Do Credit Default Swaps Mitigate the Impact of Credit Rating Downgrades?

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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. We explore the role of the CDS markets in providing information ex ante and relieving financing frictions ex post for downgraded firms. We find that the impact of CDS trading is more pronounced for firms whose debt financing is more dependent on credit ratings (e.g., those rated around the speculative-grade boundary, those with a higher number of rating-based covenants). Reductions in debt and investment, and the increase in financing costs are less severe for CDS firms than non-CDS firms following an identical credit rating downgrade. Our results suggest that CDSs mute the stock market reaction to a credit rating downgrade by alleviating the financing frictions faced by downgraded firms.

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

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1. Introduction

The announcement of a credit rating downgrade for a firm's debt leads to a significant drop in its stock price (see Hand, Holthausen, and Leftwich, 1992; Dichev and Piotroski, 2001; Jorion, Liu, and Shi, 2005). The negative market reaction to downgrades could be attributed to the revelation of negative infomation by rating agencies and to the dependence of the credit market on credit ratings. For instance, when a firm's cost of debt financing is linked to its credit rating, a credit rating downgrade can impact its cost of capital, its investment, and ultimately its expected stock return. In this paper, we examine how the introduction of a Credit Default Swap (CDS) for a firm, which is an insurance contract against the default of the underlying firm's debt, affects the economic role of credit rating downgrades. We show that when CDSs are trading for a firm, its equity market reaction to credit rating downgrades is muted by 44–52% relative to downgrades in the absence of CDS trading.

A priori, the effect of CDS trading on a firm's stock price sensitivity to credit rating downgrades is not obvious. On the one hand, a firm's equity price reaction to its credit rating downgrade announcement could be muted because CDSs relieve some of the financing frictions faced by downgraded firms (*financing frictions channel*). For instance, suppliers of capital such as banks can avoid rating-based regulatory costs and continue lending to a downgraded firm if they can transfer their costly credit-risk exposure by purchasing a CDS on the firm (Saretto and Tookes, 2013).[1] Alternately, CDS trading may itself generate information about a firm's credit quality (Acharya and Johnson, 2007) and could lower the informativeness of a credit rating downgrade announcement (*information channel*). Under both these mutually non-exclusive channels, the impact of a credit downgrade announcement on the firm's stock price is less negative after the CDS introduction. In contrast, a firm's stock price reaction to rating downgrades could be more negative if the presence of CDSs create an "empty creditors" problem (e.g., Bolton and Oehmke, 2011; Subrahmanyam, Tang, and Wang, 2014). This phenomenon can arise if creditors no longer have the incentive to monitor after offsetting their credit risk exposure by purchasing CDSs. In fact, in certain cases if creditors over-insure using CDSs, then they could force a firm into bankruptcy to trigger the CDS payments.

We test the effect of CDS introduction on the market reaction to credit rating downgrades

[1] 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.

by regressing the cumulative abnormal returns (CARs) in the 3-day window around the rating downgrade announcement on an indicator variable that signifies the presence (or absence) of CDS trading. A potential concern in our empirical analysis is that the timing of CDS introduction is not exogenous. For instance, CDS firms generally tend to be larger and have better credit ratings (Ashcraft and Santos, 2009; Saretto and Tookes, 2013). Our data also suggest that CARs associated with rating downgrades are less negative for better rated firms (e.g., investment-grade). Therefore, the improvement in a firms' credit quality over time can drive both, the CDS introduction and the muted negative market reaction to rating downgrades, causing an omitted variable bias in our favor. We mitigate such a concern by including *Prev-rating*×*DNG-notches* fixed effects in all our regression specifications. *Prev-rating* is the credit rating of the firm before the downgrade and *DNG-notches* 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 downgrade magnitude. We also include industry, year-month, and rating-agency fixed effects, and time-varying firm-level and CDS-trading controls.

The point estimates using our full sample, which includes all rating downgrade events of non-financial firms from 1996–2010, suggest that the stock market reaction to credit rating downgrades for CDS firms relative to non-CDS firms is muted by 44–52%. Next, 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. Our results are stronger for this subsample where we find that CDS trading mutes the negative market reaction to rating downgrades by 67–75%. One concern with our results could be that they simply reflect a general improvement in the credit quality of all the firms and the simultaneous growth of the CDS markets. To mitigate this concern, we focus on credit rating downgrades that occur within short balanced-time windows around the initiation of CDS trading for each firm (e.g., ±1, ±2, ±3 years). This specification allows us to exploit the staggered introduction of CDS for firms across time and compare the stock market reactions to rating downgrade events that occur just before and after the introduction of CDS trading. For a confounding time-trend to bias our results, it must also systematically covary with the staggered CDS introduction of each firm. We find that our results are stronger when we conduct our analysis using the short balanced-time windows. Additionally, our results are robust when we also estimate our regression model using a matched sample of CDS and non-CDS firms within the short balanced-time windows around CDS introductions . This allows us to compare the downgrade CARs for CDS versus non-CDS firms that are similar on multiple observable factors, especially on those that can be affected by time-varying confounding shocks.

Our empirical tests thus far do not address a potential omitted variable bias that can occur if the CDS introduction for a firm precisely coincides with or occurs due to a firm-specific unobservable event. To address this concern, we estimate an instrumental variable (IV) regression. We use two instruments to capture plausibly exogenous variation in the probability of CDS introduction on firms. We use the growth of the aggregate CDS notional amount traded globally as our first instrument to show that it is has a strong positive correlation with the likelihood of CDS introduction on firms (relevance condition). We also provide suggestive evidence that the growth of the CDS market was due to an overall unmet demand for trading in credit risk, rather than due to a change in the average credit quality of all the firms or of any particular firm (exclusion restriction). To ensure we are not just picking up time trends, we conduct our IV analysis using the short balanced-time windows around CDS introduction. Our point estimates on the instrumented CDS variable are similar or stronger than our OLS estimates which suggests a bias against finding our results. We complement our IV analysis with a second instrument for CDS trading: the average foreign exchange derivatives (forex) traded for hedging purposes by a downgraded firm's lending banks (see Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 2014, for more details).[2] This instrument mainly captures the cross-sectional variation in the likelihood of CDS introduction. Our main results remain similar in this IV analysis also.

We next examine the underlying economic channels through which CDS trading dampens the negative market reaction to credit rating downgrades. Our empirical strategy is to examine the effect of CDS introduction in samples where credit ratings are expected to matter the most. First, we find that the market reaction to rating downgrade announcements is more negative 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.

[2] This instrument is intended to capture the hedging culture of banks, which consequently predicts the introduction of CDS on the borrowing firm (relevance condition). However, the instrument likely captures a bank's need to hedge macro risk and thus, is plausibly unrelated to the borrowing firm's credit risk (exclusion restriction).

These findings are consistent with Kisgen (2006), and Kisgen and Strahan (2010) who show that a credit rating downgrade can adversely affect a firm's ability to raise debt and its cost of capital. However, we find that CDS trading mutes the stock market reaction to credit rating downgrades precisely for such firms, consistent with the view that CDS trading relieves some of the financing frictions faced by downgraded firms. Next, we test for the information channel by examining the market reaction to credit rating downgrades conditional on firms' CDS-trading activities, such as CDS spread changes, volatility, and liquidity, prior to their rating downgrade announcements. We do not find strong evidence that the variation in CDS-trading activities prior to rating downgrades affect the extent to which downgrade CARs are muted. Overall, our evidence suggests that CDS affects the equity market reaction to ratings downgrades by relieving firms' debt-financing frictions as opposed to providing new information to the equity markets.

We provide further evidence that the downgraded firms' debt-financing decisions after their credit rating downgrades 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 percentage points (pp) 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 pp, which is about 40% lower relative to non-CDS firms. This reduction is largely driven by the greater repayment of existing debt by non-CDS firms relative to CDS firms. We also 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%).

The reliance of the credit market on credit ratings has also 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). In our final empirical analysis we test whether such incentives are lower for firms in the presence of CDS trading. We exploit the fact that a firm's Debt/EBITDA ratio is an important criterion for rating agencies when they rate firms. To this end, rating agencies provide Debt/EBITDA thresholds (min and max) for each rating category which are somewhat arbitrary and based on simple intervals such as 2.0 and 2.5 (Begley, 2015). We find that firms which have Debt/EBITDA ratios that are close to the rating-based thresholds that could potentially lead to a rating downgrade, improve their Debt/EBITDA ratios by reducing their net debt issuance relative to firms that are away from the thresholds. However, in the presence of CDS trading, the sensitivity of a firm's net debt issuance to the rating-based Debt/EBITDA thresholds is lower which allows the CDS firms to have a higher net debt issuance by 2.8 pp per year. Importantly, this analysis is not conditional on a rating-change event. Therefore, it allows us to show more generally that the debt financing decisions of CDS firms are less sensitive to credit ratings compared to non-CDS firms. Additionally, we find that the distribution of firms in our sample, in relation to the rating-based Debt/EBITDA thresholds, are independent of whether firms have CDS trading on their debt. Therefore, the results from this 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, Holthausen, and Leftwich, 1992; Goh and Ederington, 1993; Dichev and Piotroski, 2001; Jorion, Liu, and Shi, 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. 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 (Oehmke and Zawadowski, 2015, 2016). We complement this literature and show that CDS trading alleviates the financing frictions faced by downgraded firms due to the regulatory and contractual dependence of the debt market on credit ratings. Consequently, we show that the presence of the CDS market can have a real impact on firms' financing and investment after mitigating such credit rating-related financing frictions. Our results also contribute to the literature on the potential empty creditor problem due to CDSs (Bolton and Oehmke, 2011; Subrahmanyam, Tang, and Wang, 2014; Danis, 2016). The presence of empty creditor problem would imply a more negative stock price reaction to credit rating downgrades. In contrast, the muted reaction that we document for credit rating downgrades after the introduction of CDS is consistent with Chakraborty, Chava, and Ganduri (2016) and suggests that shareholders are not anticipating an empty creditor problem as a result of CDS trading.

The rest of this paper proceeds as follows. Section 2 discusses the motivation and hypotheses for our empirical tests. Section 3 discusses the identification challenges and our empirical specifications. Section 4 presents our main results, and Section 5 examines the channels that drive our main finding. Section 6 provides further evidence that CDS trading relieves financing-related frictions. Section 7 concludes.

2. Motivation and Hypotheses

In this section, we start by discussing the null hypothesis under which one should not expect CDS trading to affect the market reaction to rating downgrades. We next discuss two non-mutually exclusive channels through which CDS can affect the market reaction to rating downgrades: ex ante the information channel, and ex post the financing frictions channel.

A credit rating is a particular agency's opinion of a firm's credit risk, while CDS spreads are determined through trading and thus represent market-based opinions of a firm's credit risk. However, credit ratings may have certain informational advantages over a CDS because rating agencies specialize in assessing a firm's credit quality and have access to a firm's non-public information due to an exemption from the Regulation FD (fair disclosure) act.[3] As a result, a rating agency's decision to downgrade a firm's credit rating could be informative to the equity markets even beyond what is available in the public domain and lead to a negative market reaction (Jorion, Liu, and Shi, 2005). Credit rating downgrades can also trigger subsequent events that exacerbate a downgraded firm's financing frictions if the firm's cost or access to debt is tied to credit ratings.[4] Thus, the equity market reaction to a rating downgrade can also be negative if the equity market anticipates that the downgraded firm's financial frictions

[3]Rating agencies are exempt from the Regulation FD (fair disclosure) act which prohibits firms from disclosing non-public information to any party unless the information is disclosed to the public first.

[4]For instance the interest rate on a firm's bank loans are often tied to credit ratings, and credit ratings are also used to regulate the liquidity and investment of insurance companies.

will be exacerbated due to regulatory and contractual dependence of the credit market on credit ratings. Therefore, if credit rating agencies and the equity market have informational advantages over the CDS market, or if CDSs do not affect the cost or access to financing of a downgraded firm, then the introduction of CDS should not affect the stock market reaction to credit rating downgrades (null hypothesis).

The potential for conflicts of interest inherent in the credit rating agencies' business model are well documented in the literature (e.g., White, 2010; Becker and Milbourn, 2011; Bolton, Freixas, and Shapiro, 2012; Benmelech and Dlugosz, 2009; Kraft, 2015). Such conflicts of interest could potentially lower the informativeness and timeliness of credit rating downgrades. On the other hand, CDSs are market-based measures of credit risk that provide a continuous measure of credit risk at a higher frequency. Furthermore, frictions in the equity markets such as short-selling constraints and stringent laws on insider trading can make CDS markets a preferred venue for trading on a firm's negative information (Acharya and Johnson, 2007; Oehmke and Zawadowski, 2016). We refer to this mechanism as the "information channel", and it predicts a muted equity market reaction to rating downgrades in the presence of CDS trading because CDS trading reduces the informativeness of credit rating downgrades.

In contrast, CDS trading can also alleviate the financing frictions faced by downgraded firms. For example, a downgrade, especially from the investment grade to speculative grade, can lead to a reduction in the investor pool as certain institutional investors like banks, pension funds, and insurance funds are either prohibited or disincetivized (higher capital charge) from investing in speculative grade bonds. Thus, a rating downgrade can affect a firm's ability to raise debt and its cost of capital (see also, Kisgen, 2006; Kisgen and Strahan, 2010; Kisgen, 2009). However, institutional investors may be able to keep investing in a downgraded firm while mitigating rating-based regulatory costs if they also hold a CDS on the firm.[5] We refer to this mechanism as the "financing frictions" channel, and it predicts a muted equity market reaction to credit rating downgrades in the presence of CDS trading because of CDS relieves the financing frictions faced by firms after a downgrade.

Finally, as an alternative hypothesis, CDSs can create a misalignment of incentives between a creditor and a firm when creditors can insure or offset their long credit risk position by

[5] 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.

purchasing a CDS to become "empty creditors". Ex ante, if some of these creditors are expected to monitor firms, then ex post after becoming empty creditors they may not have an incentive to do so (Chakraborty, Chava, and Ganduri, 2016). In fact in an extreme case, some creditors can over-insure using CDSs and force a firm into bankruptcy to trigger CDS payments (Bolton and Oehmke, 2011; Subrahmanyam, Tang, and Wang, 2014; Danis, 2016). If the incentives of the creditors to insure and speculate against the firm's survival are greater when they observe a deterioration in a firm's credit quality, then a credit rating downgrade for firms with a traded CDS should result in a more severe negative equity market reaction.

3. Identification Challenges and Empirical Specifications

3.1 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:

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

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 downgrade announcement, and 0 otherwise. A positive 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. Appendix A describes all the control variables in detail.

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 downgrade announcement, then the estimated coefficient of interest β will have an omitted variable bias.

The direction of this bias is not necessarily obvious. CDS firms generally tend to be larger and better rated (Ashcraft and Santos, 2009; Saretto and Tookes, 2013). At the same time, controlling for the number of notches in a rating downgrade, we find that the market reaction to credit rating downgrades for better rated firms (e.g., investment-grade firms) is also less negative. Therefore, if the improvement in a firm's credit quality quality over time drives both the introduction of CDS trading and the less negative market reaction to a rating downgrade, then the bias for the estimated coefficient of interest β will be positive. On the other hand, Oehmke and Zawadowski (2016) argue that firms that face greater information asymmetry 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 downgrade announcement. In this latter case, the bias will be negative.

We use various fixed effects in our baseline specification in Equation (1) to mitigate potential concerns resulting from an omitted variable bias. We include *Prev-rating*$\times$*DNG-notches* 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, the market reaction to a rating downgrade and the introduction of CDS. *Prev-rating* is the credit rating of the firm before the downgrade, and *DNG-notches* is the number of notches in the rating downgrade 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 (*DNG-notches*). In this setting, β captures the average difference in the market reaction to rating downgrades between CDS firms and non-CDS firms that are identically rated and are downgraded by the same number of notches.

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 downgrade 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 rating-agency fixed effects (ν_{agency}) associated with the three credit rating agencies: S&P, Moody's, and Fitch. The Fama-French 12-industry classification controls for the time-invariant average sensitivity of each industry to rating downgrade announcements. The rating-agency fixed effects control for the time-invariant average market reaction to rating downgrades 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., $\pm1, \pm2$ 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-trends that could affect the firm's stock price reaction to rating downgrades. Additionally, we also carry out a propensity score matching analysis by matching CDS and non-CDS firms based on all the firm-level controls we employ in our baseline regression. This allows us to compare CDS versus non-CDS firms that are similar on multiple observable factors, especially on those that can be potentially affected by time-varying confounding shocks. Further, matching can also account for the effect of nonlinearities in the covariates, thereby avoiding functional form restrictions imposed by linear regression.

Under the specification in Equation (1) with *Prev-rating*$\times$*DNG-notches* 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 downgrade 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 differentially affect the market reaction to rating downgrades between CDS and non-CDS firms. This is plausible if CDS introduction is timed precisely around, or occurs due to an unobserved time-varying firm-specific omitted variable. To address such an omitted-variable concern, we employ two instruments for *dCDS* in an IV regression.

Our first instrument for CDS trading is the log aggregate CDS notional amount traded globally. The instrument is constructed from the surveys conducted by the International Swaps and Derivatives Association (ISDA), and is available semiannually. Our 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 our first instrument is that it does not vary in the cross section. In order to ensure that we are not simply capturing a time trend, we conduct our analysis within the short balanced-time windows (e.g., $\pm 1, \pm 2$ years) around the CDS introduction for each firm as described earlier, and include a set of macroeconomic variables to our analysis to control for aggregate time-varying factors. Additionally, we conduct placebo tests by instrumenting counterfactual CDS introduction dates for non-CDS firms that are matched to CDS firms using a propensity score matching procedure. We describe these tests further in Section 4.4. We also complement our first instrument with a second instrument that captures the cross-sectional variation in the probability of CDS trading. Our second instrument is the foreign exchange derivatives traded for hedging purposes by banks that have a lending relationship with the firm (Saretto and Tookes, 2013; Subrahmanyam, Tang, and Wang, 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 downgrade 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).

3.2 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 downgrade for an issuer as one observation. When rating downgrades on multiple bond issues for an issuer occur on the same day, we use the issue that has been downgraded by the most number of notches.

Our final sample consists of $3,310$ credit rating downgrades of 644 unique firms observed from 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 IV analysis.

[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.

[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.

4. 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 downgrade 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.

4.1 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 downgrades concurrent with earnings announcements. Firm-level controls are collectively motivated by previous studies (e.g., Jorion, Liu, and Shi, 2005). CDS-trading controls are motivated by Oehmke and Zawadowski (2016), 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

[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.

[9] Summary statistics of these control variables are presented in Table IA-4. Consistent with Saretto and Tookes (2013) and Oehmke and Zawadowski (2016), we find that CDS firms are generally larger, better rated, and have higher analyst forecast dispersions.

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 load 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*×*DNG-notches* fixed effects. This indicates that the market indeed reacts similarly to identically rated firms that experience the same credit rating downgrade, thus underscoring the importance of including *Prev-rating*×*DNG-notches* fixed effects to absorb the effect of unobserved factors on the market reaction to rating downgrades. Thus, an unobservable omitted variable that seems as economically important as our included control variables and potentially correlated with CDS trading, might be less likely to drive the market reaction to rating downgrades within the *Prev-rating*×*DNG-notches* bins.

4.2 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 downgrade events and control for time- (year-month) fixed effects. However, it is still possible that a time-varying omitted variable within the *Prev-rating*×*DNG-notches* 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 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*×*DNG-notches* 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 downgrades, 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 downgrade 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 Table IA-7.)[10]

4.3 Matched-sample analysis

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 propensity scores 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] However, the similarity between treated and control firms in the matched sample can be achieved only on observable dimensions.[12] Section B.3 in the Internet Appendix provides details of the matching procedure. We also include all the matching covariates as controls in our matched sample CAR regressions to control for any imperfect matches.

[10] Jorion, Liu, and Shi (2005) find that CARs to rating downgrades are stronger after the Reg FD implementation.

[11] This is equivalent to controlling for factors such as $\textit{Observable factor}_{i,t} \times \textit{Unobservable shock}_t$ 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.

[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*$\times$*DNG-notches* fixed effects.

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 regression with both treated and control firms. The variable of interest is the interacted term $dTreated \times dCDS$, 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 $dTreated \times dCDS$ 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.

In the Internet Appendix Table IA-9 and Section B.4 we show that our results are robust after controlling for potential time-varying industry shocks. To demonstrate this, we use the matched sample of CDS and non-CDS firms in Table III and include $Industry \times Year$ and $Industry \times Year\text{-}month$ fixed effects in Table IA-9, Panel A and Panel B, respectively. As the CDS and non-CDS firms are matched to be in the same industry and rating group, the fixed effects control for common time-varying industry-level shocks that affect a CDS firm and its matched non-CDS firm that belong to the same industry and are rated similarly. Further, in the Internet Appendix Table IA-10 and Section B.5 we conduct placebo tests showing that CARs to downgrades between CDS and non-CDS firms are not significantly different in the absence of CDS trading.

4.4 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*×*DNG-notches* fixed effects. Despite this, and our previous tests, our results could still be potentially biased if CDS introduction is timed precisely around, or occurs due to an unobserved time-varying *firm-specific* omitted variable. We tackle this potential omitted variable bias using an instrumental variable analysis as discussed in detail in Section 3.1. 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.

We estimate the regression model using 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-11 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 IV regressions on the control (non-traded-CDS) firms from the propensity-score matched sample described in Section 4.3. 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 instrument is not simply capturing a time trend. In an alternate placebo test, we regress rating downgrade CARs directly on the

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

instrument for the traded-CDS sample and the non-traded-CDS sample separately. Results reported in Table IA-12 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 also complement our IV analysis with another instrument for CDS trading that has previously been employed in the literature. 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 because proxies for the bank's need to hedge macro currency risk (exclusion restriction). 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 (relevance condition). Saretto and Tookes (2013), and Subrahmanyam, Tang, and Wang (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-13.[14]

5. Heterogeneous effects of CDS trading on CARs to 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 main results. Specifically, we perform sample cuts along the dimensions where credit rating downgrades are likely to matter more and test whether the presence of CDS trading affects downgrade CARs differently across these dimensions. We design our sample cuts and group the analyses based on the following two broad and mutually non-exclusive channels through which credit ratings can affect a firm's value: the *financing-frictions* channel, and the *information* channel.

To achieve greater variation on the multiple dimensions of sample cuts, we include both 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

[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.

firm.[15] We first verify the main finding that the introduction of CDS trading mutes the equity price reaction to credit rating downgrades using this larger cross section of traded-CDS and non-trade-CDS firms. Table IA-14 in the Internet Appendix reports the results. 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.[16]

5.1 Financing-frictions channel

As certifiers of firms' creditworthiness, rating agencies allow firms and regulators to rely on them and also enable firms and creditors to enter into contracts that link a firm's cost of debt to credit ratings (Kisgen, 2006; Kisgen and Strahan, 2010). Thus, in imperfect capital markets with information frictions, credit ratings can have a real impact on a firm's cost and access to debt financing. We expect that credit rating downgrades should matter most for firms whose cost and access to debt financing is more dependent on credit ratings. We therefore investigate whether the presence of CDS trading has heterogeneous effects in the cross-section of firms with different degrees of dependence on credit ratings for their debt-financing.

We estimate 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.

[15]Nevertheless, we check and confirm that the general conclusions obtained in this section also hold for the smaller sample of traded-CDS firms.

[16]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.

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.

5.1.1 *Exploiting 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. 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 regulation-based 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 for 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 Appendix Table A1. 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 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.

5.1.2 Exploiting 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. For instance, 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.6 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 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. In support of this, we also find evidence of PP covenants that are explicitly tied to CDS spreads from searching through the loan covenant pricing comments in the Dealscan database.[17]

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.[18]

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.[19] Banks therefore have incentives to tie

[17]For example: "Pricing is as indicated, tied to the company's 30 day moving average credit default swap mid-rate spread … The Credit Default Swap Spread shall in no event be less than the Credit Default Swap Floor or more than the Credit Default Swap Cap. Level 1= Credit Default Swap floor of 25bps and a cap of 100bps. Level 2= Credit Default Swap floor 37.5bps and a cap of 125bps. Level 3=Credit Default Swap floor of 50bps and a cap of 150bps. Level 4=Credit Default Swap floor of 62.5bps and a cap of 175bps. Level 5=Credit Default Swap floor of 75bps and a cap of 225bps. Prime margin = CDS spread margin minus 100 bps (not less than 0 bps) …"

[18]This argument implicitly assumes that the presence of rating-based covenants and accounting-based covenants are not strongly correlated, either positively or negatively. In the presence of a strong positive (negative) correlation between rating-based and accounting-based covenants, sorting on rating-based covenants would also imply a similar (opposite) sorting outcome on accounting-based covenants. 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.

[19]For instance, the risk weights in Basel II are 20% for AAA to AA-; 50% for A+ to A-; 100% for BBB+

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)*.

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.

5.1.3 Exploiting 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

to BB-; and 150% for below BB-rated firms.

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)*.

5.2 Information channel

In this section, we test an alternate channel that can potentially explain our main results. Trading activities in the CDS market convey new information about firms ahead of their downgrades. Therefore, rating downgrade announcements could become less informative in the presence of CDS trading.

We first show that, consistent with previous studies, CDS-trading activities contain new information about the downgraded firm that is not already present in stock and bond prices. We summarize our findings below but report the full results with extensive discussions in Section D of the Internet Appendix. We follow the empirical framework in Acharya and Johnson (2007) and examine the lead-lag relationship between CDS and stock returns and find that changes in CDS spreads lead stock returns over the 90-day period leading up to credit rating downgrades. However, excluding the period prior to negative credit risk events such as credit rating downgrades, we do not find that CDS spread changes lead stock returns which is consistent with the results in Acharya and Johnson (2007). Additionally, we compare the share of credit price discovery in the CDS market relative to the bond market using the Vector Error Correction Model (VECM) as in Blanco, Brennan, and Marsh (2005). Consistent with their results, we find that unconditionally about 81–85% of the credit price discovery takes place in the CDS market as opposed to the bond market. However, prior to a rating downgrade announcement, the CDS market's share of credit price discovery increases to 90–91%.

We next conduct an analysis to test whether trading activities in the CDS market leading up to firms' rating downgrades play a role in explaining the main finding of our paper — the muted equity price reaction to credit rating downgrades in the presence of CDS trading. We estimate an augmented version of the regression model in Equation (1) where *dCDS* is now a categorical variable that takes values corresponding to the three levels of CDS-trading activities before firms are downgraded: *High*, *Low*, and *CDS=0* group. Panel D of Table V reports the results. The reported coefficients for *dCDS* can be compared against CARs to all rating downgrades that occur in the absence of CDS trading (*CDS=0*) which is the omitted category in Panel D.

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 the liquidity in the CDS market. This liquidity measure was also employed in 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.

If CDS spread changes and their trading activities contain information that lower the informativeness of credit downgrade announcements, we would expect the coefficient estimates on *dCDS (Low)* to be small and closer to zero. This is because rating downgrades corresponding to *dCDS (Low)* were preceded by low trading activity in the CDS market, which should arguably be similar to the case when firms do not have CDS trading, i.e., the *CDS=0* group. On the other hand, we would expect estimates on *dCDS (High)* to be positive and significantly larger than *dCDS (Low)*. This is because *dCDS (High)* captures the effect of the CDS market on CARs to ratings downgrades when the trading activity in the CDS market strongly signals a deterioration and uncertainty about firms' credit risk quality ahead of their downgrades.

Columns (1)–(2) of Panel D 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. Note that the differences in CDS-trading activities between the High and Low groups in Columns (1)–(2) are large. This evidence is illustrated in Appendix Table A1-D where we summarize the level of CDS-trading activities for each group. For instance, the mean of cumulative CDS spread change in the 90 days before downgrades in the above-the-median (high) group is 54.37%, while for the below-the-median (low) group, it is −15% which shows that CDS spreads do not always move in the expected positive direction which reflects an increasing default risk ahead of downgrades. Despite this stark difference in how CDS spreads change before the firm is downgraded, Column (1) of Panel D shows that the effect of CDS trading are about the same between these two groups. Similarly, the average volatility of CDS spread changes in the high group (4.87%) is more than twice that of the low group (2.07%). However, in Panel D of Table V, 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 (3) in Table V, Panel D 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 we observe greater liquidity in the CDS market. Importantly, while higher number of CDS dealer quotes could imply greater informed trading in the CDS market, it could also proxy for a greater demand to purchase credit protection ahead of an impending bad news (Qiu and Yu, 2012). Taken together, the results in Panel D do not consistently support the information channel exclusively for why CARs to rating downgrades are muted in the presence of CDS trading.

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

Evidence from Section 5 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 evidence supporting this hypothesis.

6.1 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.

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.[20] 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* and $dPostDNG \times dCDS$, which represents the overall change in net debt (or equity) issuance of

[20] 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.

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.[21] 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

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

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 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-16 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 downgraded by the same number of notches 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.

6.2 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*×*DNG-notches* 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 downgrades. 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; 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-17 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.

6.3 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-18).

6.4 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 for CDS versus non-CDS firms in a more general setting.

We use rating-based salient thresholds of Debt/EBITDA 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. The rating-based salient thresholds as defined in Begley (2015) are Debt/EBITDA ratios of 1.25, 1.50, 2.0, 2.5, 3.0, 4.0, and 5.0.[22] In Columns (1)–(4), we include *Industry*×*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-19), 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.

[22]The high-incentive zones as defined in Begley (2015) are (1.125, 1.35), (1.475, 1.70), (1.95, 2.20), (2.45, 2.70), (2.95, 3.40), (3.90, 4.40).

7. Conclusion

We demonstrate that among firms that experience identical credit rating downgrade events, firms with CDS trading on its debt exhibit a muted equity market reaction to credit rating downgrade announcements. The effect of CDS trading on the sensitivity of the stock market reaction to downgrades is driven by (a) firms that are rated near the boundary between investment grade and speculative grade, and (b) firms that have a high number of rating-based performance pricing covenants, and (c) a large number of active bank 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 compared to non-CDS firms despite experiencing an identical credit rating downgrade event. In line with the lower cost and greater availability of debt financing after a credit rating downgrade, CDS firms are further less likely to reduce their investment compared to non-CDS firms.

Broadly, our results suggest that due to the regulatory and contractual dependence of the debt market on credit ratings, downgraded firms face significant financing-related frictions, which eventually impact real investment activity. However, importantly, we further show that such financing-related frictions after credit rating downgrades are mitigated in the presence of CDS trading, which consequently explain the muted market reaction to rating downgrade announcements.

Our paper highlights an important economic role for the CDS market in relation to credit rating downgrades. We emphasize that 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. In addition, just as we observe the regulatory and contractual dependence on credit ratings, a similar 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.

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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.

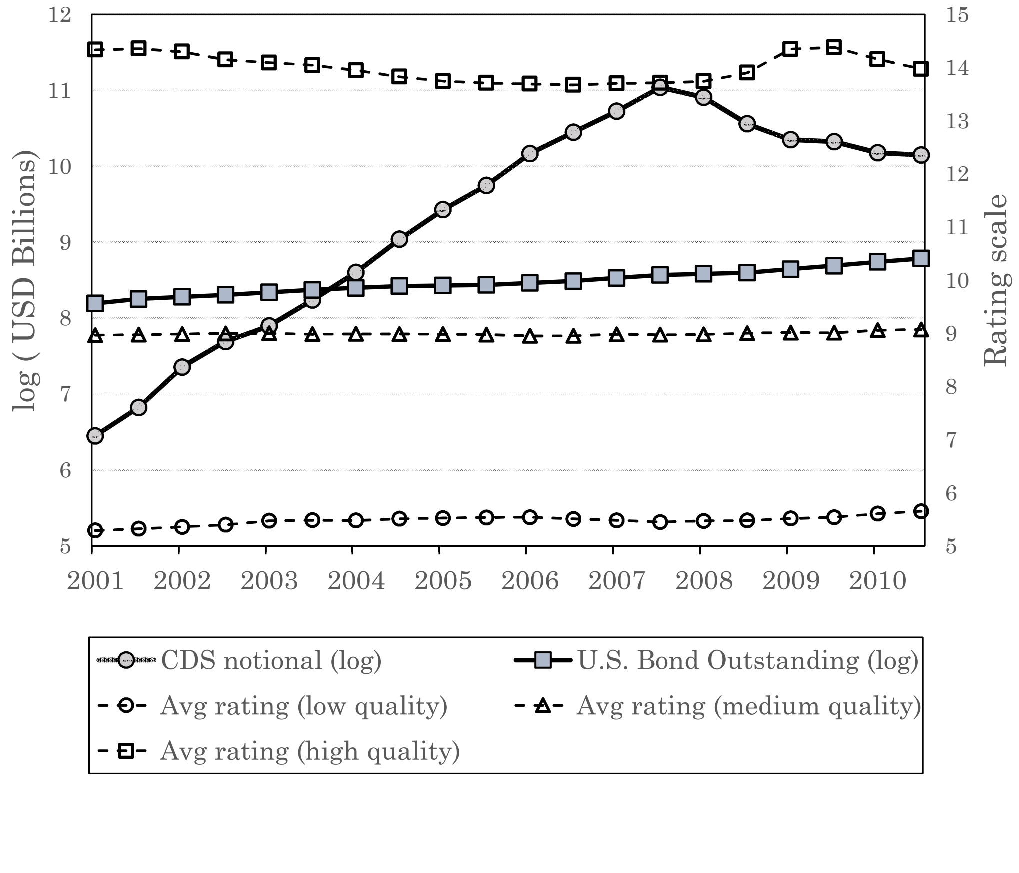

Table I: CARs to credit rating downgrades

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×DNG-notches 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×DNG-notches 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×DNG-notches FE	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
Rating-level controls	✓	✓	✓	✓	✓	✓
Firm-level controls	✓	✓	✓	✓	✓	✓
CDS-trading controls	✓	✓	✓	✓	✓	✓

Table IV: Instrumented CDS: 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 4.4 for more details. The first-stage regression results are reported in the Internet Appendix Table IA-11. 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 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×DNG-notches 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 5 for more details. All specifications include *Industry FE, Rating-type FE, Prev-rating×DNG-notches 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.

In Panel D, we examine the impact of CDS-trading activities before the firm is downgraded on CAR to credit rating downgrade announcements. The presence of CDS-trading is further divided into two categories of *high* and *low* CDS-trading activities. We then estimate our baseline model in Equation 1 with the categorical variable *dCDS* taking three values: *High*, *Low*, and *CDS=0* group. The reported coefficients *dCDS (High)* and *dCDS (Low)* are relative to the omitted category of all credit rating downgrades that occur in the absence of CDS trading (*CDS=0 group*), which has the mean of −4.41%. Observations in Columns (1) and (2) are sorted based on the average and the standard deviation of daily CDS spread changes, respectively. In Column (3), 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.

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 A1 in the Internet Appendix summarizes the number of observations and the sample mean of sorting variables corresponding to each of the grouping shown in Panels A to D.

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 based on contractual dependence on ratings

	Grouping variable:		
	Rating PP covenants	Accounting PP covenants	Active bank 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 based on credit market tightness

	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

Panel D: Heterogeneous effects of CDS based on pre-downgrade CDS-trading activities

	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

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×DNG-notches 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×DNG-notches 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×DNG-notches 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×DNG-notches 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

Appendix A. Variable Definitions

Rating-level variables

- *dCDS* is an indicator variable equal to 1 if the rating downgrade 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 downgrade 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, 2016).
- *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.

Table A1: 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, Gallmeyer, and Park, 2015).

In Panel D, we examine the impact of CDS-trading activities before the firm is downgraded on CAR to rating downgrade announcements. Observations in Columns (1) and (2) of Panel D are sorted base on the average and the standard deviation of daily CDS spread changes, respectively. In Column (3) of Panel D, 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.

Panel A: Sample split across previous rating levels before downgrades

Sample sorted by:	Range of Sorting Var.	CDS= 0 Obs. (1)	CDS= 1 Obs. (2)	%CDS= 1 (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

Sample sorted by:	Mean of Sorting Var.	CDS= 0 Obs. (1)	CDS= 1 Obs. (2)	%CDS= 1 (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 A1: Heterogeneous effects of CDS-trading: Summary of sample splits (continued)

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

Sample sorted by:	Mean of Sorting Var.	CDS= 0 Obs. (1)	CDS= 1 Obs. (2)	%CDS= 1 (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%

Panel D: Sample split based on CDS-trading activities before downgrades

Sample sorted by:	Mean of Sorting Var.	CDS= 0 Obs. (1)	CDS= 1 Obs. (2)	%CDS= 1 (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%