry FE, Rating-type FE, Prev-rating×Rating-change FE, Rating-level controls, Firm-level controls, CDS-trading controls, and Macro controls.* These variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Traded-CDS sample	non-Traded-CDS sample
Depvar: CAR	(1)	(2)
CDS Notional (log)	0.81***	0.71
	(2.75)	(1.47)
Industry FE	✓	✓
Rating-type FE	✓	✓
Prev-rating×Rating-change FE	✓	✓
Macro controls	✓	✓
Rating-level controls	✓	✓
Firm-level controls	✓	✓
CDS-trading controls	✓	✓
Nob.	1261	934
Adj. R^2	0.081	0.264

Table IA-11. Instrumented CDS (Forex Derivatives Hedging): 2SLS/IV Regression

The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. The sample consists of firms that have CDS traded at some point during our sample period (traded-CDS firms). We estimate the two-stage-least-squares (2SLS) model with the instrumental variable (IV) for *dCDS*. In the first stage, we instrument the *dCDS* variable using the amount of foreign exchange (forex) derivatives usage for hedging purposes by banks that have a lending relationship with the firm. The construction of this instrument has been extensively described in Saretto and Tookes (2013), and Subrahmanyam et al. (2014). In each column, we estimate the 2SLS/IV regression model on a subsample of rating downgrade observations that occur within a fixed window [−Y,+Y] around the initiation of CDS trading on each traded-CDS firm, where Y is in year(s). Each column also reports the univariate mean of CARs to credit rating downgrades in the absence of CDS trading for its sample (see "Mean CDS=0 CAR %"). All control variables are defined in Appendix A. The first-stage coefficient estimate of the *dCDS* variable on the instrument, as well the F-statistic test for the exclusion of the instrument are reported at the bottom of each column. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Downgrades within the specified window around CDS introductions					
	$[-1,+1]$	$[-2,+2]$	$[-3,+3]$	$[-4,+4]$	$[-5,+5]$	All
Depvar: CAR	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented dCDS	7.35**	9.88**	6.90***	5.52***	5.45***	4.67***
	(2.35)	(3.05)	(2.77)	(2.71)	(2.90)	(2.59)
N	388	576	709	846	955	1074
Adj. R^2	0.092	0.085	0.095	0.070	0.068	0.055
Avg CDS=0 CAR (%)	−3.10	−3.62	−3.49	−3.55	−3.61	−3.73
1^{st} Stg Coeff	0.853	0.952	1.011	1.103	1.106	1.095
F-stat (excl)	17.56	40.95	63.10	126.17	267.94	295.49
Industry FE	✓	✓	✓	✓	✓	✓
Rating-agency FE	✓	✓	✓	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓	✓	✓	✓
Macro controls	✓	✓	✓	✓	✓	✓
Rating-level controls	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓

Table IA-12. CARs to credit rating downgrades: Traded- and non-traded-CDS firms

The dependent variable is the cumulative adjusted stock return (CAR) calculated over the 3-day window around the date of rating downgrade announcement. The sample consists of traded-CDS and non-traded-CDS firms. *dCDS* is an indicator equal to 1 if the firm has CDS contracts traded at the time of rating downgrade, 0 otherwise. *dTradedCDS* is an indicator equal to 1 if the firm is a traded-CDS firm, and 0 otherwise. Control variables are defined in Appendix A. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Traded-CDS and Non-Traded-CDS firms		
Depvar: CAR	(1)	(2)	(3)
dCDS	1.95***	2.12***	2.18***
	(3.33)	(3.03)	(3.19)
dTradedCDS	−0.34	0.26	0.41
	(−0.51)	(0.38)	(0.58)
Rating-level controls			
Days Since Last Rating (log)		0.11	0.10
		(0.46)	(0.40)
Earnings Ann Related		−0.48	−0.51
		(−0.49)	(−0.52)
Firm-level controls			
Sales (log)		0.13	0.30
		(0.37)	(0.79)
Profitability		1.00	0.95
		(0.86)	(0.81)
Leverage		−0.89	−0.41
		(−0.48)	(−0.22)
Mkt-to-Book		0.09	0.08
		(1.12)	(1.00)
Avg Volatility (log)		−0.55	−0.80
		(−0.78)	(−1.14)
Avg Trading Volume (log)		−0.61**	−0.30
		(−2.03)	(−0.93)
Avg Return		7.05***	7.06***
		(4.34)	(4.35)
Analyst Coverage (log)			0.11
			(0.24)
CDS-trading controls			
Analyst Dispersion			0.01*
			(1.94)
Institutional Ownership			−0.02
			(−0.03)
Stock Illiquidity			1.98
			(0.78)
Bond Illiquidity			−0.60
			(−1.60)
Bond Hedging Demand (log)			−0.59
			(−1.58)
Macro controls			
SLO Survey		−1.83	−1.68
		(−1.40)	(−1.29)
Baa-Aaa Spread		−0.38	−0.48
		(−0.45)	(−0.57)
VIX		0.09	0.09
		(1.51)	(1.57)
Industry FE	✓	✓	✓
Rating-type FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
N	3310	3310	3310
Adj. R^2	0.174	0.192	0.193
Mean CDS=0 CAR (%)	−4.41	−4.41	−4.41

Table IA-13. Heterogeneous effects of CDS trading: Summary of sample splits

This table describes the number of observations used in the regression analyses shown in Panels A–C of Table V in the main paper, where we examine the heterogeneous effects on CDS trading on CARs to credit rating downgrades. The sample consists of rating downgrade observations over the 1996–2010 period on traded-CDS and non-traded-CDS firms. In each panel, we sort rating downgrade observations based on different characteristics. The number of rating downgrade observations that occur with CDS trading and without CDS trading are shown under the columns labeled *CDS=1 Obs.* and *CDS=0 Obs.*, respectively.

In Panel A, we sort observations into three groups based on firms' credit rating level before they are downgraded. In Panel B, we sort observations into two groups based on firms' contractual dependence of their bank loans on credit ratings before they are downgraded. In Panel B, Columns (1) and (2) sort observations based on the number of rating-based performance pricing (PP) covenants and accounting-based PP covenants, respectively. Panel B, Column (3), we sort observations based on the number of active loan facilities.

In Panel C, we sort observations based on the credit market's tightness when firms are downgraded. Observations in Column (1) of Panel C are sorted based on the Baa-Aaa credit spread, while in Column (2), they are sorted based on the measure of credit supply derived from the bank senior loan officer (SLO) survey. Credit tightness from the SLO survey is calculated as the number of banks reporting tightening credit standards minus the number of banks reporting easing credit standards, divided by the total number of reporting banks (Chava et al. (2015)).

Panel A: Sample split across previous rating levels before downgrades

	Range of	CDS= 0 Obs.	CDS= 1 Obs.	%CDS= 1
Sample sorted by:	Sorting Var.	(1)	(2)	(3)
Previous rating level				
High	AAA–A	589	298	33.60%
Medium	BBB	632	435	40.77%
Low	BB–C	1010	346	25.52%

Panel B: Sample split based contractual dependence on credit ratings

	Mean of	CDS= 0 Obs.	CDS= 1 Obs.	%CDS= 1
Sample sorted by:	Sorting Var.	(1)	(2)	(3)
Number Rating PP Covenants				
High	15.45	543	501	47.99%
Low	1.59	1071	320	23.01%
Number of Accounting PP Covenants				
High	7.29	528	179	25.32%
Low	0.25	1086	642	37.15%
Number of loan facilities				
High	32.52	1089	733	40.23%
Low	3.41	1142	346	23.25%

Table IA-13 Heterogeneous effects of CDS-trading: Summary of sample splits (continued)

Panel C: Sample split based on the credit market's tightness

	Mean of	CDS= 0 Obs.	CDS= 1 Obs.	%CDS= 1
Sample sorted by:	Sorting Var.	(1)	(2)	(3)
Credit Spread (Baa-Aaa)				
High	1.45	842	723	46.20%
Low	0.78	1389	356	20.40%
Senior Loan Officer (SLO) Survey				
High	0.34	1667	557	25.04%
Low	−0.10	564	522	48.07%

Table IA-14. Heterogeneous effects of CDS trading on CARs to downgrades: Traded-CDS sample

This table presents regression results examining the heterogeneous effects of CDS trading on firms' stock price reaction to their bond rating downgrades similar to Table V in the main text but using only traded-CDS firms. The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. In each panel, we sort observations into different groups as indicated by the "Grouping variable," and estimate the effect of CDS trading on CARs to credit rating downgrades across different groups in one regression. See Section III.E for more details. All specifications include *Industry FE, Rating-type FE, Prev-rating×Rating-change FE, Rating-level controls, Firm-level controls, CDS-trading controls, and Macro controls.* These control variables are defined in Appendix A. In Panel A, we sort observations into three groups based on the credit rating level before the firm is downgraded. In Panel B, we sort observations into two groups based on firms' contractual dependence on credit ratings that we observe in their bank loans before they are downgraded: (1) the number of rating-based performance pricing (PP) covenants, (2) the number of accounting-based PP covenants, and (3) the number of active loan facilities. Panel C reports results where we sort observations based on the credit market's tightness when firms are downgraded. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Heterogeneous effects of CDS trading across credit rating categories

	Grouping variable:
Depvar: CAR	Previous rating before the downgrade
dCDS (High: AAA–A)	1.45
	(1.10)
dCDS (Medium: BBB)	5.34***
	(3.00)
dCDS (Low: BB & lower)	−0.91
	(−0.40)
Δ dCDS (Medium − High)	3.90**
	(2.14)
Δ dCDS (Medium − Low)	6.25*
	(1.95)
N	1527
Adj. R^2	0.108
Mean CDS=0 CAR (%) (High)	−0.74
Mean CDS=0 CAR (%) (Medium)	−5.26
Mean CDS=0 CAR (%) (Low)	−3.17

Table V. Heterogeneous effects of CDS trading on CARs to downgrades: Traded-CDS sample (continued)

Panel B: Heterogeneous effects of CDS when firms have contractual dependence on ratings

	Grouping variable:		
	Rating PP covenants	Accounting PP covenants	Active loan facilities
Depvar: CAR	(1)	(2)	(3)
dCDS (High)	4.31***	2.37	3.46***
	(2.97)	(1.16)	(2.96)
dCDS (Low)	1.49	2.26	−1.19
	(0.74)	(1.59)	(0.69)
Δ dCDS (High − Low)	2.82	0.10	4.65**
	(1.25)	(0.04)	(2.23)
N	1120	1120	1527
Adj. R^2	0.066	0.060	0.090
Mean CDS=0 CAR (%) (High)	−4.33	−2.62	−3.63
Mean CDS=0 CAR (%) (Low)	−2.22	−3.41	−1.39

Panel C: Heterogeneous effects of CDS when the credit market is tight

	Grouping variable:	
	Baa-Aaa credit spread	Senior loan officer survey
Depvar: CAR	(1)	(2)
dCDS (High)	2.31*	2.96**
	(1.72)	(2.00)
dCDS (Low)	2.18	1.24
	(1.37)	(1.01)
Δ dCDS (High − Low)	0.13	1.72
	(0.06)	(0.85)
N	1527	1527
Adj. R^2	0.094	0.088
Mean CDS=0 CAR (%) (High)	−4.28	−3.27
Mean CDS=0 CAR (%) (Low)	−1.99	−0.73

Table IA-15. CDS trading and firms' financing decision: The role of regulatory and contractual dependence on credit ratings

We estimate a linear probability model similar to that in Panel B of Table VI, but by grouping observations based the contractual and regulatory dependence of firms on credit ratings at the time of their credit rating downgrades. We estimate the probability of large debt reduction from the four quarters before to the four quarters after the firm is downgraded. The quarter of the rating downgrade announcement is excluded. The dependent variable is a quarterly indicator that is equal to 1 if the firm reduces its debt by greater than 1.25% relative to the lagged total assets, and 0 otherwise. Specifically, we estimate the following linear probability model:

$$\begin{aligned}\mathbb{1}(\text{Large Debt Red.})_{i,t} \quad &= \quad \sum_{j=1}^{N} \mathbb{1}(\omega_j)[\beta_j \; dPostDNG \times dCDS_{i,t} + \gamma \; dPostDNG_{i,t} + \alpha_j \; dCDS_{i,t} + f(X_{i,t})] \\ &+ \quad \Gamma_{R,\Delta N} + \eta_{indus} + \varepsilon_{i,t},\end{aligned}$$

where $\mathbb{1}(\omega_j)$ is an indicator function that is equal to 1 if the observation belongs to group j, and 0 otherwise. The coefficient estimate of interest is β_j, which measures the effect of CDS trading on the downgraded firm's likelihood of a large debt reduction for group j. All specifications include *Industry FE, Prev-rating×Rating-change FE, Firm-level controls, and CDS-trading controls.* These control variables are defined in Appendix A. Columns (1) and (2) report results where observations are sorted based on the number of rating-based performance pricing (PP) covenants and accounting-based PP covenants, respectively. Column (3) reports results sorted by on the number of active loan facilities. For each credit rating level, we sort observations into above-the-median (high) and below-the-median (low) groups. Robust t-statistics clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Depvar: Indicator variable= 1 if observing large debt reduction		
	(1)	(2)	(3)
Grouping observations by:	Rating PP covenants	Accounting PP covanents	Active loan facilities
Above-the-median group (high)			
dPostDNG	0.074***	0.047*	0.076***
	(3.03)	(1.89)	(4.10)
dPostDNG×dCDS	−0.070*	−0.033	−0.058*
	(−1.82)	(−0.60)	(−1.96)
dCDS	0.033	−0.030	0.037
	(1.13)	(−0.63)	(1.61)
Below-the-median group (low)			
dPostDNG	0.057**	0.063***	0.049***
	(2.56)	(2.76)	(3.18)
dPostDNG×dCDS	−0.035	−0.040	−0.018
	(−0.94)	(−1.07)	(−0.67)
dCDS	−0.014	−0.015	−0.009
	(−0.46)	(−0.46)	(−0.35)
Industry FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
CDS-trading controls	✓	✓	✓
Firm-level controls	✓	✓	✓
N	6687	5242	12515
Adj. R^2	0.038	0.038	0.036

Table IA-16. CDS trading and firms' financing cost: The role of regulatory and contractual dependence on credit ratings

We estimate a linear regression model similar to that in Panel A of Table VII, but by grouping observations based the contractual and regulatory dependence of firms on credit ratings at the time of their credit rating downgrades. This table presents estimation results for the change in the at-issuance loan spreads for firms over the four quarters before to the four quarters after their credit rating downgrades. The quarter of the rating-downgrade announcement is excluded. We use the all-in-drawn spread obtained from Dealscan, which is the sum of the spread of loand facility over LIBOR and any annual fees paid to the lender group. Specifically, for a rating downgrade on firm i and time t, we estimate the following linear regression model:

$$\begin{aligned}\log(\text{spread})_{i,t} &= \sum_{j=1}^{N} \mathbb{1}(\omega_j)[\beta_j \; dPostDNG \times dCDS_{i,t} + \gamma \; dPostDNG_{i,t} + \alpha_j \; dCDS_{i,t} + f(X_{i,t})] \\ &+ \quad \Gamma_{R,\Delta N} + \eta_{indus} + \varepsilon_{i,t},\end{aligned}$$

where $\mathbb{1}(\omega_j)$ is an indicator function that is equal to 1 if the observation belongs to group j, and 0 otherwise. The coefficient estimate of interest is β_j, which measures the effect of CDS trading on the downgraded loan spreads for group j. All specifications include *Industry FE, Prev-rating×Rating-change FE, Firm-level controls, and CDS-trading controls*. These control variables are defined in Appendix A. Columns (1) and (2) report results where observations are sorted based on the number of rating-based performance pricing (PP) covenants and accounting-based PP covenants, respectively. Column (3) reports results sorted by on the number of active loan facilities. For each credit rating level, we sort observations into above-the-median (high) and below-the-median (low) groups. Robust t-statistics clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Depvar: log(all-in drawn spread)		
	(1)	(2)	(3)
Grouping observations by:	Rating PP covenants	Accounting PP covanents	Active loan facilities
Above-the-median group (high)			
dPostDNG	0.310***	0.110	0.280***
	(4.64)	(1.44)	(5.42)
dPostDNGxdCDS	−0.337***	−0.046	−0.212**
	(−3.10)	(−0.38)	(−2.32)
dCDS	0.184*	−0.021	0.105
	(1.91)	(−0.23)	(1.44)
Below-the-median group (low)			
dPostDNG	0.185***	0.266***	0.180***
	(4.30)	(6.64)	(4.49)
dPostDNGxdCDS	−0.040	−0.226***	−0.011
	(−0.48)	(−2.78)	(−0.15)
dCDS	0.068	0.189**	0.097
	(0.93)	(2.49)	(1.45)
Industry FE	✓	✓	✓
Prev-rating×Rating-change FE	✓	✓	✓
CDS-trading controls	✓	✓	✓
Firm-level controls	✓	✓	✓
N	3136	3136	4003
Adj. R^2	0.738	0.738	0.752

Table IA-17. Long-Run Stock Returns After Rating Downgrades

This table presents Fama-Macbeth regression results for monthly long-run stock returns after credit rating downgrades. The cross-sectional regression framework that we use follows that in Dichev and Piotroski (2001):

$$Return_t = \beta_0 + \beta_1 dPostDNG_t + \beta_2 dPostDNG_t \times dCDS_t + \beta_3 dCDS_t + \text{Controls},$$

where $Return_t$ is the firm's monthly stock return. We examine the long-run stock returns of firms over four horizons after their rating downgrade announcements. *dPostDNG* is the monthly indicator variable indicating the period after which the firm has been downgraded. In each column, the indicator *dPostDNG* is set equal to 1 for the three-, six-, nine-, and twelve-month periods, respectively, after the firm has been downgraded, and 0 otherwise. *dCDS* is an indicator variable equal to 1 if the firm has CDS contracts traded on its debt, and 0 otherwise. All control variables are defined in Appendix A and are lagged by one month. Robust t-statistics calculated using Newey-West standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

		Dependent variable: Monthly stock returns			
		Post 3-month	Post 6-month	Post 9-month	Post 12-month
		(1)	(2)	(3)	(4)
dPostDNG	(a)	−1.51**	−1.11**	−1.07***	−0.97***
		(−2.46)	(−2.33)	(−2.62)	(−2.65)
dPostDNG×dCDS	(b)	0.71*	0.58**	0.40*	0.42*
		(1.87)	(2.12)	(1.69)	(1.88)
dCDS		−0.33**	−0.34**	−0.33**	−0.37**
		(−2.07)	(−2.17)	(−2.07)	(−2.28)
Market Value (log)		0.35***	0.35***	0.35***	0.35***
		(2.82)	(2.83)	(2.83)	(2.83)
Book-to-market (log)		−1.51***	−1.52***	−1.52***	−1.52***
		(-12.62)	(-12.64)	(-12.65)	(-12.68)
Turnover (log)		1.11***	1.11***	1.11***	1.11***
		(4.92)	(4.91)	(4.90)	(4.89)
Momentum		−1.84***	−1.84***	−1.84***	−1.83***
		(-6.61)	(-6.60)	(-6.60)	(-6.58)
Traded CDS		−1.51***	−1.51***	−1.51***	−1.52***
		(-5.44)	(-5.44)	(-5.45)	(-5.50)
Coefficient sum:	(a) + (b)	−0.80	−0.53	−0.68**	−0.56*
		(−1.50)	(−1.42)	(−2.10)	(−1.80)
Industry fixed effects		✓	✓	✓	✓
Prev-rating×Rating-change FE		✓	✓	✓	✓
Rating-level controls		✓	✓	✓	✓
Observations		785,161	785,161	785,161	785,161
Avg. Adjusted R^2		0.062	0.061	0.061	0.061

Table IA-18. CDS trading and firms' reliance on credit ratings: Net equity

This table is similar to Table VIII, but with the quarterly change in firm's net equity issuance (net of new equity issuance and reduction of existing equity) over lagged total assets as the dependent variable. The row labeled "(a) +(b)" reports the sum of the coefficients denoted by (a) and (b). Rating fixed-effects correspond to the average rating level of each firm-quarter observation in cardinal scale. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Depvar: Δ Equity /Total assets				
		(1)	(2)	(3)	(4)	(5)
dHiZone	(a)	0.80***	0.21	0.19	0.14	0.14
		(5.31)	(1.32)	(1.20)	(0.89)	(0.77)
dHiZone×dCDS	(b)	0.02	0.07	0.20	0.16	0.33
		(0.08)	(0.36)	(0.94)	(0.80)	(1.41)
dCDS		−0.65***	−0.38***	−0.48***	−0.52***	−0.61***
		(−5.34)	(−3.22)	(−3.89)	(−3.14)	(−3.31)
(a) + (b)		0.82***	0.29	0.39**	0.31*	0.47**
		4.66	1.62	2.19	1.76	2.50
Industry×Rating FE		✓	✓	✓	✓	
Firm controls			✓	✓	✓	✓
CDS-trading controls				✓	✓	✓
Year-Qtr FE					✓	✓
Firm FE						✓
Rating FE						✓
N		16467	16467	16467	16467	16443
Adj. R^2		0.012	0.031	0.037	0.049	0.102

Table IA-19. Information Flow Between the CDS and Stock Markets

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:

$$\text{Stock return}_t = a + \sum_{k=1}^{5}\Big(b_k + b_k^d \text{ dPreDNG}_t\Big) \times \text{CDS innovation}_{t-k} + \sum_{k=1}^{5}\Big(c_k + c_k^d \text{ dPreDNG}_t\Big) \times \text{Stock return}_{t-k} + \varepsilon_t.$$

We surpress the 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 the stock market at time t. We estimate *CDS innovation*$_t$ firm-by-firm as the residual from the first-stage regression following Acharya and Johnson (2007). We interact lagged CDS innovations and stock returns with the dummy variable *dPreDNG* that is equal to 1 on days $[-90, -2]$ relative to when the firm is downgraded, and 0 otherwise. We report results estimated using all eligible observations consisting of 345 unique firms. Column (1) reports the baseline regression results where $dPreDNG_t = 0$. Column (2) reports results for the general regression model. Robust t-statistics clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Dependent variable: Stock return$_t$	
	(1)	(2)
Intercept	0.0004***	0.0004***
	(8.58)	(8.72)
$\sum_{k=1}^{5}$ CDS innovation$_{t-k}$	−0.0074*	−0.0038
	(−1.76)	(−0.97)
$\sum_{k=1}^{5}$ Stock return$_{t-k}$	−0.0723***	−0.067***
	(−4.41)	(−4.65)
$\sum_{k=1}^{5}$ dPreDNG$_t$×CDS innovation$_{t-k}$		−0.0428**
		(−2.12)
$\sum_{k=1}^{5}$ dPreDNG$_t$×Stock return$_{t-k}$		−0.0306
		(−0.48)
Observations	286777	286777
No. of clusters	345	345
Adjusted R^2	0.17%	0.32%

Table IA-20. Heterogeneous effects of CDS based on CDS-trading activities before downgrades

Panel A report the regression results examining the impact of CDS-trading activities before the firm is downgraded on CARs to rating downgrade announcements. The regression specification is similar to that in Table V. The sample consists of traded-CDS and non-traded-CDS firms. The dependent variable is CAR calculated over the 3-day window around the date of rating downgrade announcement. In each panel, we sort observations into different groups as indicated by the "Grouping variable." We then estimate the following regression model:

$$CAR_{i,t} = \sum_{j=1}^{N} \mathbb{1}(\omega_j)[\beta_j \times dCDS_{i,t} + f(X_{i,t}) + g(Y_t)] + \Gamma_{R,\Delta N} + \eta_{indus} + \nu_{agency} + \varepsilon_{i,t},$$

where $\mathbb{1}(\omega_j)$ is an indicator function that is equal to 1 if the observation belongs to group j, and 0 otherwise. We report the coefficient estimates of *dCDS* that are associated with each group j, as well as difference in their estimates between groups ($\Delta dCDS$). Robust t-statistics clustered at the firm-level are reported in parentheses. Observations in Columns (1) and (2) of Panel A are sorted based on the average daily CDS spread changes and the standard deviation of daily CDS spread changes, respectively. In Column (3), Panel A, we sort observations based on the average number of daily CDS dealer quotes. CDS-trading activites are calculated over the 90-day period before the firm is downgraded. All specifications in Panel A include *Industry FE, Rating-type FE, Prev-rating×Rating-change FE, Rating-level controls, Firm-level controls, CDS-trading controls, and Macro controls*; see Appendix A. Panel B summarizes the number of observations and the sample mean of sorting variables corresponding to each group in Panel A.

Panel A: CARs to rating downgrades

	Grouping variable		
	$\%\Delta CDS$	StdDev($\%\Delta CDS$)	No. dealer quotes
Depvar: CAR	(1)	(2)	(3)
dCDS (High)	1.89**	2.51***	2.68***
	(2.39)	(3.13)	(3.96)
dCDS (Low)	2.07***	1.57**	1.42*
	(3.18)	(2.48)	(1.85)
Δ dCDS (High − Low)	−0.19	0.94	1.25*
	(−0.30)	(1.55)	(1.84)
N	3310	3310	3310
Adj. R^2	0.192	0.192	0.193
Mean CDS=0 CAR (%)	−4.41	−4.41	−4.41

Panel B: Summary of sample split based on CDS-trading activities before rating downgrades

	Mean of	CDS= 0 Obs.	CDS= 1 Obs.	%CDS= 1
Sample sorted by:	Sorting Var.	(1)	(2)	(3)
$\%\Delta CDS[-90,-1]$				
High	54.37%	2285	494	17.78%
Low	−15.06%	2285	531	18.86%
$StdDev(\%\Delta CDS)$				
High	4.79%	2285	453	16.54%
Low	2.07%	2285	572	20.02%
Number of Dealer Quotes				
High	877.25	2282	528	18.79%
Low	381.75	2282	500	17.97%

Figure IA-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 into six rating classes according to their CDS spread; see Table IA-1 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 et al. (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 issued by credit rating agencies, in the rating class scale, while the dotted line plots average CDS-implied ratings.