Credit Default Swaps and the Cost of Capital

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Abstract

This study uses the universe of US public firms to examine the impact of credit default swap (CDS) trading on a firm's cost of capital during the period 2001-2018. Our results show that the initiation of CDSs significantly reduces a firm's weighted average cost of capital (WACC). We also find that highly levered firms reduce their debt, while firms with low leverage increase their usage of debt. CDS referenced firms adjust their debt placement by using more arm's length debt, while they simultaneously reduce the usage of revolving credits and term loans from banks. The change in capital financing choices may be ascribed to the increased rollover risk induced by CDS trading and reflects the fact that CDS trading increases debt renegotiation costs and simultaneously reduces capital supply side frictions.

JEL Classification: *G23 G30 G32*

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Credit Default Swaps and the Cost of Capital

1. Introduction

Credit default swaps (CDSs)[1] are credit derivatives whose primary purposes are to hedge and trade credit risks. CDSs materially alter lender-borrower relations (Bolton and Oehmke, 2011) and thus have real economic effects on the firms referenced by the CDSs (hereafter, CDS firms). Empirical studies have revealed both dark and bright sides of CDSs, e.g., reducing frictions on the capital supply side (Saretto and Tookes, 2013) and increasing the risk of bankruptcy for CDS firms (Subrahmanyam et al., 2014, 2017). Driven by the palpable impact of CDSs on referenced firms, this study evaluates the overall costs and benefits of CDSs on the economy by investigating whether the introductionof CDSs induces a change in a company's weighted average cost of capital (WACC), and if so, we explore the channels through which CDSs drive changes in a firm's WACC.

A firm's WACC plays a critical role in business decisions, such as mergers and acquisitions. To maximize shareholder wealth, the executives of the focal firm strive to stretch the spread between the WACC and the expected returns of investment opportunities, either by reducing the WACC or by increasing expected returns on investments. An investment is typically only undertaken if the expected return exceeds the minimum cost of capital a firm can obtain in the capital markets. As such, the WACC reflects the beliefs of market participants (i.e., capital suppliers) regarding the risk of the focal firm. Arguably, if the benefits of CDSs outweigh their costs, market participants will lower their required return, which results in a lower WACC for the company. Conversely, an increase in the WACC implies that the costs of CDSs outweigh their benefits and thus cause an increase in risk and investors' required rate of return. In this regard, the resulting changes in a firm's WACC following the introduction of CDSs provide useful information about the effects of CDS trading on a given firm.

Our analyses of the effects of CDSs stem from the theoretical contribution of Hu and Black (2008) and Bolton and Oehmke (2011). These theorists point out that CDS trading can lead to empty creditor issues,[2] which have both positive and negative effects for CDS firms. In terms of negative effects, the

[1] Credit default swaps are credit derivatives that compensate CDS buyers via lump sum contractual payments in case of prespecified credit events (e.g., restructuring, payment default, or bankruptcy) occurring over a predetermined period. In exchange for the insurance reimbursement, the buyers need to make periodic payments to the seller.

[2] Empty creditors are buyers who have partially or fully decoupled their debt-related cash flows and debt control rights by holding a disproportionate number of CDSs.

authors hypothesize that CDSs grant insured lenders[3] with improved bargaining power over ex-post debt renegotiations. Thus, these lenders become less accommodating in out-of-court debt workouts. Furthermore, overly insured lenders may have less or even no interest in the continued existence of distressed companies. The reason for this is that if the CDS firm goes bankrupt, lenders can get compensation from CDS sellers, provided that the overall payoff (i.e., the payoffs generated by the CDSs plus the recovery value of debt) from the bankruptcy is greater than that from a compromise in debt renegotiations. Consequently, CDS trading increases the likelihood of bankruptcy and causes inefficient liquidation for distressed corporations.

On the other hand, Bolton and Oehmke (2011) also theorize that CDSs can serve as a commitment device for borrowers not to strategically default on their debt. Therefore, CDS trading can help solve the limited-commitment problems of debt contracts when borrowers' commitment is not verifiable and thus unenforceable. Furthermore, the availability of CDS offers a new channel through which banks can efficiently move their credit risk to CDS sellers and free up more capital originally tied to borrowers with high credit risk[4] (Shan et al., 2016). Such commitment and risk hedging functions of CDSs make insured lenders more willing to extend their credits, reduce the charged interest rate, and use fewer covenants and collaterals (Shan et al., 2019), therefore reducing frictions on the credit supply side.

To explore the overall effects of CDS trading, we construct a panel sample using the universe of US companies from Compustat from 2001 to 2018. We collect CDS data from Markit and then manually match CDS firms with Compustat firms according to Markit Reference Entity Database (RED). We obtain debt compositions from Capital IQ and the cost of capital data from Bloomberg. Our final sample contains 52,450 firm-year observations from 6,289 firms. Using this large dataset, we find robust evidence that CDS trading causes a significant reduction in the WACC for CDS firms across samples and estimation measures. The estimated coefficient of -21.7 (29.5) basis points (bps) on CDS

[3] We use CDS-protected lenders, insured lenders, lenders, or CDS buyers interchangeably. All of them are corporate debt holders who purchase CDS contracts to protect their risk exposure rather than speculators whose main interest is to profit from fluctuations in the credit risk of referenced firms. The existence of speculators can enhance the liquidity and facilitate transactions of CDS markets but may not alter the lender-borrower relations, hence not having a direct real effect on the referenced companies.

[4]A bank can replace the credit risk of borrowers (usually high) by the CDS seller's credit risk (usually low). By doing so, the bank can shift assets from high-risk categories into low-risk ones and still comply with regulatory capital requirement. Therefore, the bank can have more available capital that was released from the risky borrowers.

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initiation based on the firm-year (industry-year) fixed effects is significant at the 1% level. To substantiate our results, we use quantile regressions over various quantiles and find consistent results.

Previous studies suggest that larger and transparent firms may further benefit from CDS trading, while CDSs may be detrimental to riskier firms or firms subject to asymmetric information risk (Ashcraft and Santos, 2009; Hirtle, 2009). We conjecture that CDS trading has contrary effects on the shareholders of riskier and safer firms. To examine our hypothesis, we categorize firms with a rating above BBB+ into the high-rated group and the rest into the low-rated group. The estimates from the high-rated sample indicate that high-rated firms enjoy more benefits from the reduced cost of equity. In contrast, low-rated firms realize benefits from the reduction of the cost of debt; however, their investors demand higher returns on equity after CDS trading. To substantiate our findings, we segment firms into four groups based on Bloomberg five-year predicted default probability. We re-estimate our baseline model for the sub-samples that have a low and high default probability, respectively. The results from sub-samples with high and low default probability are consistent with those from sub-samples with high and low credit quality.

To validate our conclusions, we re-estimate our baseline model with an extra dummy variable that indicates the termination of CDS trading. If the initiation of CDS trading hasmore positive effects on firms than negative effects resulting in a decrease in the WACC, we should observe an increase in the WACC because of a cessation in CDSs trading. We find a significant and positive estimate on the CDS reversal variable, validating our conjecture and conclusions from the main sample. Furthermore, to mitigate concerns that our results are driven by Bloomberg WACCs, we compute empirical WACCs (EWACCs) (Olson and Pagano, 2017) and re-estimate our baseline model. The consistent estimates from EWACCs indicate that our results are not sensitive to Bloomberg WACCs.

We conduct additional robustness tests to address potential sample selection bias and endogeneity concerns. First, we construct propensity score matched (PSM) samples using various selection criteria. The results from various PSM samples are in line with our results from the main sample. Second, we apply the instrument variable approach to our main variable of interest, CDS trading availability. Consistent estimates from instrumented CDS availability eliminate the potential endogeneity concern. To further exclude the possibility of sample selection biases, we also estimate the baseline model with CDS firms only. We observe negative and significant estimates on the variable for CDS initiation when using the cost of debt as the dependent variable, consistent with our main sample results. We further

introduce variables to control for the level of strategic default incentives and find results consistent with Kim (2016). The cost of capital significantly declines for firms vulnerable to strategic default.

Our tests may be subject to reverse causality concerns. It may be the case that investors anticipate a reduction in the cost of capital and consequently start CDSs to profit from the expected reduction of CDS spreads. To address the reverse causality and further validate our results, we construct the first difference samples and test the baseline model on them. The results validate our main sample tests. We use the CDS initiation as the dependent variable and regress it on the changes in the various measures of the cost of capital. We find insignificant coefficients on the changes of various capital costs, indicating that there is no reverse causality in our tests. We also use CDS trading liquidity variables to substitute for the CDS availability indicator variable. Estimates using CDS daily notional volume and the number of clearing dealers further corroborate our findings.

After validating our results with a battery of tests, we study the channels through which CDSs affect the WACC. Because the cost of debt is significantly less than that of equity, firms may reduce the WACC by using more debt to retire equity financing. We test this conjecture with both firm-fixed effects and quantile regressions. The estimate from regressing debt weight on CDS initiation in firm-fixed effects is positive and close to the 10% level (*t-statistics* =1.44), suggesting that debt weight of WACC increases after CDS trading. Based on this estimate, it seems that managers of CDS firms use more debt in the capital mix. However, our empirical findings on debt issuance are contrary to this conclusion. The negative and significant estimates from the regressions of net debt issuance on CDS initiation indicates that CDS firms do not raise more debt post-CDs trading. On the contrary, they reduce the issuance of debt securities. This finding is consistent with Batta and Yu (2019) who find a decrease in net debt issuance after CDS trading. Therefore, we conclude that it was the emergence of CDS markets that causes an increase in values of debt, indicated by a decreased cost of debt.

In addition, the estimates from quantile regressions show that CDSs have contrary effects on firms with high and low leverage ratios. Low levered firms significantly increase the usage of debt financing after CDS trading. This finding is consistent with Bolton and Oehmke's (2011) hypothesis that CDSs serve as a commitment device and thus increase credit supply to borrowers. Correspondingly, highly levered firms significantly reduce their debt weight by using more equity security. This finding is also in line with Bolton and Oehmke's (2011) hypothesis that protected CDS lenders with improved bargaining power become less accommodating in ex-post debt workouts. This threatening effect of

CDSs forces firms to reduce the usage of debt financing after CDS trading. Such contrary effects of CDSs on debt usage cause a marginal decrease in debt issuance on average.

Except for using more debt to reduce the WACC, managers can also lower the cost of debt to decrease the overall cost of capital. Public companies generally use multiple types of debt (Colla et al., 2013; Lin et al., 2013). For instance, syndicated facilities, loans, revolving credits, and senior or junior bonds and notes are common types of debt instruments used in capital markets. Since distinct types of debt have different required returns, the cost of capital depends on the overall borrowing costs from each of the financing sources. It could be the case that CDS firms substitute bonds for term loans because of the emergence of CDS markets, which brings information advantages to firms. Such a substitution can alter the firms' capital structure and the overall cost of debt, hence resulting in a change in WACC.

To examine the above channel, we first provide evidence that CDS trading improves CDS firms' information environment by showing an increased number of analysts recommending the purchase of the CDS firms' stocks. With less asymmetric information risk, bank debt becomes less attractive to firms than before. Therefore, we conjecture that firms may substitute public debt for bank debt. We use the definitions of Lin et al. (2013) for public debt, described as the sum of various bonds, notes, and commercial papers, and for bank debt, described as the sum of bank loans and revolving credits. We test our conjecture by regressing the ratios of each debt category to the total debt on CDS initiation. We find negative and significant estimated coefficients for bank debt. Meanwhile, CDS firms substantially use more arm's length debt, demonstrated by the positive and significant estimated coefficient on public debt. The empirical estimates support our information advantage hypothesis, that is, CDS firms replace bank debt with public debt to avail of improved information benefits from CDS trading.

However, the information advantage hypothesis itself cannot explain the significant reduction in the usage of revolving credits and an increase in other borrowings (i.e., private debt placement) after CDS initiation. Post-CDS trading, CDS firms alter their debt types to capture the benefits induced by CDS trading and avert the costs associated with it. We conjecture that firms use more arm's length debt to replace revolving credits to prevent rollover risks. To substantiate our rollover risk explanation on the reduction of revolving credits, we re-examine the relationship between ratios of revolving credits to total debt and CDS initiation with investment and non-investment grade firms, respectively. Looking into the estimated coefficients across models in the sample of non-investment grade firms, we find that the coefficients are negative and significant at the 1% level and have a larger magnitude. Furthermore,

the corresponding estimates from the sample of investment grade firms are not significant at all. Such a sharp contrast in the estimates suggests that firms with high default risk run into more rollover risk after CDs trading. Therefore, firms consciously reduce the usage of revolving credits when considering financing choices.

Our study contributes to the growing literature on the effects of CDS trading. In contrast to prior studies that examine one source of financing cost (e.g., Ashcraft and Santos, 2009; Hirtle, 2009; Shim and Zhu, 2014; Kim, 2016; Amiram et al., 2017; Narayanan and Uzmanoglu, 2018c), we consider the overall costs and benefits of CDS trading on the economy. Our results robustly show that the costs of capital are significantly reduced after CDS trading. Furthermore, we show that CDS trading exerts contrary effects on firms with high and low credit quality. Equity holders demand lower required return in firms with higher credit quality, while shareholders in firms with lower credit quality require higher returns to compensate for their increased risk associated with CDS trading. Our study also contributes to capital structure literature. We show that after CDS trading, CDS firms with improved information environment prefer arm's length debt to bank debt. In addition, to offset increased rollover risk induced by CDS trading, firms intend to use arm's length debt to replace revolving credits for liquidity. Thus, financial market innovation, particularly CDS, can affect companies' debt compositions. Considering the significant impact that CDSs have on referenced firms and thus the economy more generally, this study's findings contribute to the ongoing conversations about both the merits and drawbacks of this type of trading.

The rest of the paper is organized as follows. Section 2 outlines the literature relevant to this study. In section 3, we describe our data sample and summary statistics. We present the test methodology and baseline results in section 4 and discuss robustness tests in section 5. We analyze the impact of debt placement and the cost of capital in section 6. Section 7 concludes.

2 Literature Review

A large body of literature examines the externalities caused by CDSs on referenced firms by studying how they affect the firms' behaviours and/or policies (e.g., Fung et al., 2012; Subrahmanyam et al., 2014, 2017; Martin and Roychowdhury, 2015; Batta et al., 2016; Danis, 2016; Danis and Gamb, 2018; Narayanan and Uzmanoglu, 2018a; Fuller at al., 2018; Kim et al., 2018; Batta and Yu, 2019; and Chang et al., 2019). Another stream of literature examines the impact of CDS trading on loan and/or

bond spreads (e.g., Ashcraft and Santos, 2009; Hirtle, 2009; Shim and Zhu, 2014; Kim, 2016; Amiram et al., 2017; Narayanan and Uzmanoglu, 2018c). Those studies enhance our understanding of the mechanisms through which CDSs affect the referenced firms. In the following, we review studies in terms of both costs and benefits induced by CDS trading.

2.1 Costs of CDS trading

CDS trading presents a variety of costs to CDS firms by introducing additional frictions into debt renegotiations. For example, Subrahmanyam et al. (2014) find a substantial increase in the likelihood of both bankruptcy and rating downgrading after the emergence of CDS markets. Facing a heightened default risk after CDS trading, capital suppliers usually demand a higher return on their investment. Consistent with this finding regarding the increased risk, Narayanan and Uzmanoglu (2018b) provide evidence that CDS initiation accompanies an increase in the cost of equity. Subrahmanyam et al. (2017) find that, post-CDS trading, CDS firms significantly increase cash holdings and conclude that such a conservative liquidity policy adopted by CDS firms results from the threatening effects of exacting lenders. An increase in cash holdings could promote extra agency costs (Jensen, 1986) and suboptimal investment, and eventually destroy shareholders' wealth (Faulkender and Wang, 2006). Furthermore, Danis (2016) finds a significantly lower participation rate of distressed exchange offer among CDS firms in contrast to the rate among non-CDS firms. Narayanan and Uzmanoglu (2018a) find that CDS firms face a holdout problem caused by CDS-protected bondholders in distressed exchanges. The lower participation rate or holdout problem would eventually halt the debt workout. Ultimately, shareholders would bear the costs incurred by CDS-protected bondholders.

The risk hedging role of CDSs could also bring in costs to referenced firms because CDS-protected lenders have relatively less motivation to actively monitor borrowers (Morrison, 2005; Ashcraft and Santos, 2009; Parlour and Winton, 2013; Shan et al., 2016; Amiram et al., 2017; Kim et al., 2018). By using CDSs, the lenders transfer credit risks of referenced entities to CDS sellers, hence not achieving the same level of gains with the same level of monitoring efforts as before.

Empirical studies find a series of evidence that lenders' weakened monitoring efforts would finally increase the operating costs of CDS firms. For example, the bond spreads of riskier firms increase after CDS trading (Ashcraft and Santo, 2009). The reason lies with the lost benefits from banking monitoring, such as mitigating adverse selection and moral hazards, which exceed the potential gains (e.g., increased capital supply) for these riskier firms. Lee et al. (2017) argue that loosened monitoring intensifies the conflict of interests between managers and shareholders and incurs agency costs in the

form of additional managerial perquisites. Amiram et al. (2017) provide direct evidence of an increase in the syndicated loan spreads after CDS trading. They argue that because CDSs reduce the effectiveness of lead arrangers' shares in syndicated loans, which originally served as the device to mitigate the information asymmetry between the lead arranger and syndicate members, lead arrangers must retain larger share of loans than before to validate their continuous efforts in monitoring borrowers, which in turn increases the loan spread. Furthermore, Martin and Roychowdhury (2015) show that CDS trade initiation results in a decline in a firm's reporting conservatism. The decrease in reporting conservatism can increase business risks and thus incur additional business costs.

2.2 Benefits of CDS trading

We have discussed heretofore negative effects arising from CDS trading, but researchers have also found evidence of the positive effects of CDS trading. For instance, Ashcraft and Santos (2009) provide evidence that the spreads of bonds and bank loans decrease for high credit and informationally transparent firms. Using Asian bond data, Shim and Zhu (2014) arrive at a similar conclusion to Ashcraft and Santos (2009). Kim (2016) finds that bond spreads are significantly reduced, particularly for firms having a higher likelihood of strategic default. Saretto and Tookes (2013) provide evidence that CDS firms increase their leverage ratios and debt maturity comparing to non-CDS firms after the initiation of CDSs. Likewise, Subrahmanyam et al. (2014) also find a significant increase in the leverage of CDS firms over post-CDS periods.

While the above studies focus on the impact of CDS trading from the borrowers' perspective, other studies have examined the impact from the lenders' perspective. For example, Hirtle (2009) finds evidence that banks actively hedging risk with credit derivatives increase the maturity and volume of their term loans to larger and creditworthy companies referenced by CDSs, implying an increased credit supply after CDS trading. Shan et al. (2016) show that banks using CDSs as a risk hedging mechanism supply more capital and provide larger loans than banks that do not hedge with CDSs. Moreover, Norden et al. (2014) find consistent evidence that banks actively hedging business risk with CDSs not only supply more credits but also pass benefits from risk management to the entire portfolio of borrowers by lowering interest rate spreads. The increased supply of credit to a firm can enhance the firm's financial flexibility and reduce its financial constraints, ultimately promoting economic growth.

CDS firms also stand to benefit from improved information environment (Stulz, 2010; Berndt and Ostrovnaya, 2014). The major participants in CDS markets are financial institutions that usually generate loans to borrowers, and thus gather the borrowers' private information (Acharya and Johnson,

2007; Flannery et al., 2010; Norden et al., 2014; Ivanon et al., 2016; Norden, 2017). Acharya and Johnson (2007) show that substantial information incrementally revealed in CDS markets flows into equity markets, implying the existence of private information in the former markets. Batta et al. (2016) find that the accuracy of analysts' forecast has been significantly improved after CDS trading. They conclude that CDS trading reveals the informed traders' privileged information to equity markets, which results in the increased forecasting accuracy of stock analysts. Liu et al. (2019) argue that CDS trading reduces the probability of stock price crashes for referenced firms, in that CDS traders incorporate into spreads the bad news that reference firms' executives could suppress. With an enhanced information environment, the role of banks to produce information becomes less critical to CDS companies. Therefore, CDS firms may change their financing choices and debt types.

While we illuminate both the positive and negative effects of CDS trading on firms, we specify that the functions of CDSs are complex and need to be analyzed case by case. For instance, though we discuss how loosened monitoring efforts can incur costs, the decreased monitoring may have positive effects on referenced firms as well. Chang et al. (2019) find that CDSs promote technological innovations because of CDS firms' risk-taking activities resulting from lenders' loosened monitoring. Shan et al. (2019) find that lenders adopt less stringent covenants and collateral requirements on new loans if there has been CDS trading in the borrowers' debts. The authors suggest that lenders use CDSs as a substitution for debt covenants and collaterals because actively supervising covenants and collaterals is costly to lenders. Using CDSs to supplant covenants and/or collaterals can thus improve loan contract efficiency for both lenders and borrowers and have positive effects on CDS firms.

In summary, CDS trading involves both costs and benefits to the referenced companies. The costs from increasing frictions of renegotiation as a result of exacting effects of CDSs and from insufficient monitoring due to risk hedging can cause capital suppliers to demand higher required returns, thus escalating business costs. Correspondingly, the benefits arising from decreasing frictions in credit supply side (because of risk shifting and commitment effects of CDSs), and the improved information environment resulting from price discovery role of CDSs, can drive down the required returns of capital suppliers and enhance shareholders' wealth. Therefore, the overall effects of CDS trading on the WACC rely on the tension between the two contrary forces on the referenced firms and must be investigated empirically.

3. Sample data, variables, and summary statistics

3.1 Data sources and sample construction

To construct our research sample, we merge data from several sources, including Compustat, the Center for Research in Security Prices (CRSP), Markit Group, Bloomberg, Capital IQ, the Depository Trust and Clearing Corporation (DTCC), Thomson Reuters Institutional Holdings (13f), I/B/E/S, and Execucomp.

We start with US public firms covered by Compustat from 2001 to 2018. Followingprior studies (e.g., Saretto and Tookes, 2013), we exclude financial firms (such as banks and insurance companies) whose standard industrial classification (SIC) codes are within 6000-6999. We first merge Compustat and CRSP datasets and require firm-year observations to have non-missing total assets and debt on Compustat. We also exclude observations with missing book and market values of equity, resulting in a sample of 87,124 firm-year observations from 8,984 firms. We draw WACC, cost of debt, and cost of equity from Bloomberg and merge these data with Compustat accounting data through International Securities Identification Number (ISIN).

We begin our sample period with 2001 to coincide with the availability of Markit's CDS trading quotes. Following Subrahmanyam et al. (2014) and Amiram et al. (2017), we assign the first trading date of a CDS contract with five-year maturity denominated in US dollars on the referenced company to the CDS initiation date. We manually match each CDS firm from Markit to Compustat by using the Bloomberg RED tracking events database[5] and further validate CDS firms by exploring company events from LexisNexis[6]. Following Narayanan and Uzmanoglu (2018b), we trace a subsidiary, referenced by CDSs, back to its parent company[7]. We are consistent with studies (Amiram et al., 2017; Kim et al., 2018) that eliminate all CDS firms whose initiation trading dates are in January 2001, as there are ambiguities regarding these initiation dates because Markit started gathering quotes from that month onwards. Finally, we obtain 873 non-financial US public firms that have been referenced by

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[5] The Bloomberg RED tracking events track CDS firms' major events (such as merger, spin off, or rename) that may interfere with CDS trading. For example, Science Applications International Corporation (SACI) was split into Leidos Inc. and a new independent company that retained the SACI name in September 2013. Bloomberg RED indicates that Leidos Inc. is the primary successor of the original SACI whose debts are first referenced by CDS contracts on March 5th, 2007. Thus, we consider March 5th, 2007 as the trading date for Leidos Inc. and trace Leidos to Compustat data rather than SACI.

[6] For instance, 21st Century Fox Inc. was spun off from the News Corporation on June 23rd, 2013. The News American Inc., a subsidiary of the original News Corporation, was inferenced by CDSs on February 28th, 2001. We assign the initial CDS trading date of February 28th, 2001 to 21st Century Fox Inc and eliminate the original and new News Corporation from CDS sample although the new firm was inferenced by CDSs as well after the split. By doing so, we focus only on the impact of the initial CDS trading on firms.

[7] For example, Express Script Inc. was referenced on November 25th, 2005, according to Markit. We trace to its parent company, Express Scripts Holding Company, for accounting fundamentals in Compustat.

CDSs from 2001 to 2017[8]. We further verify all CDS firms whose trading dates fall in 2001 using Bloomberg and do not find invalid ones (i.e., the trading dates start before 2001).

Next, we obtain debt structure variables from the Capital IQ database. Capital IQ details corporate debt structures in seven categories: commercial paper, revolving credit, bank and term loans, bonds and notes, capital lease, trust preferred, and other borrowings. The sources of debt information come from SEC filings (e.g., 10-K, or 10-Q form), corporate financial reports, and press releases. Capital IQ collects these debt data several times a year (i.e., quarterly or semi-annually), consequently generating multiple inputs for identical issues. To clean our data, we first select data items with last filing or the only filing reports (i.e., *FILINGFLAG_COMPANY* = 2 or 3). We also restrict reports to those that are the latest instance for the filing date and financial period (i.e., *LATESTFILINGFORINSTANCEFLAG* =1 and *LATESTFORFINANCIALPERIODFLAG* =1). We remove duplicates, as per Choi et al. (2018). For company-year observations, we require that observations not have the following identical data items: debt issuing identifier (*COMPONENTID*), debt description (*DESCRIPTIONTEXT*), principal amount (*DATAITEMVALUE*), maturity (*MATURITYHIGH* and *MATURITYLOW*), and interest payment (*INTERESTRATEHIGHVALUE*). Next, we use two approaches to further mitigate the concerns of duplicated reports[9]. For the same company-year observations with the same data item identifiers (*COMPONENTID*), we select the maximum and mean of reported items, respectively. Also, Capital IQ records both the maximum amount of revolving credits (debt type 2 in Capital IQ) committed by banks and the actual drawn amount by firms. We follow the method of Lou and Otto (2019) to remove all observations containing the string ‘Facility’ in the *DESCRIPTIONTEXT* field because it indicates the maximum available credit to a firm, not the actual drawn amount. Last, we aggregate all fine-grained debt components based on their type at an annual frequency. We then merge Capital IQ and Compustat/CRSP based on ISIN.

We extract stock analyst data from Bloomberg and I/B/E/S. Because Bloomberg has more extensive coverage than I/B/E/S over our sample period, we use data from the former for our analyses and data from the latter for robustness tests. We acquire top executives’ (e.g., CEO, CFO, etc.) stock ownership

[8] Our CDS data spans from 2001 to 2017, while dependent variables, like WACC or cost of debt, span from 2002 to 2018, as we lag one year for all control variables in panel regressions.

[9] Although we remove duplicated reports using the abovementioned approaches, duplicated reports in terms of unique debt issuance still exist because we amass quarterly items into annual data for debt structure analyses. For example, during the 2013 fiscal year, Capital IQ collects debt data for Andeavor Inc. in March, June, September, and December, respectively. In each of these reports, the term loan identified by the unique debt issue identifier, *COMPONENTID* = 914786139, has a value of \$0m, \$499m, \$498m, and \$398m, respectively in each quarter. It is obvious that the company originated the loan in the second quarter and amortized it in the last quarter.

from Execucomp, institutional ownership from Thomson Reuters Institutional Holdings (13f), CDS average daily trading notional and total number of clearing dealers from DTCC, and long-term issuer rating data from Standard & Poor's (S&P) and Moody's Investors Service. We integrate those data based on ISIN and keep only the observations that have no missing control variables, as discussed in section 3.2. Consistent with the method of prior studies (e.g., Fuller et al., 2018; Colonnello et al., 2019), we exclude firms with total assets of less than $10 million. Our final sample contains 52,450 firm-year observations from 6,289 US public firms, of which 8,946 firm-year observations belong to 673 CDS firms and 43,504 firm-year observations come from 5,616 non-CDS firms[10]. Furthermore, 41,909 observations have Capital IQ debt structure data from 5,487 firms. In line with prior studies in capital structure, we winsorize all accounting variables at the bottom one and top one percentile to reduce the influence of potential outliers.

3.2 Variables

3.2.1 Dependent variables

We draw WACC data from Bloomberg directly for two reasons: Bloomberg specialists evaluate the cost of debt for companies using fair market value, and a multitude of institutional investors use the Bloomberg platform to reference the fair values of corporate debt. The prevalence of using Bloomberg's trading platform across the world gives us the confidence that Bloomberg WACC reflects the real cost of capital for companies. We extract the following data as our dependent variables: *WACC*, *cost of debt*, *cost of equity*, *weight of debt*, and *weight of equity*[11]. The detailed definitions and computation of these variables can be found in Appendix 1.

In addition, to measure the influence of CDS trading on corporate debt structure, which may be a channel through which CDSs affect a company's WACC, we construct other explained variables from Capital IQ. In particular, following Lin et al. (2013), we use the ratios of bank debt and public debt to total debt as two measures of the preference for debt financing. Bank debt is the sum of revolving credits and loans from banks, whereas public debt is the sum of commercial papers and bonds and notes, and total debt refers to the sum of all seven types of financing mechanisms mentioned above. In

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[10] The actual number of observations may vary in different regressions, depending on the joint availability of control variables. For example, when we control marginal tax rate in the baseline regressions, the sample size reduces to 39,300 firm-years because Compustat provides tax rates until the 2016 fiscal year.

[11] We examine both weight of debt and weight of equity because 12.6 percent of observations in our sample have non-zero preferred shares. This implies that an increase in the weight of debt is not necessarily equivalent to a same amount of decrease in the weight of equity.

addition, we follow Colla et al. (2013) in computing the ratios of each type of debt to the total debt and evaluate whether firms prefer a special category of debt funding after CDS trading.

3.2.2 Independent variables

Following the approach of prior studies on CDS (e.g., Ashcraft and Santos, 2009; Martin and Roychowdhury, 2015; Chang et al., 2019), we construct an indicator variable *CDSINIT* to capture the influence of CDS trading on companies. *CDSINIT* has a value of one in and after the year of CDS trade initiation, and zero before that. Therefore, a significant negative (positive) estimated coefficient on *CDSINIT* would reveal that CDS trading causes a material reduction (increase) on the dependent variables, i.e., *WACC*, *cost of equity*, and *cost of debt*. We also build another dummy variable *CDSFIRM* to differentiate CDS and non-CDS firms. *CDSFIRM* has a value of one for CDS firms whose debt has been referenced over the sample period, and zero for non-CDS firms (i.e., never have traded CDSs on their debts over the sample period). Thus, this dummy variable captures the time-invariant divergence from unobservable firm characteristics between CDS and non-CDS companies.

Aside from the dummy variable *CDSINIT*, which indicates the availability of CDSs, we employ two alternatives that measure the liquidity of CDS trading, the average daily trading notional scaled on natural log, and the total number of clearing dealers in a year. Shan et al. (2019) argue that most benefits of CDS trading can be ascribed to the hedging capability of CDSs. A more liquid CDS market would allow lenders to locate sellers easily and reduce the cost of hedging. Furthermore, a liquid market can incorporate relevant information into quotes and disseminate information to other markets (e.g., bonds and equities), resulting in an improvement in the firm's information environment. Consequently, if CDS trading could reduce the cost of capital, we conjecture that the more liquid a CDS market is, the more significant the effects of CDSs will be on referenced firms. We follow Narayanan and Uzmanoglu's method (2018c) in assigning zeros to these two alternative measures of CDS trading activity, if DTCC did not report the trading data[12].

3.2.3 Control variables

A multiple of internal and external factors can affect the firm's capital financing decisions, and hence influence the capital structure and the cost of capital. For instance, firms in the automobile industry use, on average, higher debt financing and leverage than firms in the information technology

[12] DTCC reports single-name CDS trading data for the most actively traded 1000 CDSs, and these data cover over 95% of CDS trading activity in the world (Narayanan and Uzmanoglu, 2018c). Therefore, assigning zeros to missed values should not cause biased estimates.

(IT) industry. Likewise, in the same industry, large firms exhibit many distinct characteristics in contrast to medium and small firms, such as having easy access to arm's length debt, less information asymmetry, or higher credit rating. Furthermore, firms are by no means randomly selected to trade CDSs. The factors that contribute to the cost of capital may also influence the determinants of selection for CDS trading. Therefore, we also control factors related to CDS firms' selection.

To isolate the effects of CDS trading on WACC, we employ a set of firm-level controls that are determinants of WACC, including *firm size, leverage, profitability, growth opportunity, capital intensity, firm maturity, business riskiness, institutional ownership, liquidity cost, uniqueness, dividends, marginal tax rate, credit risk,* and *stock liquidity*. The controls listed above are suggested by prior studies on the cost of debt and equity and capital structure selection (e.g., Titman and Wessels,1988; Davydenko and Strebulaev, 2007; Colla et al., 2013; Saretto and Tookes, 2013; Narayanan and Uzmanoglu, 2018b). Titman and Wessels (1988) argue that larger firms tend to be more diversified and thus may have greater debt capacity. We use the logarithm of total assets[13] to control firm size effects. Following Chang et al. (2019), we use an indicator variable, *S&P rated*, which has a value of one if a firm was rated by S&P, and zero otherwise, to recognize a firm credit quality[14]. Furthermore, Berger and Udell (1995) and Krishnaswami et al. (1999) find that a firm's maturity relates to a firm's borrowing costs because a mature firm has less information asymmetry than a younger one. Following Loderer and Waelchli (2010), we proxy a firm's maturity by a firm's age. We first select the earliest date of a firm's initial public offering (IPO) and the first date of inclusion in Compustat, and then use the number of years elapsed since the earliest date to approximate the firm's age.

Myers (1977) theorizes that firms with high growth opportunities may use less debt to avoid suboptimal investment issues. We control the firm's growth prospects by using the market-to-book asset ratio. We also follow Titman and Wessels (1988) in using capital expenditures scaled by sales to capture the firms' future growth. According to the pecking order theory of Myers and Majluf (1984), profitability is an important factor in determining capital structure. More profitable companies may use less external financing sources and thus may have a lower cost of capital. We define profitability by the ratio of earnings before interest and tax (EBIT) divided by assets. Titman and Wessels (1988),

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[13] We substitute log (sales) for log (assets) in our baseline regression. However, there is no material influence on our estimated coefficients.

[14] We also use Bloomberg five-year default probability to proxy firm's credit risk. The estimated coefficients are not significantly changed in either magnitude or significance level.

Davydenko and Strebulaev (2007), and Chang et al. (2009) suggest that the level of R&D (research and development) expenditure represents the uniqueness of firms' products and thus affects liquidation costs. Davydenko and Strebulaev (2007) also indicate that high liquidation costs grant equity holders stronger bargaining power during debt renegotiations, hence increasing the cost of debt. Furthermore, the trade-off theory of capital structure posits that companies balance the advantages of debt tax shields and distress costs. Therefore, we control for the tax rate, product uniqueness, and liquidation cost in our estimation. We proxy the firm's product uniqueness by the ratio of research and development expenses to sales. Following Almeida and Campello (2007) and Kim (2016), we compute liquidation cost as one minus asset tangibility, which is defined as (0.715 × Receivables + 0.547 × Inventory + 0.535 × Capital + Cash and short-term equivalent), divided by assets. Regarding the tax rate, we use the marginal tax rate computed by Blouin et al. (2010). We obtain the tax rate data from Compustat from 2001 to 2016.

Aslan and Kumar (2012) find that ownership concentration negatively affects the cost of debt capital. Further, Attig et al. (2013) provide evidence that institutional shareholders with long-term investment horizons help reduce the cost of equity as a result of their monitoring efforts. Therefore, we compute the Herfindahl-Hirschman Index (HHI) of institutional ownership and use it to proxy share ownership concentration. Charitou et al. (2011) find evidence that dividend initiation and payment can reduce business default risk. However, the dividend is also a mechanism that shareholders expropriate creditors' wealth, evidenced by common debt covenants that limit dividend payments. Consequently, dividend policy can affect a firm's agency cost and, therefore, its cost of capital. We include dividend per share (DPS) to control the dividend influence on the WACC.

In addition, high business risk may induce a high default probability and thus claim-holders could demand a higher return to compensate for the risk they bear. Arguably, business risk is the fundamental determinant of the cost of equity and debt, and hence the WACC. We use stock return volatility computed from the past five years' weekly stock prices to proxy business risk. Additionally, we use leverage ratio to approximate the companies' financial risk. Obviously, a higher leverage ratio not only increases the agency cost of debt, but also increases the firms' default probability. We define the leverage ratio as the ratio of total debt to total assets. Finally, Butler et al. (2005) find that illiquidity stock increases the cost of issuing equity, and Amihud et al. (2015) show evidence that investors across countries require higher returns for holding illiquid stocks. Thus, we control for stock liquidity effects on the cost of capital. We define stock liquidity as stock trading turnover by volume scaled on the outstanding common shares. We present the sample statistics of controls in Table 1.

3.3 Sample characteristics

Panel A of Table 1 reports the distribution of CDS firms by the initiation year. We observe the clustering of CDS trade initiations, evidenced by 89.30% of CDS inceptions centralized in the period from 2001 to 2007. After that, the initiation significantly decreases in part due to our research design, i.e., we only identify new CDS firms for our research. Our sample shows a similar pattern to that of Kim et al. (2018). To illustrate, Kim et al. (2018) document that the percentages of CDS trade initiation are 23.2, 16.2, 17.8, 15.8, and 7.9% from 2001 to 2005. Over the same period, our sample has 21.7, 15.4, 17.8, 15.1, and 6.2% of CDS initiations, respectively. The absolute numbers of CDS initiations are also close in these two studies. We show the distribution of CDS firms by one-digit SIC code in Panel B. As shown, firms in manufacturing industry (of goods and services, such as food, petroleum, paper, printing, rubber, stone, and computer) are more prone to trade CDSs, demonstrated by the high percentage of firms, that is 46.36% of the sample.

<Insert Table 1 about here>

Panel C of Table 1 presents the means, medians, and mean differences between CDS and non-CDS firms across firm-level characteristics. Starting with the upper part of Panel C which shows the summaries of explained variables, we observe that the cost of debt and equity of CDS firms are significantly greater compared to that of non-CDS firms. Notably, although CDS firms exhibit a higher cost of equity and debt than non-CDS firms, the overall cost of capital is lower for CDS firms because they use more debt capital than non-CDS firms that use more equity capital.

Debt placement is another apparent discrepancy between CDS and non-CDS firms. The former prefers public debts to bank debts, while the latter reverses the order. For example, the percentages of bonds and notes to total debt are 71.3 and 35.9% for CDS and non-CDS firms, respectively. Furthermore, 50.3% of the total debt is from banks for non-CDS firms, while this percentage decreases to 18.6 for CDS firms. This divergence may be explained by the difference in firms' information environment according to Diamond (1991) and Rajan (1992). We find related evidence for such an explanation. In our sample, a larger number of stock analysts follow CDS firms rather than non-CDS firms. On average, there are fourteen analysts recommending CDS firms' stocks, while only six analysts for non-CDS firms.

We describe firm-level controls on the lower part of Panel C. CDS firms show substantial differences from non-CDS firms across firm characteristics, indicated by the significant mean

differences. CDS firms are larger, more profitable, usually rated by credit rating agencies, and employ higher financial leverage than non-CDS firms. Those findings are consistent with literature that addresses the properties of CDS firms (Subrahmanyam et al., 2014, 2017; Martin and Roychowdhury, 2015; Chang et al., 2019). We also observe that CDS firms pay higher dividends and have higher stock trading liquidity than non-CDS firms. Regarding institutional ownership (IO), institutional investors hold more shares of CDS firms than non-CDS firms. On average, institutional investors hold 70.7% of common shares of CDS firms. In contrast, institutional shareholders hold only about 43.1% of non-CDS firms' common shares. However, the HHI of IO indicates that CDS firms have more dispersed ownership (0.058 of HHI) than non-CDS firms (0.153 of HHI). In addition, CDS firms are more mature than non-CDS ones. The average firm's age is 32.09 and 17.44 years for CDS and non-CDS firms, respectively.

We present CDS trading activity in Panel D of Table 1. The mean of *CDSINIT* is 0.144, indicating that 14.4% of firm-year observations have CDS traded over the sample period. Lastly, we present the Pearson correlations matrix of variables in Panel E of Table 1. As shown in the table, the correlation between *CDSFIRM* and *CDSINIT* is 0.90[15] and significant at the 1% level. The high correlation is the result of the variable construction method, since both variables have a value of one after CDS trading initiation. Except for this correlation, others are reasonably lower (e.g., the maximum correlation is 0.57 between S&P rating and *CDSFIRM*), implying that our tests do not suffer from multi-collinearity problems. Furthermore, the lower correlations among controls also indicate that these controls capture the different aspects of firm characteristics. The correlations in Panel E closely coincide with the statistics of Panel C. For example, the univariate correlation between firm age and public debt is 0.20, significant at the 1% level. In Panel C, CDS firms have a higher firm age and use significantly high public debts. Likewise, firm age and bank debt have a significant and negative correlation of -0.17, suggesting that mature firms (e.g., CDS firms) use fewer bank debts than younger ones (e.g., non-CDS firms).

4. Methodology and empirical results

4.1. Baseline specification

[15] To counter this high correlation, we mainly focus on firm-fixed effects models for our tests and explanations.

We aim to explore the causality between the availability of CDSs and the changes in the cost of capital. Following prior studies, such as Saretto and Tookes (2013) and Chang et al. (2019), we estimate the following multivariate model with industry- or firm-year fixed effects[16]:

$$Cost\ of\ capital_{i,t} = \alpha + \beta CDSFIRM_i + \omega CDSINIT_{i,t-1} + \gamma X_{i,t-1} + \rho Fixed_i + \phi Year_t + \varepsilon_{i,t} \quad (1)$$

where $Cost\ of\ capital_{i,t}$ is one of the explained variables (i.e., WACC, cost of debt, and cost of equity) for firm i at time t. The main variable of interest is *CDSINIT*, which is an indicator variable having a value of one in and after CDS initiation year, and zero before that. Its coefficient ω captures the effects between treated and control firms (i.e., CDS and non-CDS firms). $X_{i,t-1}$ is the vector of firm-level control variables observed at the end of fiscal year $t-1$ defined in section 3.2. We lag all controls by one year because the initiation of CDS trading may not affect the cost of capital immediately. Furthermore, using lagged controls attenuates potential endogeneity issues between the cost of capital and controls. $Fixed_i$ denotes either firm or industry fixed effects. We use it to control the effects on the cost of capital of time-invariant unobservable factors that are either at the firm or industry level. In addition, we incorporate year effects in our specification to capture aggregate time trends in the firms' cost of capital. Following the suggestion of Petersen (2009), we cluster standard errors at the firm level, given that observations of the same firm are autocorrelated across time.

4.2. Empirical results

Table 2 reports the estimates of the baseline model (1). In columns (1) and (2) of Table 2, we present regressions of dependent variables (e.g., WACC, etc.) on CDS initiation and on a set of firm-level controls without tax rate under industry-year and firm-year fixed effects, respectively. We repeat the test under firm-year fixed effects but control for marginal tax rate and report estimates in column 3[17]. As shown in the first three columns of Table 2, the overall cost of capital significantly declines after the inception of CDSs. The declines in WACCs range from 20.0 to 29.5 bps and are significant at least at the 5% level. This reduction is not only statistically significant but also economically meaningful. Using the average capital ($11.402 billion) of CDS firms, the declines in required return, when converted into monetary amount, are of $22.8 to $33.6 million. To examine whether our tests are

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[16] Model (1) is the simplified version of the following model:

$$Cost\ of\ capital_{i,t} = \alpha + \beta CDSFIRM_i + \lambda CDSFIRM_i * Posted_{i,t-1} + \omega Posted_{i,t-1} + \gamma X_{i,t-1} + \rho Fixed_i + \phi Year_t + \varepsilon_{i,t}$$

where *Posted* is an indicator variable having a value of one after the year of CDS trading initiation, and zero before that.

[17] We report estimates with and without marginal tax rates because the marginal tax rates are available up to 2016 fiscal year in Compustat. The joint availability of tax data and controls significantly reduces our sample from 54,250 to 39,300 observations. The tax rates were computed by using a non-parametric procedure by Blouin et al. (2010).

vulnerable to potential outliers, we apply quantile regressions over quantiles of 0.15, 0.35, 0.5, and 0.85. All estimated coefficients on CDS initiation are negative and significant at the 5% or 1% level, substantiating our results in Table 2. The estimated results from quantile regressions are reported in Online Appendix A1.

Turning to the estimates of the cost of debt, we find consistent evidence of declines in the cost of debt, indicated by the negative coefficients, significant at the 1% level across tests. Regarding results from the cost of equity, we observe inconsistent estimates from firm-fixed (0.27 with a *t*-statistic of 2.96) and industry-fixed (-0.03 with a *t*-statistic of -0.33) effects. Given these controversial estimates, we hold our conclusions on the cost of equity and address this issue in section 4.3. Furthermore, the decline in the cost of debt dominates the effects in the cost of equity, demonstrated by an overall decline in the cost of capital.

<Insert Table 2 about here>

The coefficients on controls are in line with those outlined in the extant literature. For example, all coefficients on profitability are negative, and 7 of 9 coefficients are significant at the 1% level, suggesting that more profitable firms rely more on internal financing than on debt or equity sources of capital. This result is compliant with the pecking order theory of financing. Similarly, all estimates on business riskiness proxied by stock volatility are positive, and 8 of 9 coefficients are significant at the 1% level, indicating that both lenders and equity holders require higher returns when facing high risk. Turning to the estimates on institutional shareholders, we notice that IO concentration negatively affects debt holders but have positive effects on shareholders. A higher IO concentration implies a higher bargaining power for shareholders; therefore, debt holders may require greater returns on their lending. Additionally, debt holders require a higher return on their lending to firms with high liquidation costs, while shareholders price firms' liquidation characteristics and ask for lower returns on their investment. As for leverage, debt holders require higher compensation for highly levered firms, while high leverage ratios seem not to affect equity holders. Lastly, firm size is positively related to the cost of debt and equity, suggesting that firm size is a risk factor to capital contributors.

4.3. Cost of equity: high- and low-rated firms

The baseline tests provide solid evidence of a decline in the cost of debt after CDS trading. Such a decline in the cost of debt results in a decrease in the overall capital cost. Nonetheless, evidence for the cost of equity is not straightforward. We conjecture that CDS trading has diverse effects on the cost of

equity, and the effects hinge on the firms' credit quality. The increase or decrease in the shareholders' required returns depends on whether shareholders are beneficial or detrimental to CDS trading. Ashcraft and Santos (2009) find that CDS trading reduces a bond's spread for larger and more transparent firms, while CDSs cause an increase in the bond spread for riskier firms. Accordingly, we hypothesize that CDSs may positively affect shareholders in high-rated firms, while they may negatively influence equity holders in low- or non-rated firms. Inconsistent estimates of regressions of the cost of equity may be due to the mixed sample of firms, i.e., the sample includes both high- and low-rated firms. To test this conjecture, we define a variable, *Investment_grade*, which has a value of one if the firm-year observation was rated above BBB+ by S&P rating agency or above Baa1 by Moody's, and zero otherwise. We re-estimate our baseline model (1) using the high- and low-rated sample firms and report the results in Table 3.

<Insert Table 3 about here>

Panel A of Table 3 shows estimates generated using high-rated firms. Starting with the cost of equity, we find consistent evidence that CDSs reduce the cost of equity for high-rated firms. The coefficients are negative and significant at the 1% level across all models. Turning to Panel B, which shows estimates from low-rated firms, we find positive coefficients of regressions from both testing procedures. The coefficient from firm-fixed effects is significant at the 1% level. This evidence suggests that the inconsistent results in Table 2 may be due to the mixed samples. The positive effects on the cost of equity from high-rated firms are counteracted by the negative effects from low- and non-rated firms. Furthermore, we note that the estimated coefficients from cost of debt in high-rated samples are not significant at the 10% level, suggesting that high-rated firms did not capture benefits from lowering debt cost after CDS trading. In contrast to high-rated firms, low-rated firms significantly reduced their cost of debt post-CDS trading.

To substantiate our results above, we use the Bloomberg five-year predicted default probability to proxy for a company's credit quality and re-sample firms into high and low default groups. More specifically, we classify firms whose default probability lies above the high 75% percentile into the high-risk group, while firms with a default probability in the lower 25% percentile are sampled into the

low-risk group[18]. We estimate the baseline model using the high and low default risk samples and present the results in Table 4.

<Insert Table 4 about here>

The results in Table 4 support the findings based on credit quality samples. Beginning with Panel A of Table 4, we observe negative coefficients of regressions on the cost of equity across all models. The estimate from the industry-fixed effects is significant at the 5% level and the estimate from firm-fixed effects is close to the 10% significance level, suggesting that CDS trading brings down the cost of equity. In contrast, the estimates from sample with high default risk are positive and significant at the 1% level across all tests. These findings indicate that shareholders in high-risk firms demand higher returns after CDS trading. In directing our analysis back to Panel A, as with the high credit sample, we find insignificant estimates from the cost of debt, implying that firms with a low default probability did not capture benefits from channels related to debt financing. The results from Tables 3 and 4 reveal that CDSs bring benefits to high-credit firms mainly through the channel of reducing equity cost, while it offers benefits to low-rated firms or firms with higher default probability through lowering the cost of debt.

In summary, the results presented in Tables 2, 3, 4, and Online Appendix A1 suggest that equity investors hold diverse views regarding CDS trading. Shareholders in firms with a high default risk view CDS trading negatively and therefore require a higher return to compensate for the increased risk. Such an increase in the cost of equity is consistent with Bolton and Oehmke's (2011) threatening effects of CDS. In contrast, shareholders in firms with a low default risk reduce their required returns after CDS trading. This phenomenon is also consistent with Bolton and Oehmke's (2011) commitment effects of CDS. Furthermore, the cost of debt decreases for sample firms with high default risk. This finding implies that firms with high and low credit quality capture the benefits of CDS trading through different channels.

The decreased cost of debt may be due to debt lenders. For example, Ivanov et al. (2015) argue that debt holders may pass some benefits of CDS trading to borrowers by requiring a lower interest rate. These benefits include decreased costs in monitoring, fewer contracting expenses, or easier hedging (Shan et al., 2019). However, the reduced cost of debt in lower rated firms or firms with higher default probability may not be due to external lenders. By adjusting capital structure and/or debt types, firms

[18] The estimates are statistically the same if we sample firms based on high 66% and low 33% percentile of predicted default probability.

can also decrease the cost of debt and capital. We discuss the channels through which firms reduce WACC in Section 6. Furthermore, although the tax rate affects the cost of capital, it does not materially alter the results. To reduce sample attrition, we ignore the tax rate in the following tests. In the next section, we validate our results with several robustness tests.

5. Robustness tests

Prior studies (e.g., Subrahmanyam et al., 2014, 2017; Martin and Roychowdhury, 2015; Chang et al. 2019) find that referenced companies are usually larger, have investment grade ratings, and demonstrate less information opacity. This finding is in compliance with the theory of adverse selection, i.e., CDS sellers desire to sell protection for trustworthy companies that have less information asymmetry risk and are highly rated to lower their information disadvantage compared to CDS buyers who usually draft loans and thus have private information regarding the borrowers. Such adverse selection may incur sample selection biases. Furthermore, it might also be that some unobservable factors drive CDS selection and simultaneously influence the firms' cost of capital. To address those sample selection and endogeneity concerns, we use various robustness tests found in the literature (Ashcraft and Santos, 2009; Subrahmanyam et al., 2014; Martin and Roychowdhury, 2015; Kim et al., 2018; Narayanan and Uzmanoglu 2018b; Chang et al. 2019), including: CDS reversal test, instrument variables, propensity score matching skills, empirical WACC , CDS samples, the first difference sample, leverage endogeneity, and CDS liquidity tests.

5.1 The reversal of CDS contracts

Following Narayanan and Uzmanoglu (2018b), we introduce a dummy variable, *CDSREVERSAL*, which has a value of one for CDS firms in the years immediately following the termination of CDSs, and zero otherwise. The rationale is that if the initiation of CDS trading can lower the WACC because of more benefits induced by CDS trading, then the termination of CDSs should cause an increase in the WACC, since the termination of CDS may eliminate the accompanied benefits. For instance, lenders may be unwilling to increase their credit supply to those CDS firms or charge a higher interest rate than before. Consequently, the cessation of CDSs may deliver a negative signal to the capital markets. To test this hypothesis, we include *CDSREVERSAL* as another independent variable in the baseline equation (1). We report the regression results in Online Appendix A2. The coefficients of *CDSINIT* and *CDSREVERSAL* are -0.351 (*t*-value of -4.32) and 0.274 (*t*-value of 2.38), respectively. Both estimates

are significant at least at the 5% level. This evidence indicates that investors may charge a higher interest rate after the termination of CDSs, which causes an increase in the WACC.

5.2 Propensity score matching (PSM) sample

While we have explicitly managed the systematic differences between CDS and non-CDS firms by employing the variable of *CDSFIRM* or firm-fixed effects with a set of controls, these two types of firms may be different due to unobserved time-variant variables. We construct matching samples to address potential sample selection biases. We use the following probit model to assess the probability of CDS trading initiation and to match firms according to their likelihood of CDS trading initiation:

$$\text{Prob}\left(CDSINIT_{i,t} = 1\right) = \emptyset\left(\alpha + \theta X_{i,t-1} + \varphi \text{Industry}_{\text{k}} + \omega \text{Year}_{\text{t}}\right) \quad (2)$$

in which $\emptyset$ is the cumulative distribution function of standard normal distribution. X is an array of firm-level characteristics that are used to predict the inception of CDS trading. Following Chang et al. (2019), we include all controls into vector X to mitigate the concerns that the factors affecting the cost of capital may also drive CDS trading initiation. In addition, following Subrahmanyam et al. (2014), we include the ratio of working capital to assets; excess stock return, defined as the difference of stock returns relative to the ones from the prior year; turnover computed, defined as the sales divided by assets; cash holding, defined as the ratio of cash and equivalent to assets; and PPE ratio, defined as the net of property, plant, and equipment (PPE) divided by assets[19]. Furthermore, we include Fama-French 48 (FF48) industry classification to isolate industry-fixed effects and year-fixed effects to tackle aggregate time trends effects on the cost of capital.

As constructed by Ashcraft and Santos (2009) and Subrahmanyam et al. (2014), we build a probit sample by using all firm-year observations of non-CDS firms whose debts are never referenced in CDS markets and firm-year observations of CDS firms until the beginning of CDS trading, i.e., eliminating firm-year observations of CDS firms for the post-CDS trading periods. We present the probit estimation results in Table 5. The model (2) forecasts the onset of CDS trading reasonably well, as indicated by the high concordant percentage (96.5%) and pseudo-R^2 (45.2%). These statistics are comparable to those generated by previous studies. For example, the pseudo-R^2 is 39% in Subrahmanyam et al. (2017), and the proportion of concordant pairs is 91.5% in Martin and Roychowdhury (2015). The coefficients of predictors are in line with those in prior studies (Martin and

[19] We also attempt to include return on assets (ROA) as do Subrahmanyam et al. (2014). However, there is a high correlation between *ROA* and *Profitability,* thus causing a multicollinearity problem. We select *Probability* as it is a control variable in our test.

Roychowdhury, 2015; Subrahmanyam et al., 2014, 2017; Chang et al., 2019). For instance, larger firms, firms with high leverage and less riskiness, profitable and rated firms induce more interests of CDS market participants, demonstrated by the significant estimated coefficients. In addition, the coefficient on firm age is positive and significant at the 1% level, further implying that mature firms are likely to have CDS trading initiation in the sample period. Lastly, the significant coefficient on liquidation cost indicates that lenders pay significant attention to the recovery values of CDS firms, consistent with the CDS structural model.

<Insert Table 5 about here>

We generate control firms (non-CDS firms) for treated ones (CDS firms) by year. Specifically, we compare the predicted likelihood of CDS initiation of non-CDS to that of CDS firms in the year prior to CDS trading initiation. Following Subrahmanyam et al. (2014), we produce three control samples using different matching criteria to further verify our results and attenuate the constraints of the propensity score matching[20]. Specifically, we construct three control samples: (1) the one non-CDS firm with the closest propensity score to the CDS firm; (2) the one non-CDS firm with the closest propensity score to the CDS firm and within the same CDS firm's one-digit SIC industry classification; and (3) the same rule as for sample (2), but using Fama-French 17 as exact matching conditions. Furthermore, we match a non-CDS firm with multiple CDS firms in control samples of (2) and (3), but not in sample (1), so as to produce diverse PSM samples. However, in samples (2) and (3), we require that the same non-CDS firm go into the control sample only once each year. This way, our samples have unique firm-year observations, even though a non-CDS firm may serve as a control for several CDS firms. Finally, for all three control samples, we require the distances of mean logit of propensity scores between CDS and non-CDS samples to not be statistically significant at the 10% level[21].

We present firm characteristics of the control-treated samples prior to the year of CDS trading initiation in Table 6. For brevity, we only present the statistics based on the matching criterion (1), which requires no multiple matching when selecting the nearest matching non-CDS firms. By doing so, we have the exact number of treated and control firms in the sample. Under criterion (1), we successfully match 402 CDS firms from 673 CDS firms. In Table 6, we observe that CDS firms and

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[20] For example, one limitation of propensity score matching is that unobservable confounders cannot be balanced in the treatment-control samples, thus resulting in biased results. Austin (2011) gives good discussions on this approach.

[21] We use SAS procedure PSMATCH to match non-CDS observations to CDS peers. We adjust the parameter of PSMATCH, 'CALIPER', to produce the maximum sample, and simultaneously make the mean difference of propensity scores between CDS- and non-CDS samples not significant at the 10% level. Following Austin (2011b), the maximum allowable caliper width is 0.2 of standard deviation of the logit of the propensity scores.

non-CDS firms are not significantly different in terms of *leverage, probability, riskiness, CAPEX, growth opportunities, IO concentration, liquidation cost, R&D,* and *S&P rated*. These statistical results suggest that these firm-level characteristics are unlikely to be the sources of difference in the cost of capital between CDS and non-CDS firms after the inception of CDS trading. As is the case in prior studies (e.g., Martin and Roychowdhury, 2015; Subrahmanyam et al., 2014, 2017; Chang et al., 2019), in spite of carefully matching, we find that CDS firms remain different from non-CDS firms in *firm size, firm age, dividends*, and *stock liquidity*, evidenced by significant differences between mean differential tests. However, the non-significant difference between propensity scores of two groups indicates that those firms have a similar propensity to trade CDSs. Finally, we note that all explained variables, *WACC, cost of debt,* and *cost of equity*, are not significantly different in both groups prior to the CDS trading. Therefore, there are no trends in these firm characteristics that may cause variances between CDS and non-CDS samples post-CDS trading.

<Insert Table 6 about here>

We re-estimate the baseline model (1) with our three PSM samples. We present the estimates in Panel A, B, and C of Table 7. For brevity, we only report the estimated coefficients on *CDSINIT* and *CDSFIRM* across samples. Consistent with the results from the whole sample, we find that all coefficients of regressions of WACC and cost of debt on CDS initiation are negative and significant at least at the 10% level across three PSM samples. The magnitude of estimates is similar to that of the whole sample as well. Overall, the evidence supports our main conclusion from the whole sample test: the availability of CDSs reduces the cost of debt and the cost of capital.

<Insert Table 7 about here>

5.3 Instrumental variable regression

Our baseline model relies on the exogenous assumption of the introduction of CDSs. An effective approach to address this exogenous concern and reverse causality (i.e., the reduction of WACC may cause the initiation of CDS trading) is to use instrument variables (IVs) that are exogenous to a firm's cost of capital decisions but have close relations with the initiation of CDS trading. We follow Chang et al. (2019) to construct an IV, *CDS_percentage*, which is the percentage of CDS firms among firms whose head offices are within the 200-mile radius of a firm and whose 2-digit SIC industry do not

belong to the firm's industry[22]. Our rationale for this IV is based on the empirical evidence of Massa et al. (2013) who document that bond investors are locally biased (i.e., they make investment decisions based on their proximity to firms). Such a herding effect of bond investors would cause bond trading locally correlated. Therefore, the initiation of CDS trading on a firm could be affected by the extent of CDS trading on its neighbouring firms. However, the extent of CDS trading on neighbouring firms should not have a direct effect on a firm's cost of capital decision because these neighbouring firms are not in the same industry as the focal one. Thus, the percentage of CDS firms satisfies both relevance and exclusion restrictions for the instrument variable[23].

We follow previous studies (such as Saretto and Tookes, 2013; Subrahmanyam et al., 2014, 2017, etc.) to adopt a two-stage least square procedure for our analyses. Specially, we first estimate a probit model that uses the percentage of neighbouring CDS trading (i.e., the IV) as a predictor of CDS trading initiation. The first-stage estimation results are reported in Online Appendix A3. The coefficient of *CDS_percentage* is positive and significant at the 1% level, indicating that the percentage of CDS trading is an effective predictor of CDS initiation. We then use the fitted probability from the first-stage probit regression as the instrumented variable to replace *CDSINIT* in the second stage of regression. The results are reported in Table 8. As shown in Table 8, coefficients on the instrumented *CDSINIT* are negative and significant across testing models and measures of cost of capital. This evidence indicates that our finding–the initiation of CDS trading reduces the cost of capital–is not vulnerable to endogeneity concerns regarding the initiation of CDS trading.

<Insert Table 8 about here>

5.4 Alternate of Bloomberg WACC

We proxy the market-required returns by Bloomberg WACCs (BWACCs), which are the weighted averages of equity return based on capital asset pricing model (CAPM) and debt returns computed from Bloomberg's proprietary methodology. It may be the case that BWACCs drive our results. To test whether our results are sensitive to BWACCs, we use Olson and Pagano's (2017) approach to estimate empirical WACCs by using equation (3).

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[22] Our results are robust if we define neighbouring firms based on 300-mile or 400-mile radius. Furthermore, our estimates are statistically the same if we use one- or three-digits of SIC to segment firms.

[23] We follow Chang et al. (2019) to compute the shortest distance between two coordinates (i.e., the latitude and longitude of firms' headquarters) on a sphere using the formula, 3963*arccos(sin(lat1) *sin(lat2) + cos(lat1)*cos(lat2)*cos(long2 - long1)), where 3963 is the radius of the earth.

$$NOPAT_{i,t} = k_i\left(Total\_Capital_{i,t-1}\right) + \varepsilon_{i,t} \quad (3)$$

where $NOPAT_{i,t}$ is the net operating profit after taxes for firm i in the period t, $Total\_Capital_{i,t-1}$ is the average of book and market value of firm i in the period *t-1*. Following Olson and Pagano (2017), we first compute the moving sums of four-quarter NOPATs for each firm, starting from the 1st quarter of 1993. We then use the rolling windows analysis, ranging from 16 to 22 quarters, to regress *NOPAT*s on total capitals. The coefficients of regression proxy the average cost of capital of a company over the rolling window period. We re-estimate our baseline model (1) with EWACCs and report the results in Online Appendix A4. We present the results based on 16- and 20-quarter rolling windows regression in columns (1) and (2), respectively. Both coefficients of *CDSINIT* are negative and significant at the 5% level. This evidence corroborates our conclusions as per Bloomberg WACCs.

5.5 The first difference sample test

It may be the case that investors forecast a company's success and are willing to provide CDSs on the company's debt to profit from the foreseeable lowered spreads. Such transactions can cause a decrease in the focal firm's CDS spreads as well as credit risk. The positive information can disperse into both bond and stock markets. Consequently, the required returns from various investors will decline. To further address the reverse causality of CDS trading, we regress the first differences of the various costs of capital on the CDS initiation. Specifically, we estimate the following model with the first difference samples.

$$\Delta Cost\ of\ capital_{i,t} = \omega CDSINIT_{\mathrm{i,t-1}} + \gamma \Delta \mathrm{X}_{\mathrm{i,t-1}} + \rho \mathrm{Fixed}_{\mathrm{i}} + \phi \mathrm{Year}_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \quad (4)$$

where $\Delta Cost\ of\ capital_{\mathrm{i,t}}$ is the first difference between the cost of capital (e.g., WACC, etc.) in a fiscal year and its value in the prior year. Likewise, $\Delta X_{i,t-1}$ represents the first difference of control variables discussed in section 3.2.3. *CDSINIT* is defined as before. $Fixed_i$ denotes firm-fixed effects. We also control for year effects to attenuate the time trends in the cost of capital. To investigate the reverse causality from the cost of capital to CDS initiation, we use CDS initiation as the dependent variable and regress it on the lagged changes of the cost of capital and lagged changes of controls. We estimate the model (4) with or without firm-fixed effects and present the results in Panel A and B of Table 9, respectively. For brevity, we only present the coefficients of interested variables, *CDSINIT*. The full results are reported in Panel A and B of Online Appendix A5.

<Insert Table 9 about here>

Beginning with Panel A of Table 9, we consistently observe negative and significant coefficients on CDS initiation from the cost of debt regressions. The coefficients are significant at the 5% level across tests. The estimates from the cost of equity are insignificant even at the 10% level. Lastly, we find one out of two negative estimates from the regressions of WACC on CDS initiation to be significant at the 10% level. So far, these estimates corroborate our main findings based on the whole sample.

In Panel B of Table 9, we observe that all coefficients of regressions of CDS initiation on lagged changes in the various costs of capital are not significant at the 10% level. This evidence indicates that it is the CDS initiation that reduces the cost of capital. There is no reverse causality from the cost of capital to the CDS initiation. Besides the test above, we also run a probit model and include the changes in the cost of capital as an input factor. We find no significant coefficients on the changes in the cost of capital across probit tests. This extra test corroborates our conclusion that there is no causal relation between the changes in the cost of capital and the CDS initiation. The results are presented in Online Appendix A6.

5.6 CDS trading liquidity test

Prior studies have shown that the degree of CDS trading liquidity produces different effects on referenced firms. For example, Saretto and Tookes (2013) examine liquidity proxy with the number of CDS quotes and CDS bid-ask spreads and find evidence that companies can maintain a higher leverage ratio and longer debt maturity if CDSs are traded more actively on their debt. Likewise, Narayanan and Uzmanoglu (2018a, b) show that the activity of CDS trading relates to a firm's value and cost of capital, respectively. We follow these studies to use CDS trading liquidity variables as replacements of the indicator variable, *CDSINIT*, to verify our results. We obtain CDS trading activity data from DTCC over the period 2009 to 2018. Specifically, we use the log of average daily trading notional volume and the total number of clearing dealers in a fiscal year to proxy the liquidity of CDS trading. We scale the notional volume by the natural log because the original notional amounts are significantly skewed right[24].

<Insert Table 10 about here>

We present the estimated coefficients in Table 10. Starting from regressions of the cost of debt, all estimates are negative and significant at the 1% level, indicating that high liquidity of CDS trading

[24] Over the period 2009 to 2018, we have 4,757 firm-year observations from 581 CDS firms, of which 1,881 observations have trading data from 246 CDS firms.

substantially reduces the cost of debt financing. With respect to regressions of WACC, we observe that three out of four estimates are negative and significant at either 5% or 1% level. Lastly, we still observe inconsistent estimates from regressions of the cost of equity under the industry- and firm-fixed effects, like the results from the main sample.

5.7 Samples excluding financial crisis and 2001 period

Our estimation significantly relies on the initiation dates of five-year CDS contracts. We deleted all CDS firms whose quotes were in January 2001, to reduce potential ambiguity. To alleviate concerns that some of our CDS firms in 2001 may already be traded before 2001, we re-estimate our baseline model without CDS firms that have quotes in 2001. We present estimates in Panel A of Online Appendix A6. All estimates are statistically the same as those based on our whole sample. Furthermore, firms' financial policies and activities could be substantially influenced by the 2008-2009 financial crisis, as was the initiation of CDS trading. To eliminate the concerns that our results may be driven by observations in financial crisis periods, we remove all firm-years in 2008 and 2009 and estimate our baseline model with the reduced sample. Still, we arrive at consistent estimates across models, when comparing the estimates from the main sample. We report the test results in Panel B of Online Appendix A7.

5.8 CDS sample test

The whole sample results are based on comparing outcomes of CDS and non-CDS peers by controlling a set of covariates. However, some latent factors may drive CDS firms to behave differently from non-CDS firms, and those factors are absent in our model. While we have used the PSM procedure to mitigate sample selection concerns, another way to reduce such concerns is to use CDS firms only. In contrast to non-CDS firms, which are benchmarks for assessing CDS trading effects, a CDS firm may be more appropriate as a benchmark to another CDS firm because a CDS firm may be more comparable to another CDS firm than to a non-CDS firm. Following Ashcraft and Santos (2009), we estimate the baseline model using the treated sample (CDS firms) only. Additionally, we introduce *CDSLAG* into the baseline model, which is an indicator variable but lagged one year for *CDSINIT* to capture the potential dynamic effects of CDS trading over time. We present the estimates in Online Appendix A8.

The estimates from the cost of debt are in line with our estimates from the whole sample and various PSM samples. We find that three out of four coefficients on *CDSINIT* and *CDSLAG* are negative and

significant at least at the 10% level, indicating that CDS trading reduces the cost of debt financing. The coefficients on *CDSLAG* are greater than those on *CDSINIT*, suggesting that CDS trading has more impact on firms in the second year than in the first year. Furthermore, all estimated coefficients from cost of equity are non-significant, consistent with our main samples' estimation. With respect to WACC regressions, all estimates are negative, and both estimates on the *CDSLAG* are close to the 10% significance level, suggesting a reduction in WACC after CDS trading.

Overall, the estimates from the cost of debt are congruent with all estimates from the various samples so far, while the estimates from *WACC* in Online Appendix A8 are weak in contrast to the estimates from the whole sample. One may conclude that the underlying variances between CDS and non-CDS firms drive the results. To mitigate such concerns, we follow Kim (2016) in using the interaction between strategic variables and CDS trading to explicitly capture the advantages generated by CDS trading. The logic is that firms that are vulnerable to strategic default concerns will benefit more from CDS trading than firms without such concerns. For example, shareholders of companies with high liquidation costs or stronger CEO's ownership will have more bargaining power than creditors, hence those firms possess greater incentives to strategically default. We introduce a dummy variable, *High_liquidation*, which equals one if the CDS firm's liquidation cost at the time of CDS initiation is above the median of CDS sample firms, and zero otherwise. We present the estimated results in Panel A of Online Appendix A9. We observe that the estimated coefficients on interactions are significant and negative at either the 5% or 1% level for *WACC* and the *cost of debt*, while the estimate on the *cost of equity* is negative but non-significant as before. Additionally, Colonnello et al. (2019) find evidence that institutional ownership is positively related to the net outstanding amount of CDSs and the existence of empty creditors. We use institutional ownership concentration as an alternative strategic variable and assign a value of one for firms whose HHI of institutional ownership are above the median value, and zero otherwise. Panel B of Online Appendix A9 presents the estimates. The results are consistent with the findings when using liquidation cost as a strategic variable, thus verifying the conclusions based on CDS samples. Overall, the results from the CDS sample confirm our main sample results.

5.9 Leverage endogeneity

In our baseline model, we presume that leverage is an exogenous variable when evaluating the effects of CDS trading. However, previous studies (Saretto and Tookes, 2013; Tookes Subrahmanyam et al., 2014) show that CDS trading leads to an increase in the leverage of a CDS firm. The variation in

leverage consequently causes a change in WACC. To remove such indirect effects of CDS trading on WACC through the channel of changing leverage, we obtain the residuals from regressing leverage on CDS initiation and re-estimate our baseline model with the residuals. Specifically, we estimate the following two-stage least square models.

$$Leverage_{\mathrm{i,t}} = \alpha + \beta CDSFIRM_{\mathrm{i}} + \omega CDSINIT_{\mathrm{i,t-1}} + \rho \mathrm{Fixed}_{\mathrm{i}} + \phi \mathrm{Year}_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \quad (5)$$

$$Cost\ of\ capital_{\mathrm{i,t}} = \alpha + \beta CDSFIRM_{\mathrm{i}} + \omega CDSINIT_{\mathrm{i,t-1}} + \gamma \mathrm{X}_{\mathrm{i,t-1}} + k * Res_{\mathrm{i,t-1}} + \rho \mathrm{Fixed}_{\mathrm{i}} + \phi \mathrm{Year}_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \quad (6)$$

where X is a vector of controls without leverage, Res is the residuals from regression model (5). We report the estimated results of model (6) in Online Appendix A10. All coefficients on *CDSINIT* across estimation measures are negative and significant at the 1% level, indicating that CDS trading reduces the cost of capital even after controlling the indirect effects on WACC through changing leverage.

Taken together, our evidence indicates that the overall cost of capital was reduced after CDS trading. For firms with medium or lower credit quality, their cost of debt financing declines, while investment-grade firms benefit from a reduction in the cost of equity. The rest of the paper investigates the channels through which firms lower their cost of capital.

6. Debt placement and WACC

A firm's capital structure optimization and financing choices are the outcomes of the interplay between various factors, such as business risk, growth options, a firm's information environment, the cost of financing, and major stakeholders (e.g., shareholders, creditors, top executives) (Myers, 1977, 1984; Myers and Majluf, 1984; Diamond, 1991; Hovakimian et al., 2001; Frank and Goyal, 2003; Rauh and Sufi, 2010; Lemmon and Zender, 2010; Denis and McKeon, 2012). Post-CDS trading, many of these factors have changed because CDSs have real economic effects on referenced firms and improve a firm's information environment. For example, Kim (2016) argues that CDSs bring down the cost of bond financing because of the commitment function of CDSs. Ashcraft and Santos (2009) and Batta et al. (2016) show that CDS markets enhance a firm's information environment and thus reduce information asymmetry between internal managers and external investors. Confronted with these ever-changing milieus, firms may consequently amend their capital financing policies and adjust capital leverage to seize benefits and avoid the costs associated with CDS trading.

A CDS company's cost of capital could change for either external or internal channels. Regarding external channels, CDS-protected lenders may share some benefits of CDS trading, therefore lowering the required interest rate. For instance, Ivanon et al. (2016) state that the cost of bank financing is lowered because CDSs reduce bank monitoring costs. As per internal channels, managers can substitute debt for equity, or inversely. As the cost of debt is usually much lower than cost of equity, a firm can, to some extent, reduce the overall cost of capital by using more debt. Managers can also adjust debt types when financing externally. For example, retiring bank loans by issuing a new bond or using more subordinated debts instead of secured ones. As different types of debt charge different interest rates and with different covenants, managers may alter their debt financing orders, thus resulting in a change in the overall cost of capital.

6.1 Substitute debt for equity security

Throughout our tests, we find consistent evidence that CDS firms experience a decline in the cost of debt after CDS trading. Such a decrease reduces the overall cost of capital. However, we cannot rule out the possibility that managers alter financial leverage to capture the benefits of CDS trading, thus resulting in a decline in the WACC. The mean of after-tax cost of debt of CDS firms is 3.08%, which is substantially lower than the mean of the cost of equity, which is 10.85%. By adjusting the weight of debt and equity, CDS firms can reduce the WACC. To investigate this channel of changing WACC, we estimate the relations between the market weight of debt and equity and CDS initiation. We obtain the market weight of debt and equity from Bloomberg. Appendix 1 provides details regarding the computation of weights.

Table 11 presents the results of regressions of the weight of debt and equity on CDS initiation and a set of control variables. We present the results estimated under firm-fixed effects in column (1) for weight of debt and weight of equity. We also report estimates based on quantile regression in columns (2), (3), and (4) over quantiles of 0.15, 0.50, and 0.85, respectively. We employ quantile regressions because we observe that CDS trading exerts greater effects on firms with high book leverage ratios than firms on the other end. We conjecture that CDSs have contrary effects on firms with high and low weight of debt as well.

<Insert Table 11 about here>

Examining the left side of Table 11, we find two noteworthy results. First, CDS trading has contradictory effects on companies with low and high leverage ratios. The estimate on CDS initiation

over the quantile of 0.15 in column (2) is positive (0.63) and significant at the 1% level, suggesting that firms originally employing lower debt financing would substantially increase the use of debt. In contrast, the estimate in column (4) over the quantile of 0.85 is negative (-1.92) and significant at the 1% level, indicating that firms with a high leverage ratio would decrease debt usage after CDS trading. Such contrary effects are because CDSs have both commitment and exacting functions on the focal firms. Firms with higher leverage are more likely to confront stronger threatening effects from empty creditors, while firms with lower leverage ratios may capture more commitment benefits of CDS, i.e., the latter can increase flexibility and access to capital markets, thus leading to using more debt financing than before. The results on the right side of Table 11, which show the various quantile estimates for the weight of equity, support the arguments above.

Second, the estimated coefficient on CDS initiation from the market weight of debt with firm-fixed effects is positive (0.86) and significant at the 14% level. Correspondingly, we observe a negative coefficient on the weight of equity (-0.96) and significant at the 12% level. Though both estimates are not statistically significant at the 10% level, the estimates suggest that the weight of debt marginally increases while the weight of equity marginally decreases correspondingly after CDS trading. To verify our estimates, we regress market and book leverage ratios on CDS initiation and report estimates in the Online Appendix A11. Both estimates on CDS initiation are positive and significant minimally at the 5% level, indicating an increased percentage of debt in the firms' capital compositions. This finding is consistent with prior studies, such as Saretto and Tookes (2013) and Batta and Yu (2019)[25], that demonstrate an increased leverage post-CDS trading.

At first glance, it seems that, post-CDS trading, the capital supply effects of CDS on firms with lower leverage ratios outweigh the threatening effects on firms with higher leverage ratios. As a result, firms use more debt financing and less equity financing, resulting in an increase (decrease) in the weight of debt (equity). Nonetheless, the increase in the market weight of debt may be attributed to a firm's debt issuance, as well as to the decreased required returns on debt from investors, or a mix of these two factors. To further ascertain the channels that reduce the WACC, we estimate the relations between CDS trading and security issuance. We regress net debt and net equity issuance on CDS initiation and on an array of firm's controls used before. We present the results in Online Appendix A12. Starting from the net debt issuance, we find negative estimates significant at the 1% or 5% level

[25] The weight of debt and equity we use in this study is the ratio of long-term debt to the firm's market value, in contrast to Saretto and Tookes (2013) and Batta and Yu (2019) who use the total debt scaled by the total book or the market value of assets.

on CDS initiation across tests. This evidence demonstrates that, on average, firms do not issue more debt after CDS trading. On the contrary, they reduce the issuance of debt, which is consistent with Batta and Yu's findings (2019). Turning to net equity issuance, we observe that one of the two estimates is negative and significant at the 1% level, indicating a reduced equity issuance after CDS trading. However, the negative effect on equity issuance is weaker than the effect on debt issuance, evidenced by comparably smaller estimated coefficients.

In summary, we find evidence that, on average, a firm's weight of debt marginally increases after CDS trading. However, such an increase is not because of increased debt issuance. One explanation of the increased debt value is due to the hedging functions of CDSs. Interestingly, we also find the weight of equity to be marginally decreased and associated with less equity issuance. Therefore, the decrease in WACC could partially be ascribed to the improved proportion of debt in the capital mix. However, such benefits are not due to managers actively adjusting debt usage, but to the hedging function of CDS markets.

5.2 Debt placement and rollover risk

To advance our understanding of how CDSs reduce the cost of debt, we follow Saretto and Tookes (2013) in analyzing the relation between CDS initiation and various debt compositions. Since different types of debt have distinct interest costs and covenants, a firm can replace a high cost of debt instrument with others that have lower required returns. Furthermore, the increased information transparency between firms and capital markets may give CDS firms more access to public debt markets, and they may use more bonds or notes, rather than bank loans, as a result[26]. Such a conversion would reduce the overall cost of debt financing. We follow Colla et al. (2013) to classify debts into seven categories: bank loans, revolving credits, bonds and notes, commercial papers, capital leases, other borrowings, and trusted preferred. Furthermore, we follow Lin et al. (2013) to construct public and bank debt categories. We scale those debt compositions by total debt and use the ratios in our analysis.

<Insert Table 12 about here>

[26] CDS markets play a critical role in producing and disseminating information (Ashcraft and Santos, 2009; Stulz, 2010) because the participants in CDS markets are all institutions, such as banks or insurance companies that usually possess private information regarding the borrowers' business and financial status. Prior studies find that information flows into stock markets from CDS markets, implying an overall improvement in a firm's information transparency (Acharya and Johnson, 2007). We use the number of analysts as the dependent variable and regress it on CDS initiation to measure the changes of CDS firms' information quality. We do find statistical evidence that CDS firms experience an improvement in their information environment because more analysts follow CDS firms and hence produce and release more information for the firms. Online Appendix A13 reports the regression results of the number of analysts on CDS initiation.

We present the estimates of regressions of debt composition ratios on CDS initiation and a set of firm's previously used characteristics in Table 12. Beginning with public debt, we observe positive coefficients on CDS initiation, significant at the 5% level across tests.[27] In terms of their components, the estimates from bonds are positive and significant at the 1% level. Although the estimates from commercial papers are negative and significant at the 1% level as well under firm-fixed effects, the magnitude of coefficients is much smaller than that of bond. This evidence indicates that CDS trading has a less negative effect on the usage of commercial papers but promotes firms to use substantially more arm's length debt. The coefficient from bond regression under firm-fixed effects is 0.049, implying that CDS firms increase bond/note sources of financing by 4.9% on average after CDS trading. This percentage is equivalent to a $140[28] million increase in a firm's bond financing, on average. As a result of using more bond financing, the public debt ratio increases.

In sharp contrast to the increase in public debt, bank debt significantly decreases, demonstrated by the negative coefficient of -0.052 (significant at the 1% level) from the firm-fixed effects[29]. When further examining estimates from bank loans and revolving credit regressions, we find that both bank loans and revolving credits are negatively and significantly affected by CDS trading. Lastly, we also observe that CDS trading has positive and significant effects on other borrowings, suggesting that firms increasingly pay attention to other sources of financing (e.g., private debt placement) after CDS trading.

In contrast to the scholarship of Saretto and Tookes (2013) and Chen et al. (2018), which does not separately examine the effects of CDSs on revolving credits and loans, we treat bank loans and drawn revolving credits individually. On one hand, the revolving credits are the material composition of bank debt, evidenced by the weight in bank source debt. For example, the mean percentages of revolving credits to bank debt are 33.8% and 53.6% for CDS and non-CDS firms, respectively. On the other hand, the financing costs are different for these two financing vehicles. We find a substantial reduction in the usage of revolving credits post-CDS trading. The reduction in both revolving credits and in bank loans significantly contributes to the overall decrease in bank debt.

The shifting of bank loans to public bonds/notes could be explained by the decreased information asymmetry risk and/or decreased monitoring benefits of bank loans after CDS trading. However, the

[27] The estimates are close to those in Chen et al. (2018). For example, the estimated coefficient for public debt with firm-fixed effects is 0.048 and significant at the 1% level in their paper. Our estimate is 0.034 and significant at the 5% level.

[28] 4.9%*68.4%*4.198 = $140.7 million, where $4.198 billion is the mean of total debt.

[29] This estimate also aligns with Chen et al. (2018). Their corresponding estimate is negative (-0.05) and significant at the 5% level.

reasons above cannot explain the reduction in revolving credits post-CDS trading. One motivation for reducing revolving credits may relate to the threatening effects of CDS trading. Borrowers may use long-term notes/bonds to facilitate their short-term sources of liquidity to avoid the rollover risk of revolving credits. To substantiate our arguments, we re-examine the relation between debt compositions and CDS initiation, with investment and non-investment grade firms. Firms with non-investment grade credit generally have a higher rollover risk than firms with investment grade credit. If CDS trading aggravates banks' concerns of repayment for these firms, we would observe a more significant and negative effect on those firms in terms of the usage of revolving credits. We present estimates in Panel B of Table 13. The coefficients of regressions of revolving credits on CDS initiation are negative and significant at the 1% level across tests in Panel B of Table 13. Furthermore, the magnitude of coefficients (-0.055) from firm-fixed effects is almost double compared to the corresponding one (-0.029) from the whole sample. In contrast, the corresponding estimates from firms with investment grade credit presented in Panel A of Table 13 are not significant even at the 10% level and have a smaller magnitude. These findings support the rollover risk explanations for the reduction in revolving credits.

<Insert Table 13 about here>

However, the reduction in revolving credits may also be due to the increased costs associated with revolving credits. Because of the increased default probability after CDS trading, banks may demand higher commitment fees or set stricter covenants on short-term lending. To further pinpoint whether the reduction of revolving credits is due to rollover risk or due to cost-saving, we estimate the relation between the cost of debt and the usage of revolving credits. If firms substitute bonds or notes for revolving credits for cost-effective reasons, we should observe a positive relationship between the cost of debt and the usage of revolving credits. We test this conjecture and report the estimates in Online Appendix A14, in which we observe negative estimates on revolving credits (significant at the 1% level) from cost of debt regressions across models, indicating that revolving credits are negatively associated with the cost of debt. Therefore, though a higher usage of revolving credits sees a lower cost of debt, firms substantially cut down the usage of revolving credits after CDS trading. This finding supports the rollover risk assumption, that is, post-CDS trading, firms attempt to reduce the usage of revolving credits to avoid rollover risk.

In summary, after CDS trading, the market weight of debt marginally increases, while the weight of equity marginally decreases. The increase in debt weight is not because of issuing more debt securities,

but because of the increased values of debt instruments caused by CDS markets. We also find that CDS firms adjust their debt placement by substituting arm's length debt for bank debt over post-CDS trading. The substitution may be due to CDS threatening effects, or because the firms would like to capture the advantages of CDSs, such as longer maturity or easier access to public debt. As the cost of bond is lower than cost of bank loans, such a substitution reduces the cost of capital.

6. Conclusions

The CDS market has generated substantial controversies (Stulz, 2010). Some believe that CDSs are partially to blame for the subprime crisis in the United States that led to the subsequent 2008-2009 financial crisis. As a result, opponents of CDS have called for a ban on CDS trading. Others have pointed out that CDS trading completes financial markets by providing simple and inexpensive hedging vehicles. Researchers have examined the various tangible effects of CDSs on both firms and the economy by studying how CDSs affect corporate policies and activities. Our study expands these analyses and evaluates the overall costs and benefits associated with CDSs by evaluating their impact on a firm's cost of capital. We construct a panel dataset using the universe of US public companies to examine whether CDS trading affects the WACC, cost of debt, and cost of equity.

Our findings show that CDSs significantly reduce the cost of capital, suggesting that investors view CDS trading positively. The channels that affect the cost of capital are different for high- and low-rated firms. Equity holders require a lower return on high-rated firms after CDS trading, while most low-rated firms benefit from a reduced cost of debt financing. Compared to shareholders in high-rated firms, investors in low-rated firms raise their required returns because of the increased risk associated with CDSs. However, the reduction in the cost of debt dominates the increase in the cost of equity, resulting in an overall decrease in the cost of capital.

We explore the channels through which CDS firms reduce the cost of capital. Results of quantile regressions show that CDS trading has an opposing effect on firms with high- and low- leverage ratios. Firms with low leverage experience a significant increase in their debt weight and correspondingly a reduction in their equity weight, while firms with high and medium leverage show significant reduction in the weight of debt in their capital structure. Both effects are consistent with the empty creditor hypothesis, which posits that CDS simultaneously exerts two contrary effects on firms. On one hand, it increases the credit supply for borrowers, while on the other hand, it introduces frictions into debt

renegotiation. Furthermore, we find a decrease in the firms' debt issuance, but an increase in debt weight in WACC after CDS trading. One reason to explain this finding is that the risk hedging function of CDSs may increase the value of debt. Therefore, the increase in the weight of debt is a channel that decreases the overall cost of capital.

Finally, we find sound evidence that CDS firms alter their debt structure. Post-CDS trading, CDS firms use more arm's length debt than bank debt. In particular, they reduce their usage of revolving credits and use fewer term loans than before. This fact reflects the exacting effects of CDS trading. To avoid rollover risk, firms prefer arm's length debt to short-term bank debt for liquidity. Therefore, the alteration of debt types is another channel that reduces the cost of capital. These two channels interplay together and result in a reduction of the overall cost of capital. Our findings suggest that financial market innovations, such as CDSs, affect a firm's financing decisions and consequently their capital structure.

References

Acharya, V.V., & Johnson, T.C. (2007). Insider trading in credit derivatives. *Journal of Financial Economics, 84*(1), 110–141.

Almeida, H., & Campello, M. (2007). Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies, 20*(5), 1429–1460.

Amihud, Y., Hameed, A., Kang, W., & Zhang, H. (2015). The illiquidity premium: international evidence. *Journal of Financial Economics, 117*(2), 350-368.

Amiram, D., Beaver, W.H., Landsman, W.R., & Zhao, J. (2017). The effects of CDS trading initiation on information asymmetry in syndicated loans. *Journal of Financial Economics, 126*(2), 364–382.

Ashcraft A.B., & Santos J.A. (2009). Has the CDS market lowered the cost of corporate debt? *Journal of Monetary Economics, 56*(4), 514–23.

Aslan, H., & Kumar, P. (2012). Strategic ownership structure and the cost of debt. *Review of Financial Studies, 25*(7), 2257–2299.

Attig, N., Cleary, S., El Ghoul, S., & Guedhami, O. (2013). Institutional investment horizons and the cost of equity capital. *Financial Management, 42*(2)*,* 441–477.

Augustin P, Subrahmanyam MG, Tang DY, & Wang SQ. (2014). Credit default swaps: A survey. *Foundations and Trends in Finance, 9*(1–2), 1–196.

Augustin, P., Subrahmanyam, M.G., Tang, D.Y. & Wang, S.Q. (2016). Credit default swaps: Past, present, and future. *Annual Review of Financial Economics, 8*, 175–196.

Austin, P.C. (2011a). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate behavioral research, 46*(3), 399–424.

Austin, P.C. (2011b). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical Statistics, 10*(2), 150–61.

Batta, G.E., Qiu, J., & Yu, F. (2016). Credit derivatives and analyst behavior. *The Accounting Review, 91*(5), 1315–1343.

Batta, G.E., & Yu, F. (2019). *Credit derivatives and Firm investment*. (Working Paper No. 2923236). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2923236

Berger, A., & Udell, G. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business, 68*(3), 351–381.

Berndt, A., & Ostrovnaya, A. (2014). Do equity markets favor credit market news over options market news? *Quarterly Journal of Finance, 4* (2), 1–51.

Blouin, J., Core, J., & Guay, W. (2010). Have the tax benefits of debt been overestimated? *Journal of Financial Economics, 98*(2), 195–213.

Bolton, P., & Oehmke, M. (2011). Credit default swaps and the empty creditor problem. *Review of Financial Studies, 24*(8), 2617–2655.

Butler, A., Grullon, G., & Weston, J.P. (2005). Stock market liquidity and the cost of issuing equity. *Journal of Financial and Quantitative Analysis, 40*(2), 331–348.

Campello, M., Graham, J.R., & Harvey, C.R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics, 97*(3), 470-487.

Chang, C., Lee, A. & Lee, C. (2009). Determinants of capital structure choice: A structural equation modeling approach. *The Quarterly Review of Economics and Finance, 49*(2), 197–213.

Chang, X.S., Chen, Y., Wang, S.Q., Zhang, K., & Zhang, W. (2019). Credit default swaps and corporate innovation. *Journal of Financial Economics, 134*(2), 474–500.

Charitou, A., Lambertides, N., & Theodoulou, G. (2011). Dividend increases and initiations and default risk in equity returns. *Journal of Financial and Quantitative Analysis, 46*(5), 1521-1543.

Chen, Y., Saffar, W., Shan, C.Y., &, Wang, S.Q. (2018). *Credit default swaps and corporate debt structure*., Working Paper at SSRN.

Choi, J., Hackbarth, D., & Zechner, J. (2018). Corporate debt maturity profiles. *Journal of Financial Economics, 130*(3), 484–502.

Colla, P., Ippplito, F., & Li, K. (2013). Debt specialization. *Journal of Finance, 68*(5), 2117–2141.

Colonnello, S., Efing, M., & Zucchi, F. (2019). Shareholder bargaining power and the emergence of empty creditors. Forthcoming. *Journal of financial Economics, 134*(2), 297–317.

Danis, A. (2016). Do empty creditors matter? Evidence from distressed exchange offers. *Management Science, 63*(5), 1285–1301.

Danis, A., & Gamba, A. (2018). The real effects of credit default swaps. *Journal of Financial Economics, 127*(1), 51–76.

Davydenko, S. & Strebulaev, I. (2007). Strategic actions and credit spreads: An empirical investigation. *Journal of Finance, 62*(6), 2633–71.

Denis, D., & McKeon, S. (2012). Debt financing and financial flexibility: Evidence from proactive leverage increases. *Review of Financial Studies, 25*(6), 1897–1929.

Diamond, D.W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies, 51*(3), 393–414.

Diamond, D.W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy, 99*(4), 689–721.

Faulkender, M., & Wang, R. (2006). Corporate financial policy and the value of cash. *Journal of Finance, 61*, 1957–1989.

Flannery, M.J., Houston, J.F., & Partnoy, F. (2010). Credit default swap spreads as viable substitutes for credit ratings. *University of Pennsylvania Law Review, 158*(7), 2085–2123.

Frank, M., & Goyal, V. (2003). Testing the pecking order theory of capital structure. *Journal of financial Economics, 67*(2), 217–248.

Frank, M., & Shen, T., (2016). Investment and the weighted average cost of capital. *Journal of Financial Economics, 119*(2), 300–315.

Fuller, K. P., Yildiz, S., & Uymaz, Y. (2018). Credit default swaps and firms' financing policies. *Journal of Corporate Finance, 48*, 34–48.

Fung, H.G., Wen, M.M., & Zhang, G. (2012). How does the use of credit default swaps affect firm risk and value? Evidence from U.S. life and property/casualty insurance companies. *Financial Management, 41*(4), 979–1007.

Grennan, J., Michaely, R., & Vincent, Ch.J. (2017). *The deleveraging of U.S. firms and institutional investors' role*. Working Paper at SSRN.

Guest, P.M., Karampatsas, N., Petmezas, D., & Travlos, N.G. (2017). *Credit default swaps and corporate acquisitions*. Working Paper at SSRN.

Hirtle, B. (2009). Credit derivatives and bank credit supply. *Journal of Financial Intermediation, 18*(2), 125–150.

Hong, H.A., Ryou, J.W., & Srivastava, A. (2018). *Managerial incentives and changes in corporate investments following the inception of credit default swap trade*. Tuck School of Business. Working Paper No. 2973275.

Hovakimian, A., Opler, T., & Titman, S. (2001). The debt-equity choice. *Journal of Financial and Quantitative Analysis, 36*(1), 1–24.

Hu, H. T., & Black, B. (2008). Debt, equity and hybrid decoupling: Governance and systemic risk implications. *European Financial Management, 14*(4), 663–709.

Ivanov, I.T., Santos, J.A.C., & Vo, T. (2016). The transformation of banking: Tying loan interest rates to borrowers' CDS spreads. *Journal of Corporate Finance, 38*, 150–165.

Jensen, M. (1986). Agency costs of free cash flow, corporate finance and takeovers. *American Economic Review, 76*(2), 323–329.

Kim, J. B., Shroff, P., Vyas, D., & Wittenberg-Morman, R. (2018). Credit default swaps and managers' voluntary disclosure. *Journal of Accounting Research, 56*(3), 953–988.

Lee, J., Oh, J., & Yermack, D. (2017). Credit default swaps, agency problems, and management incentives. SSRN Scholarly Paper. Rochester, NY: Social Science Research Network.

Lemmon, M., & Zender, J. (2010). Debt capacity and tests of capital structure theories. *Journal of Financial and Quantitative Analysis, 45*(5), 1161-1187.

Li, J.Y., & Tang, Y. (2016). The leverage externalities of credit default swaps. *Journal of Financial Economics, 120*(3), 491–513.

Lin, C., Ma, Y., Malatesta, P., & Xuan, Y. (2013). Corporate ownership structure and the choice between bank debt and public debt. *Journal of Financial Economics, 109*, 517–534.

Liu, J., NG, J., Tang, Y., & Zhong, R. (2019). *CDS trading and stock price crash risk*. Working Paper at SSRN.

Loderer, C. F., & Waelchli, U. (2010). *Firm age and performance*. ECGI Working Paper Series in Finance. Online at https://mpra.ub.uni-muenchen.de/26450/.

Lou, Y., & OTTO, A.A. (2019). Debt heterogeneity and covenants. Forthcoming in Management Science.

Martin, X., & Roychowdhury, S. (2015). Do financial market developments influence accounting practices? Credit default swaps and borrowers' reporting conservatism. *Journal of Accounting and Economics, 59*(1), 80–104.

Massa, M., Yasuda, A., & Zhang, L. (2013). Supply uncertainty of the bond investor base and the leverage of the firm. *Journal of Financial Economics, 110*(1), 185–214.

Myers, S. (1977). Determinants of corporate borrowing. *Journal of Financial Economics, 5*(2), 147–76.

Myers, S. (1984). The capital structure puzzle. *Journal of Finance, 39*(3), 575–592.

Myers, S. & Majluf, N. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics, 13*(2), 187–221.

Narayanan, R. P., & Uzmanoglu, C. (2018a). How do firms respond to empty creditor holdout in distressed exchanges? *Journal of Banking and Finance, 94*(9), 251–266.

Narayanan, R.P, & Uzmanoglu, C. (2018b). Credit default swaps and firm value. *Journal of Financial and Quantitative Analysis, 53*(3), 1227–1259.

Narayanan, R.P, & Uzmanoglu, C. (2018c). Credit insurance, distress resolution costs, and bond spreads. *Financial Management*, 47(4), 931–951.

Norden, L. (2017). Information in CDS spreads. *Journal of Banking and Finance, 75*(2), 118–135.

Norden, L., Buston, C.S., & Wagner, W. (2014). Financial innovation and bank behavior: Evidence from credit markets. *Journal of Economic Dynamics and Control, 43*, 130-145.

Olson, G.T., & Pagano, M.S. (2017). The empirical cost of capital: A new approach to estimating the cost of corporate funds. *Journal of Applied Corporate Finance, 29*, 101-110.

Parlour, C.A., & Winton, A. (2013). Laying off credit risk: Loan sales versus credit default swaps. *Journal of Financial Economics, 107*(1), 25–45.

Petersen, M.A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*(1), 435–480.

Qiu, J., & Yu, F. (2012). Endogenous liquidity in credit derivatives. *Journal of Financial Economics, 103*(3), 611–631.

Rajan, R. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance, 47*(4), 1367–1400.

Rauh, J., & A. Sufi. (2010). Capital structure and debt structure. *Review of Financial Studies, 23*(2), 4242–4280.

Saretto, A., & Tookes, H.E. (2013). Corporate leverage, debt maturity, and credit supply: The role of credit default swaps. *Review of Financial Studies, 26*(5), 1190–1247.

Shan, S.C., Tang, Y., & Winton, A. (2015). *Market versus contracting: Credit default swaps and creditor protection in loans*. Unpublished working paper. Shanghai University of Finance and Economics, The University of Hong Kong, and University of Minnesota.

Shan, S. C., Tang, Y., & H. Yan (2016). *Regulation-induced financial innovation: The case of credit default swaps and bank capital*. Working paper. University of Hong Kong.

Shan, S., Tang, Y., & Winton, A. (2019). Do banks still monitor when there is a market for credit protection? *Journal of Accounting and Economics, 68*(2–3), 1–25.

Shim, I., & Zhu, H. (2014). The impact of CDS trading on the bond market: Evidence from Asia. *Journal of Banking and Finance, 40*, 460–475.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business, 74*(1), 101–124.

Subrahmanyam, M.G., Tang, Y., & Wang, Q. (2014). Does the tail wag the dog? The effect of credit default swaps on credit risk. *Review of Financial Studies, 27*(10), 2927–2960.

Subrahmanyam, M. G., Tang, Y., & Wang, Q. (2017). Credit default swaps, exacting creditors and corporate liquidity management. *Journal of Financial Economics, 124*(2), 395–414.

Stulz, R. M. (2010). Credit default swaps and the credit crisis. *The Journal of Economic Perspectives, 24*(1), 73–92.

Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. *Journal of Finance, 43*(1), 1-21.

Vos, E., & Forlong, C. (1996). The agency advantage of debt over the lifecycle of the firm. *Journal of Entrepreneurial and Small Business Finance, 5*(3), 193–211.

Wooldridge, J.M. (2002). *Econometric analysis of cross section and panel data*. MIT Press.

Table 1. Sample distribution and firm-level statistics

Panel A. Sample distribution of CDS firms based on the inception year

Year	Number of new CDS firms	Percentage	Cumulative percentage
2001	146	21.69	21.69
2002	101	15.01	36.70
2003	119	17.68	54.38
2004	100	14.86	69.24
2005	41	6.09	75.33
2006	43	6.39	81.72
2007	51	7.58	89.30
2008	10	1.49	90.79
2009	4	0.59	91.38
2010	6	0.89	92.27
2011	8	1.19	93.46
2012	10	1.49	94.95
2013	3	0.45	95.39
2014	7	1.04	96.43
2015	9	1.34	97.77
2016	4	0.59	98.37
2017	11	1.63	100
Total	673	100	

Panel B. Sample distribution of CDS firms based on one-digit SIC industry

SIC Industry	Number of CDS firms	Number of firm-year observations	Percentage of all CDS firms
Agriculture, forest and fishing (0)	2	30	0.30
Construction and mining (1)	64	767	9.51
Manufacturing (2,3)	312	4,318	46.36
Transportation (4)	118	1,576	17.53
Wholesale and retail (5)	70	968	10.40
Services (7,8,9)	107	1,287	15.90
Total	673	8,946	100

Panel C. Summary statistics of firm-level variables

This table presents sample statistics for both CDS and non-CDS firms. The explained and debt composition variables span from 2002 to 2018, while firm-level controls are over the period 2001 to 2017. Variables are summarized at the firm level. The actual number of observations varies for different variables, depending on the joint availability of controls when testing the baseline model. WACC, cost of debt, and cost of equity are presented in percentage. Assets, long-term debts, and CDS notional are in billion dollars. STD is the standard deviation. N indicates the number of firm-year observations. Public debt, CPs, bonds/notes, bank debt, drawn revolving credits, bank loans, capital leases, trusted preferred, and other debt are the ratios of each type of debt to total debt. Variable definitions can be found in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	CDS firms				Non-CDS firms				
Variables	N	Mean	Median	STD	N	Mean	Median	STD	Mean difference
Explained variables									
WACC	8,946	8.477	8.308	2.433	43,504	9.073	8.829	3.137	-0.595***
Cost of debt	8,946	3.081	3.116	1.799	43,504	2.641	2.606	2.107	0.439***
Cost of equity	8,946	10.847	10.373	2.851	43,504	10.394	10.147	3.191	0.453***
Weight of debt	8,946	0.300	0.256	0.218	43,504	0.196	0.113	0.228	0.104***
Weight of equity	8,946	0.695	0.742	0.216	43,504	0.794	0.880	0.237	-0.099***
Debt decompositions									
Public debt	8,445	0.713	0.815	0.295	33,464	0.359	0.155	0.397	0.354***
CPs	8,445	0.022	0	0.051	33,464	0.002	0	0.017	0.019***
Bonds/Notes	8,445	0.684	0.770	0.294	33,464	0.356	0.152	0.396	0.327***
Bank debt	8,445	0.186	0.057	0.258	33,464	0.503	0.501	0.414	-0.317***
Drawn revolving credits	8,445	0.063	0	0.146	33,464	0.227	0.000	0.338	-0.164***
Bank loans	8,445	0.123	0	0.222	33,464	0.277	0.029	0.365	-0.154***
Capital leases	8,445	0.021	0	0.088	33,464	0.085	0	0.241	-0.064***
Trusted preferred	8,445	0.001	0	0.007	33,464	0.000	0	0.003	0.001***
Other borrowings	8,445	0.077	0.001	0.179	33,464	0.053	0	0.177	0.024***
Firm-level characteristics									
Assets ($ billion)	8,946	14.170	5.158	26.323	43,504	2.985	0.287	14.259	11.185***
Leverage	8,946	0.337	0.304	0.217	43,504	0.207	0.151	0.232	0.129***
Growth	8,946	2.944	2.110	5.435	43,504	2.749	1.840	5.129	0.195***
Profitability	8,946	0.082	0.083	0.120	43,504	-0.017	0.054	0.284	0.099***
IO concentration	8,946	0.058	0.041	0.074	43,504	0.153	0.072	0.203	-0.094***
IO ratio	8,946	0.707	0.767	0.248	43,504	0.431	0.395	0.353	0.276***
Age	8,946	32.094	29.000	18.752	43,504	17.443	14.000	12.866	14.651***
R&D	8,946	0.035	0	0.355	43,504	0.464	0.005	2.301	-0.429***
Liquidation	8,946	0.573	0.562	0.133	43,504	0.467	0.469	0.178	0.106***
Riskiness	8,946	0.398	0.344	0.209	43,504	0.585	0.519	0.328	-0.187***
CAPEX	8,946	0.099	0.042	0.205	43,504	0.136	0.035	0.425	-0.037***
Stock liquidity	8,946	2.485	1.892	2.115	43,504	1.690	1.075	1.966	0.795***
Tax rate	8,946	0.297	0.338	0.086	43,504	0.225	0.271	0.118	0.073***
Dividends	8,946	0.569	0.280	0.750	43,504	0.164	0	0.430	0.405***
Credit rating	8,946	0.821	1.000	0.384	43,504	0.147	0	0.354	0.666***
Analyst	8,827	13.869	12	8.896	36,484	5.594	4	6.126	8.276***
Long-term debt	8,929	4.031	1.282	8.844	43,062	0.711	0.012	3.893	3.319***
Capital	8,946	11.402	3.902	22.201	43,504	2.416	0.210	12.627	8.986***

Panel D. Summary statistics of CDS trading activities

Variables	N	Mean	Median	STD
CDSINIT	52,450	0.144	0	0.351
CDSFIRM	52,450	0.171	0	0.376
Notional	1,881	0.018	0.011	0.018
Dealers	1,881	10.117	10.75	4.126

Panel E. Pearson correlation between selected variables

This table illustrates the Pearson correlations for firm-level characteristics. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
CDSFIRM (1)	1.00																		
CDSINIT (2)	0.90***	1.00																	
WACC (3)	-0.07***	-0.07***	1.00																
Public debt (4)	0.34***	0.33***	-0.02***	1.00															
Bond debt (5)	-0.31***	-0.30***	-0.05***	-0.77***	1.00														
Log (Assets) (6)	0.51***	0.49***	-0.03*	0.33***	-0.28***	1.00													
Leverage (7)	0.20***	0.19***	-0.32***	0.22***	-0.07***	0.20***	1.00												
Profitability (8)	0.14***	0.13***	-0.07***	0.02***	0.01***	0.32***	-0.02***	1.00											
CAPEX (9)	-0.03***	-0.03***	0.03***	0.04***	-0.03***	-0.03***	0.04***	-0.21***	1.00										
Growth (10)	0.01***	0.01***	0.10***	0.01**	-0.03***	0.00	-0.08***	0.01**	0.02***	1.00									
Log (Age) (11)	0.36***	0.38***	-0.10***	0.20***	-0.17***	0.32***	0.04***	0.18***	-0.10***	-0.03***	1.00								
Riskiness (12)	-0.22***	-0.22***	0.15***	-0.10***	0.05***	-0.44***	-0.01**	-0.35***	0.12***	-0.00	-0.36***	1.00							
Dividends (13)	0.29***	0.30***	-0.12***	0.20***	-0.17***	0.43***	0.08***	0.17***	-0.03***	0.03***	0.38***	-0.33***	1.00						
Tax rate (14)	0.25***	0.22***	-0.01**	0.07***	-0.04***	0.52***	-0.10***	0.52***	-0.13***	0.01	0.28***	-0.52***	0.30***	1.00					
IO concentration (15)	-0.18***	-0.17***	-0.15***	-0.15***	0.15***	-0.49***	0.02***	-0.20***	0.03***	-0.05***	-0.10***	0.24***	-0.18***	-0.33***	1.00				
Liquidation (16)	0.22***	0.21***	-0.20***	0.08***	0.03***	0.34***	0.30***	0.19***	-0.14***	-0.08***	0.18***	-0.22**	0.16***	0.25***	-0.07***	1.00			
R&D (17)	-0.07***	-0.07***	0.11***	-0.02**	-0.02***	-0.17***	-0.05***	-0.39***	0.47***	0.04***	-0.10***	0.16***	-0.07**	-0.24***	0.08**	-0.25***	1.00		
S&P rated (18)	0.57***	0.53***	-0.10***	0.38***	-0.31***	0.56***	0.28***	0.17***	-0.01**	-0.01***	0.27***	-0.24***	0.26***	0.26***	-0.24***	0.28***	-0.10***	1.00	
Stock liquidity (19)	0.15***	0.15***	0.25***	0.13***	-0.13***	0.11***	-0.00	-0.04***	0.04***	0.05***	-0.01**	0.13***	-0.07***	0.06***	-0.14***	-0.08***	0.05***	0.07***	1.00

Table 2. The relationships between CDS trading and the cost of capital

This table reports regression results of the cost of capital on CDS availability and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and the costs of capital are from 2002 to 2018. Constants are computed but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present estimates with industry- and firm-year fixed effects models in columns (1) and (2), respectively. Column (3) shows estimates with firm-year fixed effects controlling for the marginal tax rate. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	WACC			Cost of debt			Cost of equity		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CDSFIRM	-0.097			-0.077			-0.419***		
	(-1.21)			(-1.05)			(-4.56)		
CDSINIT	-0.295***	-0.217***	-0.200**	-0.307***	-0.203***	-0.221***	-0.031	0.278***	0.353***
	(-3.73)	(-2.80)	(-2.50)	(-4.66)	(-3.31)	(-3.57)	(-0.33)	(2. 96)	(3.64)
Controls									
Tax rate			0.772***			-1.087***			-0.320
			(2.71)			(-6.03)			(-1.05)
Log (Assets)	0.205***	0.311***	0.322***	0.054***	0.231***	0.207***	0.411 ***	0.660***	0.705***
	(10.42)	(7.97)	(7.03)	(3.48)	(8.87)	(6.98)	(22.28)	(15.99)	(14.43)
Leverage	-3.611***	-2.372***	-2.344***	2.347***	1.362***	1.325***	0.065	0.127	-0.052
	(-28.48)	(-19.51)	(-17.19)	(31.01)	(17.84)	(14.73)	(0.64)	(0.94)	(-0.36)
Profitability	-0.579***	-0.097	-0.136	-0.462***	-0.337***	-0.287***	-0.784***	-0.410***	-0.386***
	(-6.33)	(-1.08)	(-1.36)	(-9.10)	(-7.27)	(-5.39)	(-8.79)	(-4.53)	(-3.77)
CAPEX	-0.038	-0.031	-0.093	0.219***	0.115***	0.134***	0.089	0.024	-0.057
	(-0.61)	(-0.45)	(-1.12)	(6.22)	(3.19)	(2.97)	(1.39)	(0.36)	(-0.71)
Growth	0.033***	0.015***	0.015***	0.002	0.003*	0.002	0.014***	0.013***	0.015***
	(9.74)	(5.65)	(4.90)	(1.23)	(1.82)	(0.98)	(4.27)	(4.81)	(4.57)
Log (Age)	-0.039	-0.209**	-0.595***	-0.056***	-0.003	-0.124*	0.018	0.065	-0.470***
	(-1.20)	(-2.41)	(-5.40)	(-2.60)	(-0.05)	(-1.65)	(0.52)	(0.68)	(-3.96)
Riskiness	1.115***	1.622***	1.883***	0.356***	0.210***	0.110	1.896***	2.162***	2.346***
	(9.93)	(11.87)	(12.29)	(6.99)	(3.31)	(1.45)	(14.10)	(13.36)	(11.73)
Dividends	-0.241***	0.126***	0.095	-0.195***	0.068*	0.093**	-0.480***	-0.103*	-0.178***
	(-5.31)	(2.77)	(1.52)	(-4.84)	(1.86)	(2.30)	(-10.24)	(-1.95)	(-2.90)
IO concentration	-1.734***	-0.586***	-0.639***	0.220***	0.249***	0.133*	-1.125**	-0.206	-0.400**
	(-14.05)	(-4.44)	(-4.24)	(3.18)	(3.77)	(1.73)	(-8.60)	(-1.43)	(-2.47)
Liquidation	-1.179***	-0.984***	-1.234***	1.334***	0.933***	0.902***	-0.643***	-0.698***	-1.088***
	(-8.95)	(-5.89)	(-6.58)	(13.83)	(8.11)	(6.89)	(-4.92)	(-3.94)	(-5.47)
R&D	0.052***	0.015	0.009	-0.030***	-0.005	-0.014	0.034***	0.007	0.001
	(4.16)	(0.89)	(0.49)	(-3.72)	(-0.55)	(-1.22)	(2.76)	(0.49)	(-0.04)
S&P rated	-0.076***	-0.127**	-0.337***	0.562***	0.566***	0.821***	0.133**	0.093	0.120
	(-1.27)	(-2.09)	(-4.31)	(11.48)	(12.12)	(12.31)	(2.06)	(1.27)	(1.17)
Stock liquidity	0.251***	0.137***	0.159***	0.008	0.003	0.014*	0.309***	0.208***	0.230***
	(19.58)	(11.57)	(12.38)	(1.08)	(0.50)	(1.87)	(22.97)	(16.54)	(15.96)
Industry-fixed effects	Yes			Yes			Yes		
Firm-fixed effects		Yes	Yes		Yes	Yes		Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	52,450	52,450	39,300	52,450	52,450	39,300	52,450	52,450	39,300
#Firms	6,289	6,289	5,148	6,289	6,289	5,148	6,289	6,289	5,148
Adjusted R^2	0.314	0.603	0.630	0.355	0.658	0.670	0.290	0.563	0.599

Table 3. The relationships between CDS trading and the cost of capital based on high- and low-rated firms

This table reports regression results of the cost of capital on CDS initiation and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and the costs of capital are from 2002 to 2018. Constants are computed but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present estimates with industry- and firm-year fixed effects in columns (1) and (2), respectively. In Panel A, we report estimates using observations from high-rated firms that have a credit rate of above 'BBB+', while Panel B reports estimates using observations from low- and medium-rated firms, which have a credit rate of below 'A-'. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. The impact of CDS trading on high-rated firms

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.202		-0.028		-0.033	
	(1.30)		(0.19)		(-0.22)	
CDSINIT	-0.125	-0.200	0.129	0.095	-0.462***	-0.403***
	(-0.96)	(-1.54)	(1.06)	(0.92)	(-3.29)	(-2.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	3,198	3,198	3,198	3,198	3,198	3,198
Adjusted R^2	0.564	0.712	0.404	0.734	0.481	0.609

Panel B. The impact of CDS trading on low- and medium-rated firms

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	-0.151*		-0.061		-0.474***	
	(-1.65)		(-0.78)		(-4.49)	
CDSINIT	-0.343***	-0.212**	-0.411***	-0.310***	0.104	0.437***
	(-3.67)	(-2.31)	(-5.55)	(-4.41)	(0.94)	(3.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	49,252	49,252	49,252	49,252	49,252	49,252
Adjusted R^2	0.308	0.602	0.365	0.659	0.291	0.565

Table 4. The relationships between CDS trading and the cost of capital based on high and low default probability

This table reports regression results of the cost of capital on CDS initiation and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and the costs of capital are from 2002 to 2018. Constants are computed but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present estimates with industry- and firm-year fixed effects in columns (1) and (2), respectively. In Panel A, we report estimates using firm-year observations whose default probability lies below 25% quantile, while Panel B reports estimates using firm-year observations whose default probability lies above 75% quantile. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. The impact of CDS trading on firms with low default probability

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.017		-0.138		-0.130	
	(0.13)		(-1.01)		(-0.99)	
CDSINIT	-0.423***	-0.312***	-0.131	0.100	-0.286**	-0.167
	(-3.43)	(-2.58)	(-1.01)	(0.81)	(-2.36)	(-1.37)
Industry-fixed effects	Yes		Yes			Yes
Firm-fixed effects		Yes		Yes	Yes	
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	10,979	10,979	10,979	10,979	10,979	10,979
Adjusted R^2	0.455	0.713	0.301	0.720	0.363	0.645

Panel B. The impact of CDS trading on firms with high default probability

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.249		-0.113		-0.452*	
	(1.27)		(-0.81)		(-1.68)	
CDSINIT	-0.588**	-0.300	-0.411***	-0.339*	0.645**	1.212***
	(-2.53)	(-1.24)	(-2.86)	(-1.84)	(2.08)	(3.38)
Industry-fixed effects	Yes		Yes			Yes
Firm-fixed effects		Yes		Yes	Yes	
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	10,908	10,908	10,908	10,908	10,908	10,908
Adjusted R^2	0.270	0.652	0.437	0.732	0.309	0.643

Table 5. Probit regression results on the probability of CDS trading initiation

This table presents the coefficient estimates of the probit model specified by equation (2) which is used to predict the inception of CDS trading. The sample includes all firm-year observations for non-CDs companies and firm-year observations until the CDS trading initiation for CDS companies (i.e., we eliminate all observations in the post-CDS period). The sample period is from 2001 to 2017. The dependent variable, *CDSINIT*, equals one in and after CDS trading initiation for CDS firms, and zero otherwise. All control variables are lagged one year. The definitions of control variables are listed in Appendix 2. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Dependent variable = Prob (CDSINIT=1)	
Variables	Coefficients
Constant	-11.639 (-2.60) ***
Log (Assets)	0.341 (14.58) ***
Growth	0.007 (1.39)
Risk	-0.454 (-2.56) ***
Profitability	0.282 (1.23)
PPE ratio	0.945 (3.71) ***
CAPEX	0.225 (2.22) **
Dividends	-0.004 (-0.09)
IO concentration	0.573 (2.01) **
Leverage	0.806 (5.65) ***
Log (Age)	0.271 (7.56) ***
Cash	0.973 (2.42) ***
Turnover	0.169 (5.88) ***
Liquidation	2.336 (5.37) ***
R&D	-0.076 (-1.19)
WCAP	0.921 (3.27) ***
Excess return	0.106 (1.95) *
S&P rated	1.106 (13.22) ***
Stock liquidity	0.150 (11.32) ***
Likelihood Ratio	2,532.061***
Industry-fixed effects	Yes
Year-fixed effects	Yes
Pseudo R^2	45.28%
Percent Concordant /C	96.5%
C	0.965
#Observations	43,436

Table 6. Comparison of control-treated firm characteristics

This table compares CDS and matched non-firms' characteristics in the year prior to the CDS trading initiation. The control observations are selected based on the nearest likelihood of CDS trading initiation by year without multiple matching. The details of the definition of variables are listed in Appendix 2. All control variables are winsorized at the top and bottom 1%. The number in parentheses is *t* statistics. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	Mean of CDS firm	Mean of non-CDS firm	Difference
WACC	8.278	8.218	-0.060 (-0.37)
Cost of debt	4.177	4.238	-0.061 (-0.46)
Cost of equity	9.924	9.909	-0.015 (-0.08)
Log (Assets)	15.095	14.816	0.279 (2.98) ***
Leverage	0.337	0.348	-0.011 (-0.73)
Profitability	0.077	0.067	0.010 (1.05)
CAPEX	0.114	0.138	-0.024 (-1.22)
Growth	2.865	3.110	0.245 (0.60)
Log (Age)	2.930	2.726	0.207 (3.70) ***
Riskiness	0.441	0.460	-0.019 (-1.38)
Dividends	0.362	0.249	0.113 (2.99) ***
IO concentration	0.057	0.060	-0.003 (-0.65)
Liquidation	0.566	0.557	0.009 (-0.97)
R&D	0.041	0.039	-0.001 (-0.11)
S&P rated	0.905	0.898	0.007 (0.36)
Stock liquidity	1.86	2.217	-0.308 (-1.94) *
Logit of Propensity of initiation	-2.295	-2.430	0.135 (1.43)
#Observations	402	402	

Table 7. The impact of CDS trading on the cost of capital using PSM samples

This table presents regression results based on propensity score matching samples constructed as per the three criteria listed in section 4.3. The probit sample has 42,352 observations spanning from 2001 to 2017. Dependent variables are *WACC*, *cost of debt*, and *cost of equity*. We report industry- and firm-fixed effects in columns (1) and (2) for each dependent variable, respectively. All regressions include year-fixed effects to control time trends on the cost of capital. All control variables are winsorized at the top and bottom 1% and lagged one year compared to the cost of capital. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Panel A. Regression results using nearest-one matching sample without multiple matching

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.257***		0.159*		0.147	
	(2.58)		(1.84)		(1.31)	
CDSINIT	-0.195**	-0.265**	-0.178**	-0.222***	-0.301***	-0.170
	(-1.99)	(-2.32)	(-2.03)	(-2.51)	(-2.56)	(-1.29)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes			
Firm-fixed effects		Yes		Yes	Yes	Yes
Adjusted R^2	0.463	0.621	0.414	0.669	0.476	0.599
#Observations	10,039	10,039	10,039	10,039	10,039	10,039
#Firms	804	804	804	804	804	804

Panel B. Regression results using nearest-one matching sample with exact one-digit SIC industry classification

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.184*		0.132		0.062	
	(1.80)		(1.51)		(0.55)	
CDSINIT	-0.181*	-0.175*	-0.175**	-0.224***	-0.306***	-0.121
	(-1.94)	(-1.70)	(-2.16)	(-2.80)	(-2.74)	(-1.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Adjusted R^2	0.481	0.635	0.430	0.668	0.494	0.618
#Observations	9,993	9,993	9,993	9,993	9,993	9,993
#Firms	767	767	767	767	767	767

Panel C. Regression results using nearest-one matching sample with FF17 industry classification

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.208**		0.138		0.036	
	(1.98)		(1.38)		(0.33)	
CDSINIT	-0.186*	-0.258**	-0.135*	-0.178**	-0.297***	-0.173
	(-1.93)	(-2.43)	(-1.73)	(-2.18)	(-2.63)	(-1.41)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes			
Firm-fixed effects		Yes		Yes	Yes	Yes
Adjusted R^2	0.464	0.617	0.436	0.671	0.487	0.601
#Observations	9,472	9,472	9,472	9,472	9,472	9,472
#Firms	725	725	725	725	725	725

Table 8. The relationships between instrumented *CDSINIT* and the cost of capital

This table reports regression results of the cost of capital on the instrumented CDS initiation and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and the costs of capital are from 2002 to 2018. Constants are computed but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present estimates with industry- and firm-year fixed effects models in columns (1) and (2), respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.055		-0.032		-0.198**	
	(0.61)		(-0.55)		(-2.06)	
Instrumented CDSINIT	-2.048***	-0.770***	-1.040***	-0.405***	-1.883***	-0.018
	(-13.88)	(-4.98)	(-10.75)	(-3.67)	(-11.94)	(-0.11)
Controls						
Log (Assets)	0.476***	0.397***	0.126***	0.193***	0.666 ***	0.710***
	(19.71)	(8.68)	(8.44)	(6.47)	(26.42)	(14.37)
Leverage	-3.552***	-2.397***	2.369***	1.476***	0.041	0.109
	(-24.80)	(-17.42)	(28.73)	(17.11)	(0.36)	(0.72)
Profitability	-0.697***	-0.151	-0.559***	-0.312***	-0.863***	-0.488***
	(-6.49)	(-1.45)	(-9.25)	(-5.53)	(-8.25)	(-4.70)
CAPEX	-0.185**	-0.147	0.199***	0.119***	-0.023	-0.017
	(-2.37)	(-1.61)	(4.82)	(2.67)	(-0.28)	(-0.19)
Growth	0.024***	0.011***	0.003	0.003	0.005	0.007**
	(6.16)	(3.33)	(1.45)	(1.45)	(1.32)	(2.18)
Log (Age)	-0.062	-0.229*	0.090***	-0.008	-0.010	-0.108
	(-1.43)	(-1.83)	(3.49)	(-0.10)	(-0.22)	(-0.79)
Riskiness	1.639***	1.845***	0.515***	0.254***	2.703***	2.348***
	(9.89)	(11.21)	(7.87)	(3.30)	(12.25)	(10.74)
Dividends	-0.051	0.085	-0.112***	0.099***	-0.309***	-0.196***
	(-1.11)	(1.53)	(-3.19)	(2.77)	(-6.42)	(-3.27)
IO concentration	-1.450***	-0.583***	0.591***	0.289***	-1.004**	-0.289*
	(-10.03)	(-3.86)	(7.85)	(3.79)	(-6.51)	(-1.75)
Liquidation	-1.800***	-1.284***	1.270***	0.973***	-1.141***	-0.870***
	(-12.37)	(-6.65)	(12.56)	(7.38)	(-7.84)	(-4.29)
R&D	0.066***	0.008	-0.035***	-0.011	0.040***	-0.013
	(4.42)	(0.40)	(-3.52)	(-1.06)	(2.72)	(-0.65)
S&P rated	0.113*	-0.095	0.798***	0.590***	0.391***	0.152**
	(1.81)	(-1.50)	(18.14)	(11.72)	(5.52)	(2.03)
Stock liquidity	0.216***	0.141***	0.010	0.009	0.262***	0.207***
	(16.48)	(10.44)	(1.39)	(1.35)	(18.57)	(14.26)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	38,078	38,078	38,078	38,078	38,078	38,078
#Firms	4,736	4,736	4,736	4,736	4,736	4,736
Adjusted R^2	0.369	0.626	0.395	0.658	0.352	0.594

Table 9. The cost of capital and CDS trading initiation based on the first difference sample

Panel A reports estimates of regressions on the first differences of dependent variables on CDS initiation, while Panel B reports regressions of CDS trading initiation on changes of each dependent variable. Variable definitions are listed in Appendix 2. The first difference data are from 2002 to 2018, while controls and CDS variables span from 2001 to 2017. We control industry-year and firm-year fixed effects in columns (1) and (2), respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses are *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. The effects of CDS trading on changes of the cost of capital

	ΔWACC		ΔCost of debt		ΔCost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	-0.060*	-0.053	-0.028**	-0.081**	-0.028	-0.073
	(-1.80)	(-1.14)	(-2.53)	(-2.16)	(-1.53)	(-1.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,449	47,449	47,449	47,449	47,449	47,449
#Firms	5,928	5,928	5,928	5,928	5,928	5,928
Adjusted R^2	0.108	0.195	0.178	0.240	0.122	0.204

Panel B. The effects of changes of the cost of capital on the inception of CDS trading initiation

	CDSINIT					
	(1)	(2)	(1)	(2)	(1)	(2)
ΔWACC	0.000	-0.000				
	(1.27)	(-1.15)				
ΔCost of debt			-0.001	-0.000		
			(-1.49)	(-1.04)		
ΔCost of equity					-0.000	-0.000
					(-1.05)	(-1.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,449	47,449	47,449	47,449	47,449	47,449
#Firms	5,928	5,928	5,928	5,928	5,928	5,928
Adjusted R^2	0.308	0.910	0.309	0.911	0.326	0.912

Table 10. The impact of CDS trading on cost of capital using trading liquidity

This table presents regression results using CDS trading activity. Dependent variables are the *cost of capital*, *cost of debt*, and *cost of equity*. Independent variables are *CDS daily trading notional volume* and the *total number of clearing dealer in a fiscal year*, respectively. The notional volume and number of clearing dealer are zeros for non-CDS firms and firms whose CDSs are not covered by DTCC. We scale the notional volume on the log to reduce skewness of distribution. All controls are included but ignored for brevity. We report industry-fixed effect in columns (1) and (3) and firm-fixed effect in columns (2) and (4) for each independent variable, respectively. All regressions include year-fixed effects to control time trends on the cost of capital. All control variables are winsorized at the top and bottom 1% and lagged one year than the cost of capital. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	WACC				Cost of debt				Cost of equity			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDSFIRM	-0.225***		-0.271***		-0.252***		-0.261***		-0.453***		-0.513***	
	(-2.15)		(-2.65)		(-3.63)		(-3.80)		(-4.24)		(-4.92)	
Notional	-0.045***	-0.001			-0.016***	-0.021***			-0.044***	-0.006		
	(-6.27)	(-0.20)			(-3.55)	(-4.20)			(-4.24)	(-0.76)		
Dealers			-0.059***	-0.018**			-0.023***	-0.032***			-0.052***	-0.012
			(-5.85)	(-2.37)			(-3.79)	(-5.90)			(-4.64)	(-1.27)
Controls												
Industry-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Adjusted R^2	0.284	0.666	0.285	0.665	0.263	0.717	0.263	0.717	0.276	0.651	0.276	0.635
#Observations	27,091	27,091	27,091	27,091	27,091	27,091	27,091	27,091	27,091	27,091	27,091	27,091
#Firms	4,335	4,335	4,335	4,335	4,335	4,335	4,335	4,335	4,335	4,335	4,335	4,335

Table 11. The relationships between CDS trading and weight of capital

This table reports regression results of the weight of debt and equity on the CDS initiation and a set of firm-level explanatory variables (excluding leverage ratio). CDS activity and firm-level controls are from 2001 to 2017, and the weight of debt and equity in percentage are from 2002 to 2018. Constants are ignored for brevity. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present regression results with firm-year fixed effects in column 1. Columns 2, 3, and 4 report estimates from quantile regressions with quantile of 0.15, 0.50, and 0.85, respectively. We control the industry-year fixed effect for quantile regressions. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses are *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Weight of debt				Weight of equity			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDSFIRM		-0.834***	-1.239***	-2.697***		2.722***	1.296	0.843***
		(-4.02)	(-5.24)	(-4.62)		(4.96)	(5.16)	(3.88)
CDSINIT	0.861	0.627***	-0.744***	-1.923***	-0.968	2.050***	0.873***	-0.607***
	(1.44)	(2.87)	(-2.93)	(-3.15)	(-1.54)	(3.51)	(3.24)	(-2.65)
Controls								
Log (Assets)	3.602***	0.336***	0.571***	0.889***	-3.485***	-0.748***	-0.619***	-0.319***
	(14.72)	(19.41)	(16.50)	(12.74)	(-13.26)	(-8.83)	(-17.35)	(-16.23)
Leverage	35.726***	32.479***	68.932***	95.443***	-35.582***	-93.963***	-69.853***	-33.911***
	(35.85)	(132.20)	(161.69)	(114.25)	(-34.99)	(-100.57)	(-146.83)	(-149.95)
Profitability	-4.101***	0.103	-0.970***	-5.789***	5.027***	9.336***	1.865***	0.078
	(-9.06)	(1.42)	(-5.01)	(-9.29)	(9.04)	(12.95)	(6.61)	(0.99)
CAPEX	0.617*	-0.012	0.219	2.023***	-0.488	-2.258***	-0.293**	0.002
	(1.68)	(-0.16)	(1.49)	(5.45)	(-1.23)	(-5.43)	(-1.97)	(0.03)
Growth	-0.061***	-0.157***	-0.329***	-0.433***	0.073***	0.491***	0.376***	0.180***
	(-3.88)	(-22.15)	(-17.04)	(-19.91)	(4.24)	(18.85)	(17.26)	(19.27)
Log (Age)	3.461***	-0.040	-0.017	-0.064	-3.510***	-0.173	-0.028	0.029
	(6.63)	(-1.20)	(-0.32)	(-0.44)	(-6.31)	(-1.21)	(-0.47)	(0.78)
Riskiness	-0.414	0.372***	1.949***	8.602***	-0.349	-11.674***	-2.877***	-0.412***
	(-0.69)	(5.57)	(8.97)	(13.53)	(-0.55)	(-18.20)	(-12.07)	(-6.31)
Dividends	-1.472***	-0.147**	-1.150 ***	-1.779***	1. 648***	1.771***	1.168***	0.195***
	(-4.07)	(-2.11)	(-9.57)	(-9.02)	(4.63)	(10.09)	(9.71)	(2.71)
IO Concentration	5.928***	1.136***	5.997***	15.894***	-5.932***	-18.596***	-7.652***	-1.282***
	(7.54)	(8.14)	(14.54)	(17.51)	(-6.95)	(-19.45)	(-16.82)	(-9.38)
Liquidation	8.465***	1.336***	1.915***	8.360***	-9.177***	-10.010***	-2.400***	-1.356***
	(8.90)	(9.42)	(8.47)	(12.54)	(-9.08)	(-13.30)	(-10.02)	(-9.02)
R&D	-0.065	0.049***	0.00	-0.325***	0.062	0.447***	0.027	-0.035*
	(-0.87)	(2.70)	(0.19)	(-7.64)	(0.80)	(7.98)	(1.27)	(-1.81)
S&P rated	3.184***	2.744***	3.055***	2.244***	-3.418***	-2.710***	-2.993***	-2.693***
	(7.55)	(20.33)	(15.70)	(6.62)	(-7.80)	(-7.75)	(-15.11)	(-20.73)
Stock liquidity	0.143**	-0.052***	-0.097***	-0.125***	-0.117*	0.185***	0.113***	0.049***
	(2.28)	(-4.19)	(-5.59)	(-2.80)	(-1.80)	(3.91)	(5.49)	(3.44)
Industry-fixed effects		Yes	Yes	Yes		Yes	Yes	Yes
Firm-fixed effects	Yes				Yes			
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	52,424	51,727	51,727	51,727	52,424	51,727	51,727	51,727
Firms	6,287	6,287	6,287	6,287	6,287	6,287	6,287	6,287
Adjusted R^2	0.787				0.786			

Table 12. CDS trading and debt placement

This table reports regression results of debt compositions on CDS initiation and a set of firm-level explanatory variables. The dependent variables span from 2001 to 2017. Constants are estimated but not reported, and all controls lag one year than dependent variables. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Public debt		Bond		Commercial		Capital lease	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.082***		0.061***		0.009***		-0.001	
	(4.78)		(3.58)		(4.75)		(-0.17)	
CDSINIT	0.038**	0.034**	0.047***	0.049***	0.001	-0.004**	0.016**	0.004
	(2.37)	(2.37)	(2.93)	(3.45)	(0.45)	(-2.47)	(2.47)	(0.70)
Controls								
Log (Assets)	0.027	0.044***	0.025***	0.043***	0.002***	0.001	-0.007***	-0.006*
	(8.70)***	(6.65)	(8.10)	(6.60)	(6.33)	(1.53)	(-4.75)	(-1.72)
Leverage	0.259***	0.270***	0.268***	0.274***	-0.004***	-0.001*	-0.172***	-0.124***
	(15.30)	(15.03)	(15.85)	(15.22)	(-5.15)	(-1.82)	(-19.74)	(-13.43)
Profitability	-0.110***	-0.023**	-0.109***	-0.025**	-0.002***	0.001*	-0.019**	0.005
	(-8.47)	(-2.05)	(-8.35)	(-2.14)	(-3.70)	(1.66)	(-2.30)	(0.73)
CAPEX	0.029***	0.004	0.029***	0.005	-0.000	-0.000	-0.009**	-0.003
	(3.18)	(0.48)	(3.18)	(0.57)	(-0.18)	(-1.31)	(-2.08)	(-0.72)
Growth	0.001***	0.000	0.001***	-0.000	0.001***	0.002***	0.000	-0.001
	(3.63)	(0.08)	(2.90)	(-0.14)	(4.66)	(2.87)	(0.18)	(-1.57)
Log (Age)	0.038***	0.006	0.035***	0.004	0.002***	0.001	-0.008***	-0.009
	(7.06)	(0.48)	(6.42)	(0.32)	(5.15)	(0.46)	(-2.99)	(-1.43)
Riskiness	0.017	0.033**	0.019	0.035***	-0.001	-0.001***	0.028***	0.012
	(1.42)	(2.49)	(1.55)	(2.63)	(-0.95)	(-2.87)	(3.65)	(1.51)
Dividends	0.037***	0.032***	0.027***	0.030***	0.007***	0.003***	-0.004	0.001
	(4.61)	(3.65)	(3.48)	(3.32)	(7.01)	(2.87)	(-1.34)	(0.25)
IO	-0.022	0.042**	-0.027**	0.044**	0.003***	-0.001**	-0.051***	-0.005
concentration	(-1.16)	(2.46)	(-1.43)	(2.55)	(4.66)	(-2.06)	(-5.26)	(-0.58)
Liquidation	-0.078***	-0.107***	-0.082***	-0.108***	0.001	0.002	-0.201***	-0.139***
	(-3.10)	(-3.70)	(-3.22)	(-3.76)	(1.02)	(1.51)	(-13.38)	(-7.42)
R&D	-0.005**	-0.002	-0.004**	-0.002	0.000	0.000**	0.002	-0.001
	(-2.25)	(-0.87)	(-2.29)	(-0.91)	(0.59)	(2.08)	(1.14)	(-1.18)
S&P rated	0.159***	0.074***	0.154***	0.072***	0.002***	0.001	-0.021***	-0.025***
	(13.65)	(6.72)	(13.24)	(6.55)	(3.15)	(0.20)	(-4.69)	(-4.68)
Stock liquidity	0.018***	0.006***	0.019***	0.007***	-0.001***	-0.001**	-0.000	0.000
	(9.29)	(4.09)	(9.82)	(4.47)	(-7.25)	(-2.09)	(-0.09)	(0.13)
Industry-fixed effects	Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	41,909	41,909	41,909	41,909	41,909	41,909	41,909	41,909
#Firms	5,487	5,487	5,487	5,487	5,487	5,487	5,487	5,487
Adjusted R^2	0.252	0.673	0.234	0.665	0.167	0.582	0.118	0.624

Table 12. Continued

	Bank debt		Bank loan		Revolving credit		Other borrowings	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	-0.054***		-0.038***		-0.016		-0.036***	
	(-3.48)		(-2.62)		(-1.53)		(-5.37)	
CDSINIT	-0.085***	-0.052***	-0.051*	-0.022**	-0.034***	-0.029***	0.035**	0.020***
	(-5.93)	(-4.22)	(-3.90)	(-2.09)	(-3.66)	(-3.71)	(5.30)	(3.02)
Controls								
Log(assets)	-0.035***	-0.039***	-0.004	-0.009*	-0.031***	-0.029 ***	0.019***	0.002
	(-5.93)	(-6.13)	(-1.55)	(-1.68)	(-13.30)	(-6.44)	(12.01)	(0.70)
Leverage	-0.027	-0.115***	0.066***	0.016	-0.093***	-0.130***	-0.060***	-0.032***
	(-1.60)	(-6.46)	(4.25)	(0.97)	(-8.29)	(-10.65)	(-9.18)	(-4.31)
Profitability	0.151***	0.023**	0.064***	0.023**	0.087***	-0.000	-0.024***	-0.005
	(11.37)	(2.12)	(5.48)	(2.48)	(9.26)	(-0.05)	(-4.35)	(-0.97)
CAPEX	-0.013	-0.003	-0.024***	0.002	0.011*	-0.005	-0.007**	0.003
	(-1.40)	(-0.35)	(-2.88)	(0.34)	(1.69)	(-0.75)	(-2.21)	(0.78)
Growth	-0.001***	0.001	-0.001*	0.001*	-0.001***	-0.000	-0.000	-0.000
	(-3.83)	(1.16)	(-1.32)	(1.84)	(-3.99)	(-0.89)	(-0.26)	(-0.63)
Log (Age)	-0.038 ***	-0.009	-0.063***	-0.024*	0.024***	0.015	0.00***	0.013*
	(-6.87)	(-0.69)	(-12.39)	(-1.93)	(5.67)	(1.47)	(2.97)	(1.77)
Riskiness	-0.063***	-0.058***	-0.003**	-0.010	-0.059***	-0.048***	0.019***	0.011*
	(-4.55)	(-3.95)	(-0.30)	(-0.83)	(-5.43)	(-4.60)	(3.55)	(1.83)
Dividends	-0.036***	-0.018**	-0.015**	-0.018**	-0.020***	-0.000	0.004	-0.014**
	(-4.54)	(-2.25)	(-2.08)	(-2.32)	(-4.05)	(-0.01)	(1.04)	(-2.41)
IO concentration	0.044**	-0.031*	0.072***	0.001	-0.027	-0.032**	0.034***	-0.002
	(2.18)	(-1.78)	(3.95)	(0.05)	(-1.60)	(-2.29)	(4.42)	(-0.29)
Liquidation	0.297***	0.276***	0.084***	0.079***	0.214***	0.196***	-0.027***	-0.031**
	(11.32)	(9.33)	(3.49)	(3.08)	(11.07)	(9.47)	(-2.82)	(-2.31)
R&D	0.003	0.003	0.008*	0.003	-0.005***	-0.000	0.000	0.000
	(1.19)	(1.21)	(3.64)	(1.29)	(-4.24)	(-0.08)	(0.12)	(0.43)
S&P rated	-0.137***	-0.051***	-0.020**	0.020**	-0.116***	-0.071***	-0.004	-0.002
	(-12.37)	(-4.75)	(-2.04)	(2.17)	(-15.62)	(-8.74)	(-0.98)	(-0.64)
Stock liquidity	-0.015***	-0.006***	-0.011***	-0.002**	-0.004***	-0.003***	-0.027***	-0.000
	(-8.07)	(-3.96)	(-6.88)	(-2.00)	(-2.90)	(-2.87)	(-2.82)	(-0.41)
Industry-fixed effects	Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	41,909	41,909	41,909	41,909	41,909	41,909	41,909	41,909
#Firms	5,487	5,487	5,487	5,487	5,487	5,487	5,487	5,487
Adjusted R^2	0.212	0.658	0.106	0.610	0.162	0.613	0.049	0.407

Table 13. The effects of CDS trading on debt compositions: investment and non-investment grade firms

This table reports regression results of debt compositions on CDS initiation and a set of firm-level explanatory variables for investment and non-investment grade firms. The dependent variables span from 2002 to 2018, while CDS initiation and controls are from 2001 to 2017. Constants are estimated but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. The relationship between CDS trading and debt heterogeneity: investment grade firms

	Public debt		Bond		Commercial		Bank debt		Bank loan		Revolving credit	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)				
CDSFIRM	0.129***		0.094***		0.013**		-0.084***		-0.076***		-0.007	
	(5.31)		(3.85)		(2.39)		(-4.00)		(-4.17)		(-0.63)	
CDSINIT	0.011	-0.021	0.031	-0.008	-0.001	-0.001	-0.033**	0.021	-0.019	0.015	-0.013	0.006
	(0.55)	(-1.03)	(1.48)	(-0.41)	(-0.30)	(-0.19)	(-1.99)	(1.30)	(-1.34)	(-1.06)	(-1.49)	(0.69)
							(1.74)					
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	7,037	7,037	7,037	7,037	7,037	7,037	7,037	7,037	7,037	7,037	7,037	7,037
Adjusted R^2	0.154	0.535	0.153	0.537	0.171	0.551	0.145	0.582	0.147	0.589	0.121	0.545

Panel B. The relationship between CDS trading and debt heterogeneity: non-investment grade firms

	Public debt		Bond		Commercial		Bank debt		Bank loan		Revolving credit	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)				
CDSFIRM	0.045**		0.046**		-0.001*		-0.034*		-0.030		-0.004	
	(2.11)		(2.16)		(-1.75)		(-1.66)		(-1.50)		(-0.31)	
CDSINIT	0.038*	0.074***	0.037*	0.074***	0.001	0.001	-0.075***	-0.080**	-0.027	-0.025*	-0.048***	-0.055***
	(1.76)	(3.96)	(1.68)	(3.95)	(1.57)	(0.81)	(-3.53)	(-4.79)	(-1.35)	(-1.71)	(-3.57)	(-4.74)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	34,872	34,872	34,872	34,872	34,872	34,872	34,872	34,872	34,872	34,872	34,872	34,872
Adjusted R^2	0.186	0.662	0.185	0.662	0.042	0.589	0.137	0.632	0.087	0.606	0.132	0.603

Appendix 1. Bloomberg methodology for computing WACC, cost of debt, and cost of equity

1.WACC cost of debt (after tax)

The after-tax weighted average cost of debt for the security is calculated using government bond rates, a debt adjustment factor, the proportions of short- and long-term debt to total debt, and the stock's effective tax rate. The debt adjustment factor represents the average yield above government bonds for a given rating class. The lower the rating, the higher the adjustment factor. The debt adjustment factor (AF) is only used when a company does not have a fair market curve (FMC). When a company does not have a credit rating, an assumed rate of 1.38 (the equivalent rate of a BBB+ Standard & Poor's long-term currency issuer rating) is used. The exact calculation of the debt adjustment factor is Bloomberg proprietary calculation.

Cost of Debt = [[(SD/TD) * (CS*AF)] + [(LD/TD) * (CL*AF)]] * [1-TR]

Where SD = Short Term Debt, TD = Total Debt, CS = Pre-Tax Cost of Short-Term Debt, AF = Debt Adjustment Factor, LD = Long-Term Debt, CL = Pre-Tax Cost of Long-Term Debt, TR = Effective Tax Rate.

2. WACC Cost of Equity

The cost of equity is derived from the Capital Asset Pricing Model (CAPM).

The cost of equity = Risk-free rate + [beta * Country risk Premium]

The default value for the risk-free rate is the country's long-term bond rate (10-year).

3. WACC (Weighted Average cost of Capital)

The cost of capital is computed as:

WACC = [KD * (TD/V)] + [KP * (P/V)] + [KE * (E/V)]

Where: KD = Cost of Debt, TD = Total Debt, V = Total Capital, KP = Cost of Preferred, P = Preferred Equity, KE = Cost of Equity, E = Equity Capital

Total Capital = Total Debt + Preferred Equity + Equity Capital. Figures are drawn from the company's most recent report, annual or interim.

3. WACC Weight of Equity

The ratio of market capital to total capital, calculated as:

Historical Market Cap/ (Historical Cap + ST Borrowings + LT Borrowings + Preferred Equity).

4. WACC Weight of Debt

The ratio of total debt to total capital, calculated as:

(ST Borrowings +LT Borrowings) / (Historical Market Cap + ST Borrowings + LT Borrowings + Preferred Equity)

Appendix 2. Variable definitions

Variable Name	Definition	Source
WACC	The weighted average of cost of debt (after tax) and cost of capital, please see Appendix 1 for details.	Bloombrg
Cost of debt	The overall cost of debt, including all sources of debt financing, please see Appendix 1 for details.	Bloombrg
Cost of equity	The required rate of return of investors, computed from capital asset pricing model (CAPM), please see Appendix 1 for details.	Bloombrg
Weight of debt	The weight of debt evaluated on market values, please see Appendix 1 for details.	Bloombrg
Weight of equity	The weight of equity evaluated on market values, please see Appendix 1 for details.	Bloombrg
Default	The five-year predicted default probability.	Bloombrg
Public debt	The ratio of the sum of bank loans, term loans, and revolving credit to total debt.	Capital IQ
Bond	The ratio of the sum of senior bonds and notes and subordinated bonds and notes to total debt.	Capital IQ
Commercial	The ratio of commercial papers to total debt.	Capital IQ
Bank debt	The ratio of the sum of senior bonds and notes, subordinated bonds and notes, and commercial papers to total debt.	Capital IQ
Bank loan	The ratio of the sum of bank loans and term loans to total debt.	Capital IQ
Revolving credit	The ratio of the revolving credit to total debt.	Capital IQ
Lease	The ratio of the capital lease to total debt.	Capital IQ
Other	The ratio of other borrowings to total debt.	Capital IQ
CDSFIRM	A dummy variable that has a value of one for CDS firms and zero for non-CDS firms in which CDSs have never been referenced on their debts in CDS markets over the sample period.	Constructed
CDSINIT	A dummy variable that has a value of one for the CDS firms in and after the CDS initiation year and zero before that.	Constructed
CDSREVERSAL	A dummy variable that has a value of one for the CDS firms in the years immediately following the termination of CDS trading, and zero otherwise.	Constructed
CDSLAG	The lagged variable of *CDSINIT* by one year.	Conctructed
Dealer	The total number of clearing dealers in the fiscal year scaled on the log.	DTCC
Notional	The average daily trading notional volume scaled by the long-term debt in the fiscal year.	DTCC
Log (Assets):	Total assets (AT) on the natural log scale.	Compustat
Profitability	Earnings before interest and taxes (EBIT) divided by total assets (AT).	Compustat
Liquidation	1-tangibility.	Compustat
Tangibility	The ratio of (0.715 × Receivables + 0.547 × Inventory + 0.535 × Capital + 1 × Cash Holdings) divided by the total assets (AT).	Compustat
CAPEX	The ratio of capital expenditures (CAPX) to total sales (SALE).	Compustat
Cash	Cash and equivalent (CHE) divided by total assets (AT).	Compustat
PPE ratio	PPE ratio defined as the net of property, plant, and equipment (PPENT) divided by assets (AT).	Compustat

Appendix 2. Continued

Variable Name	Definition	Source
MTBV	The ratio of equity market value to its book value.	Compustat
EWACC	Empirical WACC computed by regressing net operating profit after taxes on total capital.	Compustat
NOPAT	Net operating profit after taxes.	Compustat
Total_Capital	The average of book value and market value of a firm.	Compustat
Log (Age):	A firm's age is computed by selecting its earliest initial public offering (IPO) date and the first date when the firm was included in COMPUSTAT. The number of years elapsed since the earliest date is used to approximate a firm's age.	Compustat/CRSP
Riskiness	The stock volatility over the past five fiscal years.	CRSP
Stock liquidity	The yearly stock turnover by volume divided by outstanding common shares.	Compustat
R&D	The ratio of R&D expenditure to total sales.	Compustat
S&P rated	An indicator variable that has a value of one if a firm is rated by S&P, and zero otherwise.	S&P
INVTGRADE	An indicator variable that has a value of one if a firm's rating is above BBB, and zero otherwise.	S&P
Leverage	The ratio of total debt (DT) to total assets (AT).	Compustat
Res	The residual of regressing leverage on *CDSINIT* in a firm-year fixed effects model.	Computed
IO concentration	Herfindahl-Hirschman Index of institutional ownership is defined as: $HHI_{i,t} = \sum_{i,j,t}^{N_{i,t}} S_{i,j,t}^2$, where $N_{i,t}$ is firm *i*'s total number of owners at time *t* and $S_{i,j,t}^2$ is square of the percentage ownership in a company *i* at time *t* of owner *j*.	Thomson 13f
Dividends	Cash dividend payments divided total assets.	Compustat
ROA	Net income (NI) divided by total assets (AT).	Compustat
FF48	FF48 is the Fama-French 48 industry classification.	Compustat
FF17	FF17 is the Fama-French 17 industry classification.	
WCAP	The ratio of working capital (WCAP) to total assets (AT).	Compustat
Net equity issuance	Sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC) scaled by start-of-period assets (AT).	Compustat
Net debt issuance	Debt issuance (DLTIS) less debt repayments (DLTR) plus the change in short-term debt (DLCCH), scaled by assets (AT).	Compustat
High_liquidation	An indicator variable that has a value of one if liquidation cost is above the sample median, and zero otherwise.	Compustat
High_Leverage	An indicator variable that has a value of one if leverage ratio is above the sample median, and zero otherwise.	Compustat
High_IO_Concentration	An indicator variable that has a value of one if HHI of institutional ownership is above the sample median, and zero otherwise.	Thomson 13f
CDS percentage	The percentage of CDS firms among firms whose head offices are within the 200-mile radius of a firm and whose 2-digits SIC industry do not belong to the firm's industry.	Constructed

Online Appendix A1. The quantile regressions of WACC on CDS trading

This table reports estimates of regression of WACC on CDS availability and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and WACC is from 2002 to 2018. Constants are ignored for brevity. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. Columns 1, 2, 3, and 4 report estimates from industry-year fixed effects model with quantile over 0.15, 0.35, 0.50, and 0.85, respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are computed, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	WACC			
	(1)	(2)	(3)	(4)
CDSFIRM	-0.003 (-0.05)	-0.087 (-1.84) *	-0.056(-1.10)	-0.072 (-0.95)
CDSINIT	-0.123 (-2.07) **	-0.143 (-2.85) ***	-0.228 (-4.35) ***	-0.463 (-6.12) ***
Controls				
Log (Assets)	0.189 (19.68) ***	0.196 (20.06) ***	0.182 (20.86) ***	0.152 (11.06) ***
Leverage	-3.912 (-38.98) ***	-3.890 (-53.98) ***	-3.785 (-57.55) ***	-3.290 (-46.89) ***
Profitability	0.279 (2.77) ***	-0.212 (-3.00) ***	-0.414 (-5.63) ***	-0.898 (-8.33) ***
CAPEX	-0.109 (-2.16) **	-0.124 (-2.43) **	-0.165 (-3.61) ***	0.028 (0.40)
Growth	0.043 (13.66) ***	0.043 (18.03) ***	0.042 (14.87) ***	0.025 (8.01) ***
Log (Age)	0.051 (2.68) ***	0.031 (1.93) *	0.001 (0.03)	-0.139 (-6.50) ***
Riskiness	0.024 (0.36)	0.987 (14.99) ***	1.521 (20.48) ***	3.335 (24.58) ***
Dividends	-0.184 (-7.40) ***	-0.213 (-8.33) ***	-0.230 (-11.28) ***	-0.195 (-6.91) ***
IO concentration	-1.827 (-18.04) ***	-1.981 (-20.97) ***	-2.028 (-26.16) ***	-2.031 (-19.00) ***
Liquidation	-0.416 (-4.68) ***	-0.661 (-8.10) ***	-0.943 (-11.94) ***	-1.739 (-15.74) ***
R&D	0.062 (5.87) ***	0.083 (7.84) ***	0.087 (9.31) ***	0.070 (3.39) ***
S&P rated	0.106 (3.00) ***	-0.007 (-0.21)	-0.049 (-1.47)	-0.181(-4.09) ***
Stock liquidity	0.234 (39.11) ***	0.268 (36.40) ***	0.277 (32.38) ***	0.259 (18.73) ***
Industry-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
# Observations	51,753	51,753	51,753	51,753

Online Appendix A2. The effects of the termination of CDS trading on WACC

This table reports regression results of the *WACC* on *CDSINIT*, *CDSREVERSAL*, and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and the costs of capital are from 2002 to 2018. Constants are computed but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. We present estimates with industry- and firm-year fixed effects in columns (1) and (2), respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	CDS Reversal
CDSFIRM	-0.105 (-1.29)
CDSINIT	-0.351 (-4.32) ***
CDSREVERSAL	0.274 (2.38) **
Controls	
Log(assets)	0.207 (10.53) ***
Leverage	-3.616 (-28.61) ***
Profitability	-0.582 (-6.36) ***
CAPEX	-0.038 (-0.60)
Growth	0.034 (9.77) ***
Log (Age)	-0.038 (-1.16)
Riskiness	1.113 (9.91) ***
Dividends	-0.243 (-5.37) ***
IO concentration	-1.731 (-14.04) ***
Liquidation	-1.184 (-8.99) ***
R&D	0.052 (4.15) ***
S&P rated	-0.075 (-1.25)
Stock liquidity	0.252 (19.62) ***
Industry-fixed effects	Yes
Year-fixed effects	Yes
#Observations	52,450
#Firms	6,289
Adjusted R^2	0.314

Online Appendix A3. Probit regression estimates for computing fitted probability of CDS trading initiation

This table presents the coefficient estimates of the probit model specified by equation (2) which is used to predict the inception of CDS trading. The sample includes all firm-year observations for non-CDS and CDS. The sample period is from 2001 to 2018. The dependent variable, *CDSINIT*, equals one in and after CDS trading initiation for CDS firms, and zero otherwise. All control variables are lagged one year. CDS percentage is an instrument variable which is the percentage of CDS firms among firms whose headquarters are within the 200-mile radius of a firm and whose 2-digits SIC industry do not belong to the firm's industry. The definitions of control variables are listed in Appendix 2. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Dependent Variable = Prob (CDSINIT=1)	
Variables	Coefficients
Constant	-16.569 (-55.28) ***
Log (Assets)	0.921 (59.80) ***
Growth	-0.001 (-0.07)
Risk	0.382 (4.99) ***
Profitability	-0.025 (-0.22)
PPE ratio	0.154 (1.44)
CAPEX	-0.522 (-6.84) ***
Dividends	0.227 (9.78) ***
IO concentration	0.504 (3.32) ***
Leverage	1.163 (18.05) ***
Log (Age)	0.432 (20.12) ***
Cash	0.038 (0.22)
Turnover	0.043 (5.92) ***
Liquidation	-0.829 (-4.45) ***
R&D	-0.015 (-0.35)
WCAP	-0.566 (-4.59) ***
Excess return	0.012 (0.38)
S&P rated	1.083 (32.05) ***
Stock liquidity	0.035 (4.86) ***
CDS percentage	**1.976 (9.75)** ***
Likelihood Ratio	2,6305.182***
Industry- and year-fixed effects	Yes
Pseudo R^2	75.83%
Percent Concordant /C	97.6%
C	0.976
#Observations	46,495

Online Appendix A4. The sensitivity tests of Bloomberg WACCs

This table reports regression results of *EWACC* on CDS trading and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and EWACCs are from 2002 to 2018. Constants are estimated but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	EWACC	
	16-quarter rolling windows	20-quarter rolling windows
	(1)	(2)
CDSINIT	-0.007**	-0.005**
	(-2.32)	(-2.02)
Controls		
Log (Assets)	0.010***	0.014**
	(7.50)	(10.23)
Profitability	0.056***	0.097***
	(16.00)	(12.83)
CAPEX	-0.001	0.001
	(-0.70)	(0.10)
Growth	0.001	0.001
	(1.50)	(1.46)
Log (Age)	0.004	0.031
	(0.93)	(0.72)
Riskiness	-0.029***	-0.040***
	(-6.30)	(-8.50)
Dividends	0.006**	0.004***
	(3.84)	(3.50)
IO concentration	-0.021***	-0.015***
	(-4.62)	(-3.71)
Liquidation	-0.017***	-0.008
	(-2.91)	(-1.47)
R&D	-0.008**	0.001
	(-2.16)	(1.06)
S&P rated	-0.002	-0.002
	(-0.79)	(-1.03)
Stock liquidity	0.002***	0.001***
	(4.41)	(4.08)
Firm-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
#Observations	37,134	39,708
Adjusted R^2	0.708	0.757

Online Appendix A5. The cost of debt and CDS trading based on the first difference

This table reports estimates from regressions of the first differences in costs of capital on CDS availability variables. Variable definitions are listed in Appendix 2. The first difference data are from 2002 to 2018, while controls and CDS variables span from 2001 to 2017. We control industry-year and firm-year fixed effects in columns (1) and (2), respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses are *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. The effects of CDS initiation on the changes of the cost of capital

	ΔWACC		ΔCost of debt		ΔCost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	-0.060*	-0.053	-0.028**	-0.081**	-0.028	-0.073
	(-1.80)	(-1.14)	(-2.53)	(-2.16)	(-1.53)	(-1.30)
Controls						
ΔLog (Assets)	-0.091*	-0.241***	0.356***	0.360***	0.336***	0.193***
	(-1.79)	(-3.85)	(12.96)	(10.76)	(6.60)	(3.24)
ΔLeverage	-2.843***	-2.880 ***	1.356***	1.310***	0.227*	0.271*
	(-19.87)	(-18.30)	(16.30)	(14.15)	(1.77)	(1.90)
ΔProfitability	0.128*	0.267 ***	-0.272***	-0.305***	-0.183***	-0.094
	(1.77)	(3.32)	(-7.08)	(-7.23)	(-2.62)	(-1.19)
ΔCAPEX	-0.042	-0.059	0.019	0.012	-0.039	-0.018
	(-0.62)	(-0.81)	(0.70)	(0.40)	(-0.57)	(-0.25)
ΔGrowth	-0.001	-0.001	-0.001	-0.001	-0.000	-0.000
	(-0.35)	(-0.50)	(-0.45)	(-0.83)	(-0.36)	(-0.31)
ΔLog (Age)	1.029***	1.045**	-0.171**	-0.068	1.162***	0.455
	(5.66)	(2.28)	(-2.38)	(-0.35)	(5.86)	(0.92)
ΔRiskiness	1.163***	1.202***	0.024	0.055	2.132***	2.261***
	(8.02)	(6.84)	(0.39)	(0.74)	(12.07)	(11.04)
ΔDividends	-0.086*	-0.124 **	0.042	0.048	-0.188***	-0.195***
	(-1.82)	(-2.43)	(1.47)	(1.54)	(-3.35)	(-3.25)
ΔIO concentration	-1.060***	-0.960***	0.068	0.049	-0.932***	-0.882***
	(-6.83)	(-5.74)	(0.88)	(0.58)	(-5.69)	(-5.04)
ΔLiquidation	-0.543***	-0.489***	0.557***	0.542***	-0.396**	-0.342**
	(-3.27)	(-2.81)	(5.49)	(4.96)	(-2.41)	(-1.98)
ΔR&D	0.008	0.002	0.006	0.008	0.002	-0.002
	(0.69)	(0.14)	(0.94)	(1.05)	(0.19)	(-0.18)
S&P rated	0.023	-0.049	0.007	0.059**	0.115***	0.024
	(1.40)	(-1.24)	(0.92)	(2.23)	(6.55)	(0.52)
ΔStock liquidity	-0.000	-0.000	0.000	0.001	-0.000	-0.000*
	(-0.46)	(-0.19)	(0.60)	(0.61)	(-1.39)	(-1.78)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,449	47,449	47,449	47,449	47,449	47,449
#Firms	5,928	5,928	5,928	5,928	5,928	5,928
Adjusted R^2	0.108	0.195	0.179	0.240	0.123	0.204

Panel B. The effects of the changes of the cost of capital on CDS initiation

	CDSINIT					
	(1)	(2)	(1)	(2)	(1)	(2)
ΔWACC	0.000	-0.000				
	(1.27)	(-1.15)				
ΔCost of debt			-0.001	-0.000		
			(-1.54)	(-1.04)		
ΔCost of equity					-0.000	-0.000
					(-1.05)	(-1.12)
Controls						
ΔLog (Assets)	-0.023***	-0.017***	-0.022***	-0.017***	-0.023***	-0.017
	(-4.82)	(-6.29)	(-4.75)	(-6.22)	(-4.81)	(-1.12)
ΔLeverage	-0.028***	-0.002	-0.028***	-0.001	-0.029***	-0.002
	(-3.21)	(-0.52)	(-3.19)	(-0.35)	(-3.35)	(-0.43)
ΔProfitability	0.015***	0.009***	0.014***	0.009***	0.015***	0.009***
	(4.53)	(5.28)	(4.47)	(5.23)	(4.53)	(5.26)
ΔCAPEX	0.004*	-0.001	0.004**	-0.001	0.004**	-0.001
	(1.99)	(-0.89)	(2.00)	(-0.88)	(1.98)	(-0.88)
ΔGrowth	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-1.22)	(0.53)	(-1.23)	(0.54)	(-1.23)	(0.54)
ΔLog (Age)	-0.549 ***	0.074**	-0.549***	0.075 ***	-0.548***	0.075**
	(-15.06)	(2.49)	(-15.06)	(2.48)	(-15.04)	(2.49)
ΔRiskiness	-0.020**	-0.008*	-0.019**	-0.008*	-0.019**	-0.008*
	(-2.28)	(-1.80)	(-2.23)	(-1.84)	(-2.16)	(-1.77)
ΔDividends	0.055***	-0.000	0.055***	-0.000	0.055***	-0.000
	(5.35)	(-0.12)	(5.36)	(-0.10)	(5.34)	(-0.12)
ΔIO concentration	0.028***	-0.005*	0.027***	-0.004	0.027***	-0.005*
	(3.55)	(-1.66)	(3.52)	(-1.58)	(3.47)	(-1.65)
ΔLiquidation	-0.023**	-0.001	-0.022**	-0.001	-0.024***	-0.001
	(-2.55)	(-0.38)	(-2.51)	(-0.31)	(-2.58)	(-0.38)
ΔR&D	0.000**	0.000	0.000**	0.000	0.001**	0.000
	(2.07)	(1.09)	(2.10)	(1.10)	(2.08)	(1.09)
S&P rated	0.442***	-0.001	0.442***	-0.000	0.442***	-0.001
	(33.17)	(-0.20)	(33.37)	(-0.19)	(33.18)	(-0.19)
ΔStock liquidity	0.000	0.000	0.000	0.000	0.000	0.000
	(0.38)	(0.04)	(0.38)	(0.0 3)	(0.38)	(0.02)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,449	47,449	47,449	47,449	47,449	47,449
#Firms	5,928	5,928	5,928	5,928	5,928	5,928
Adjusted R^2	0.325	0.913	0.309	0.913	0.326	0.912

Online Appendix A6. Probit regressions with the various costs of capital as inputs

This table presents estimates of the probit model specified by equation (2). The sample includes all firm-year observations for non-CDs companies and firm-year observations until the CDS trading initiation for CDS companies (i.e., we eliminate all observations in the post-CDS period). The sample period is from 2001 to 2017. The dependent variable, *CDSINIT*, equals one in and after CDS trading initiation for CDS firms, and zero otherwise. We enlarge the control variables with each measure of the costs of capital to detect the anticipating ability of changes in the cost of capital. All control variables are lagged one year. For brevity, we ignore coefficients on control variables. The definitions of control variables are listed in Appendix 2. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level respectively.

	Dependent variable = Prob (CDSINIT=1)		
	(1)	(2)	(3)
ΔWACC	-0.005 (-0.34)		
ΔCost of debt		0.029 (1.27)	
ΔCost of equity			0.002 (0.10)
Control variables	Yes	Yes	Yes
Likelihood ratio	2,407.251***	2409.871***	2463.075***
Industry-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Pseudo R^2	44.19%	44.23%	44.08%
Percent Concordant /C	96.3%	95.5%	95.5%
C	0.963	0.955	0.955
Tau-a	0.023	0.023	0.023
#Observations	42,197	42,197	42,197

Online Appendix A7. The impact of CDS trading on the cost of capital using samples of non-financial crisis and samples of 2002 to 2018

Panels A presents regression results based on sample firms spanning from 2002 to 2018. Dependent variables are the *cost of capital*, *cost of debt*, and *cost of equity*. Interested variables are *CDSINIT*s. We report industry-fixed and firm-fixed effects in columns (1) and (2), respectively. All regressions include year-fixed effects to control time trends on the cost of capital. All control variables are winsorized at the top and bottom 1% and are lagged one year compared to the dependent variables. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Panel A. CDS trading effects based on sample spanning from 2002 to 2018

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	0.019		-0.063		-0.224	
	(0.21)		(-0.87)		(-2.09)	
CDSLAG	-0.392***	-0.290***	-0.225***	-0.152**	-0.270**	0.139
	(-4.38)	(-3.32)	(-3.34)	(-2.27)	(-2.50)	(1.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.290	0.615	0.377	0.676	0.288	0.582
#Observations	40,124	40,124	40,124	40,124	40,124	40,124
#Firms	5,411	5,411	5,411	5,411	5,411	5,411

Panel B. CDS trading effects based on sample excluding financial crisis periods of 2008 and 2009

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	-0.086		-0.103		-0.355***	
	(-1.03)		(-1.48)		(-3.86)	
CDSLAG	-0.260***	-0.269***	-0.165***	-0.136**	-0.129	0.112
	(-3.26)	(-3.39)	(-2.64)	(-2.19)	(-1.34)	(1.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.298	0.623	0.420	0.700	0.291	0.587
#Observations	37,147	37,147	37,147	37,147	37,147	37,147
#Firms	5,427	5,427	5,427	5,427	5,427	5,427

Online Appendix A8. The impact of CDS trading on the cost of capital using CDS firms

This table presents regression results based on CDS (treatment) firms only. Dependent variables are the *WACC, cost of debt*, and *cost of equity*. Independent variables are *CDSINIT* and *CDSLAG*, respectively. We report industry-fixed effect in columns (1) and (3) and firm-fixed effect in columns (2) and (4) for each independent variable, respectively. All regressions include year fixed effects to control time trends in the various cost of capital. All control variables are winsorized at the top and bottom 1% and are lagged one year compared to the dependent variables. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	WACC				Cost of debt				Cost of equity			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDSINIT	-0.054	-0.042			-0.152**	-0.082			-0.006	0.184		
	(-0.57)	(-0.46)			(-2.12)	(-1.22)			(-0.06)	(1.62)		
CDSLAG			-0.137	-0.129			-0.201***	-0.125*			-0.141	0.042
			(-1.43)	(-1.36)			(-2.84)	(-1.91)			(-1.33)	(0.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Adjusted R^2	0.503	0.666	0.503	0.665	0.495	0.682	0.495	0.678	0.569	0.674	0.570	0.680
#Observations	8,737	8,737	8,737	8,737	8,737	8,737	8,737	8,737	8,737	8,737	8,737	8,737
#Firms	672	672	672	672	672	672	672	672	672	672	672	672

Online Appendix A9. The impact of CDS trading on the cost of capital using CDS firms, controlling strategic variables

This table presents regression results based on CDS (treatment) firms only. Dependent variables are the *cost of capital*, *cost of debt*, and *cost of equity*. Independent variable is *CDSINIT*. We introduce interaction items between CDSINIT and high IO concentration in Panel A, and CDSINIT and high leverage in Panel B to capture the effects of high shareholder bargaining power, respectively. All controls are included but ignored for brevity. All control variables are winsorized at the top and bottom 1% and lagged one year compared to the cost of capital. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Panel A. The cost of capital and CDS trading controlling liquidation cost

	WACC	Cost of debt	Cost of equity
CDSINIT	-0.036 (0.28)	0.051 (0.60)	0.058 (0.45)
CDSINIT*High_liquidation	-0.292 (-2.84) ***	-0.175 (-2.00) **	-0.124 (-1.24)
High_liquidation	-0.137 (-0.97)	0.086 (0.83)	-0.007 (-0.05)
Controls	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Adjusted R^2	0.504	0.497	0.567
#Observations	8,419	8,419	8,419
#Firms	672	672	672

Panel B. The cost of capital and CDS trading controlling institutional ownership concentration

	WACC	Cost of debt	Cost of equity
CDSINIT	-0.234 (-1.72) *	0.035 (0.41)	-0.020 (0.16)
CDSINIT*High IO concentration	-0.186 (-1.55)	-0.217 (-2.43) **	0.003 (0.04)
High IO concentration	-0.280 (-1.78) *	0.209 (2.00) **	-0.092 (-0.61)
Industry-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Adjusted R^2	0.442	0.493	0.569
#Observations	8,419	8,419	8,419
#Firms	672	672	672

Online Appendix A10. Two stage least square test of leverage endogeneity

This table reports estimates of regression of WACC on CDS availability and a set of firm-level explanatory variables. We use residuals from regressing *leverage* on *CDSINIT* to supplant leverage in baseline model. CDS activity and firm-level controls are from 2001 to 2017, and WACC is from 2002 to 2018. Constants are ignored for brevity. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. Columns (1) and (2) report estimates from industry-year and firm-year fixed effects model, respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are computed, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	WACC	
	(1)	(2)
CDSFIRM	-0.171 (-1.96) *	
CDSINIT	-0.35 (-4.15) ***	-0.284 (-3.68) ***
Controls		
Log (Assets)	0.182 (8.70) ***	0.311 (7.97) ***
Res	-2.156 (-17.97) ***	-2.372 (-19.51) ***
Profitability	-0.444 (-4.96) ***	-0.096 (-1.08)
CAPEX	-0.138 (-2.01) **	-0.031 (-0.45)
Growth	0.039 (11.37) ***	0.015 (5.65) ***
Log (Age)	0.003 (0.11)	-0.209 (-2.41) **
Riskiness	0.847 (7.38) ***	1.622 (11.87) ***
Dividends	-0.170 (-3.40) ***	0.126 (2.77) ***
IO concentration	-2.083(-15.83) ***	-0.586 (-4.44) ***
Liquidation	-2.153 (-15.94) ***	-0.984 (-5.89) ***
R&D	0.071 (5.47) ***	0.015 (0.89)
S&P rated	-0.450 (-7.00) **	-0.126 (-2.09) **
Stock liquidity	0.257 (18.52) ***	0.137 (11.56) ***
Industry-fixed effects	Yes	
Firm-fixed effects		Yes
Year-fixed effects	Yes	yes
Adjusted R^2	0.262	0.603
# Observations	52,450	52,450

Online Appendix A11. The relationships between CDS trading and market and book leverage ratios

This table reports regression results of market and book leverage ratios on the CDS trading activity and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and leverage ratios are from 2002 to 2018. Constants are estimated but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses are *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Book leverage	Market leverage
	(1)	(2)
CDSINIT	0.018**	0.020***
	(2.28)	(2.74)
Controls		
Log (Assets)	0.011***	0.04***
	(3.10)	(13.64)
Profitability	-0.084***	-0.058***
	(-10.08)	(-11.95)
CAPEX	-0.005	-0.001
	(-0.81)	(-0.25)
Growth	-0.001***	-0.001***
	(-2.87)	(-7.01)
Log (Age)	0.044***	0.030***
	(5.81)	(5.12)
Riskiness	0.032***	0.018***
	(3.56)	(2.67)
Dividends	0.011***	-0.013***
	(2.46)	(-2.88)
IO concentration	0.054**	0.069***
	(4.89)	(7.57)
Liquidation	0.132***	0.129***
	(7.86)	(11.50)
R&D	-0.002	-0.001*
	(-1.53)	(-1.71)
S&P rated	0.068***	0.050***
	(11.50)	(10.07)
Stock liquidity	0.002*	0.002**
	(1.67)	(2.44)
Firm-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
#Observations	51,136	52,168
Firms	6,263	6,264
Adjusted R^2	0.724	0.728

Online Appendix A12. The relationships between CDS trading and security issuance

This table reports regression results of debt and equity issuance on the CDS trading activity and a set of firm-level explanatory variables. CDS activity and firm-level controls are from 2001 to 2017, and net debt and equity issuance are from 2002 to 2018. Constants are estimated but not reported. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Net debt issuance		Net equity issuance	
	(1)	(2)	(1)	(2)
CDSFIRM	0.008 (2.48) **		0.009 (4.05) ***	
CDSINIT	-0.012 (-3.61) ***	-0.011 (-2.56) **	-0.008 (-3.88) ***	-0.000 (-0.17)
Controls				
Log (Assets)	-0.001 (-2.29) **	-0.017 (-8.52) ***	-0.009 (-15.85) ***	-0.040 (-19.68) ***
Profitability	-0.018 (-3.74) ***	0.004 (0.88)	-0.163 (-17.53) ***	-0.076 (-9.30) ***
CAPEX	0.014 (5.09) ***	0.009 (1.84) *	0.006 (1.60)	0.002 (0.42)
Growth	0.001 (3.90) ***	0.000 (0.85)	0.007 (3.94) ***	0.000 (1.82) *
Log (Age)	-0.004 (-5.04) ***	-0.004 (-1.24)	-0.014 (-12.53) ***	-0.016 (-5.01) **
Riskiness	0.003 (1.20)	-0.003 (-0.67)	0.015 (4.57) ***	0.013 (3.24) ***
Dividends	0.005 (5.17) ***	0.010 (5.85) ***	0.006 (5.34) ***	0.008 (6.49) ***
IO concentration	-0.013 (-3.34) ***	-0.013 (-2.12) **	0.005 (0.98)	-0.003 (-0.54)
Liquidation	0.006 (1.36) ***	0.008 (0.94)	-0.002 (-0.42)	0.111 (11.94) ***
R&D	-0.001 (-1.84) *	-0.000 (-0.04)	0.011 (10.58) ***	0.005 (3.82) ***
S&P rated	0.008 (4.38) ***	0.019 (5.44) ***	0.013 (4.57) ***	0.012 (6.39) ***
Stock liquidity	0.001 (2.38) **	0.000 (0.52)	-0.000 (-0.15)	0.000 (1.59)
Industry-fixed effects	Yes		Yes	
Firm-fixed effects		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes
#Observations	25,791	25,791	47,629	47,629
#Firms	4,589	4,589	6,062	6,062
Adjusted R^2	0.033	0.283	0.321	0.577

Online Appendix A13. Stock analysts and CDS trading

This table reports estimates of regressions of the number of analysts recommending buying stocks on CDS availability variables. Variable definitions are listed in Appendix 2. The analyst data ranges from 2002 to 2018, while controls and CDS variables span from 2001 to 2017. We control industry-year and firm-year fixed effects in columns (1) and (2), respectively. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level for column (1), and the number in parentheses are *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Analysts	
	(1)	(2)
CDSFIRM	3.768 (9.35) ***	
CDSINIT	1.268 (3.43) ***	0.912 (3.95) ***
Controls		
Log (Assets)	1.766 (20.79) ***	2.479 (28.16) ***
Leverage	-2.094 (-7.52) ***	-0.917 (-4.11) ***
Profitability	1.013 (5.85) ***	0.5088 (4.08)
CAPEX	0.705 (4.54) ***	0.168 (1.61)
Growth	0.154 (15.61) ***	0.049 (9.97) ***
Log (Age)	-0.658 (-6.99) ***	-1.031 (-5.12) ***
Riskiness	-2.368 (-11.71) ***	-0.657 (-3.69) ***
Dividends	-0.799 (-3.99) ***	0.784 (6.33) ***
IO concentration	-0.889 (-3.02) ***	-0.836 (-4.81) ***
Liquidation	-2.132 (-5.05) ***	-2.017 (-6.66) ***
R&D	-0.039 (-1.58)	-0.009 (-0.51)
S&P rated	-0.379 (-1.79) *	0.306 (2.26) **
Stock liquidity	0.882 (19.95) ***	0.263 (12.61) ***
Industry-fixed effects	Yes	
Firm-fixed effects		Yes
Year-fixed effects	Yes	Yes
#Observations	45,311	45,311
#Firms	5,475	5,475
Adjusted R^2	0.507	0.879

Online Appendix A14. Cost of capital and ratio of drawn revolving credits to total debt

This table reports regression results of costs of capital on the ratio of drawn revolving credits to total debt and a set of firm-level explanatory variables. The dependent variables span from 2001 to 2017, while independent variables lag one year compared to dependent ones. Columns (1) and (2) report estimated coefficients with industry- and firm-fixed effects, respectively. Variable definitions are listed in Appendix 2. All accounting variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) are clustered at the firm level, and the number in parentheses is *t* statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
Revolving credit	-0.265***	-0.015	-0.289***	-0.212***	0.016	-0.079
	(-3.70)	(-0.23)	(-7.55)	(-5.31)	(0.23)	(-1.14)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.294	0.620	0.398	0.694	0.301	0.591
#Observations	41,909	41,909	41,909	41,909	41,909	41,909
#Firms	5,487	5,487	5,487	5,487	5,487	5,487