The impact of credit default swaps on corporate capital structure and investment policies

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ABSTRACT

The impact of credit default swaps on corporate capital structure and investment policies

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Credit default swaps (CDSs) are credit derivatives whose primary purposes include hedging and the trading of credit risks. Unlike other derivatives, such as options or futures, CDSs materially alter lender-borrower relations and thus have real economic effects on the companies referenced by the CDSs. In this thesis, I explore the impact of CDS trading on the cost of capital, corporate capital structure, and corporate social responsibility.

First, I use the universe of U.S. public firms to examine the impact of CDS trading on a firm's cost of capital during the period 2001 – 2018. My results robustly show that the inception of CDSs causes a significant reduction in a firm's weighted average cost of capital (WACC). Further analyses reveal that highly levered firms tend to reduce their debt weight, while firms with low leverage increase their usage of debt. Moreover, CDS referenced firms adjust their debt types by using more arm-length debts, while they simultaneously decrease the usage of revolving credits and term loans from banks. The alteration in capital financing choices may be ascribed to the improved information environment and reflects the fact that CDS trading increases debt renegotiation costs but simultaneously also reduces capital supply-side frictions.

After confirming that CDS can impact firms' financing decisions, I further investigate whether CDS trading can affect a company's investment in corporate social and environmental activities. A longitudinal sample spanning from 2002 to 2017 across 11 countries and regions was constructed to evaluate the impact. I find that the inception of CDS trading causes a significant reduction in the metric of environmental emission reduction. In addition, the initiation of CDS trading weakly but negatively influences other aspects of CDS firms' social and environmental performance. Further analysis reveals that investments in emission reduction activities have no relationship to shareholder value creation, whereas engaging in CSR activities related to, e.g., employee, community, or eco-product innovation, etc., increases shareholder wealth. Collectively, my findings reveal one of the downsides of CDSs arising from CDS-protected lenders who become less accommodating over post-CDS periods.

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CHAPTER ONE

INTRODUCTION

Credit default swap (CDS) is an insurance-like credit derivative contract in which CDS sellers compensate CDS buyers when the underlying entity referenced by CDS triggers prespecified credit events (e.g., bankruptcy, payment default, restructuring, etc.) over a fixed contract period. Since its initiation in the late 1990s, the CDS market has grown exponentially over its first decade. According to the Bank for International Settlements, the gross notation amount of CDS reached $17 trillion at the end of 2005, a 95-fold increase compared to its level at the end of 1997, and peaked at $62.2 trillion in 2007. While the CDS market has gradually shrunk over the post-financial crisis period, the notional amount of CDS has remained flat at around $10 trillion since 2016 (International Swaps and Derivatives Association, 2019). Given the importance of CDS in financial markets, it is crucial to quantify the real effects of CDS trading on the economy.

Unlike other derivative contracts (e.g., future, forward, etc.), CDS can materially alter the relationships between the borrowers (e.g., companies) and lenders (e.g., banks, insurance companies) (Hu and Black, 2008; Bolton and Oehmke, 2011) because CDSs grant insured lenders an alternative option in case of debt renegotiation or restructuring, i.e., when borrowers default, CDS sellers reimburse lenders. Hence, the protected lenders become less accommodating over debt renegotiation. Furthermore, insured lenders have shifted the credit risk of borrowers to CDS sellers. Therefore, lenders may shirk their monitoring efforts on the borrowers because they cannot extract the same level of benefits from monitoring as before.

The alteration in the lender-borrower relationship consequently changes the incentives of the firms' decision-makers and thus has real economic effects on corporate policies and activities. Researchers have revealed various externalities induced by CDS trading, for example, less conservative accounting standard (Martin and Roychowdhury, 2015), further voluntarily disclosing corporate public information (Kim et al., 2018), enhanced corporate innovation (Chang et al., 2019), and more. However, no research has been developed on the influence of CDS trading on corporate social responsibility (CSR). Given the fact that modern businesses and communities have embraced CSR with open arms, evidenced by the tremendous fund managed with CSR metrics (see the Forum for Sustainable and Responsible Investment, 2018 Facts), it is meaningful to fill in this gap.

Furthermore, empirical researches on how CDS affects a firm's investment activities, and thus its value, have reached mixed results. For example, Narayanan and Uzmanoglu (2018b) find a decline in firm value after CDS trading, while Danis and Gamb (2018) conclude that a firm's value increases once CDSs refer its debt. To address this controversy, I assess the overall benefits and costs induced by CDS trading by analyzing the impact of CDSs on firms' weighted average cost of capital (WACC). I use WACC instead of Tobin'q to indirectly measure the influence of CDS trading on a firm's value because scholars have challenged Tobin'q as a proxy of a firm's value (Bartlett and Partnoy, 2018) and WACC is determined by the capital markets. As a result, WACC reflects the market participants' opinions on the risk of the focal firm. If CDS trading brings more costs than benefits to a CDS firm, thus increasing the firm's risk, we would observe an increase in WACC. The reverse is true as well.

I explore the effects of CDS trading on WACC in Chapter 2. I construct a panel sample using the universe of US companies from Compustat over 2001 - 2018 to conduct my tests. To assess the impact of CDSs on corporate capital structure, I also obtain debt compositions from Capital IQ. After integrating all sources of data, my final sample contains 48,850 firm-year observations from

5,575 firms, of which 8,597 firm-year observations belong to 677 CDS firms, and 40,253 firm-year observations come from 4,898 non-CDS firms.

With the large sample, I find strong statistical evidence that CDS trading brings more benefits than costs to the focal firm and causes a significant reduction in WACC. The estimated coefficient is -23.9 basis points (BPs) and is significant at the 1% level. In an economic sense, the decline of -23.9 BPs in WACC is equivalent to a decrease of $21.85 million in firm financing costs. Furthermore, I also find that CDSs exert diverse effects on firms with different leverage ratios. Post-CDS trading, highly levered firms prefer decreasing their debt level, while firms with low leverage desire to increase their usage of debt by reducing equity issuances. Such diverse functions of CDSs reflect the threatening and credit supply effects of the empty creditors hypothesis.

I investigate the impact of CDS trading on CSR performance in Chapter 3. I construct a longitude sample of globally public companies from eleven countries and regions over the period from 2002 to 2017. The corresponding financial fundamental data was extracted from Worldscope. I measure the companies' CSR performance with Thomson Reuters ASSET4 environmental and social (E&S) scores. After removing all lost data, my final sample has 23,901 firm-year observations from 3,383 firms.

By employing a multivariate panel regression and controlling firm-year fixed effects, I find robust evidence that CDS trading significantly and negatively impact a firm's environmental emission reduction activities. The estimated coefficient of CDS trading is -4.9%, with a p-value of 0.065. To obtain an economic sense of the decline in emission reduction, I regress selling, general and administrative (SG&A) expenses on emission reduction score, and then convert the decline into an absolute dollar amount. I find that, on average, CDS firms cut their investment on environmental emission reduction activities to the amount of $35.94 million based on the mean of SG&A

expenses of CDS firms. I also find that CDS trading negatively but weakly affects other CSR performance. I use several robustness tests to verify my findings, including propensity score matching, event study, Monte Carlo simulation, and various subsamples tests. All analyses corroborate my main tests from the whole sample.

CHAPTER TWO

Credit Default Swaps and the Cost of Capital

1. Introduction

Credit default swaps (CDSs)[1] are credit derivatives whose primary purposes include hedging and the trading of credit risks. Unlike other derivatives, such as options or futures, CDSs materially alter lender-borrower relations (Bolton and Oehmke, 2011) and thus have real economic effects on the companies referenced by the CDSs. 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 bankruptcy risk of referenced firms (Subrahmanyam et al., 2014, 2017). In this study, I aim to evaluate the overall costs and benefits of CDSs on the economy by investigating whether the introduction of CDSs can induce a change in a company's weighted average cost of capital (WACC). In addition, I explore the channels through which CDSs drive the 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, by either reducing the WACC or increasing expected returns. 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

[1] Credit default swaps are credit derivatives that compensate CDS buyers (e.g., corporate bond holders, speculators, etc.) 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. A CDS is labeled a single-name CDS if it references the debt of a single entity, such as a corporation.

company. Arguably, if the benefits of CDSs outweigh their costs for the focal company, market participants will lower their required return which will result 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, changes in a firm's WACC following the introduction of a CDS provide us with a barometer of the effects of CDS trading for a given firm.

A large body of literature examines the externalities induced 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; Narayanan and Uzmanoglu, 2018a, 2018c; Fuller at al., 2018; Kim et al., 2018; Batta and Yu, 2019; and Chang et al., 2019). For instance, Martin and Roychowdhury (2015) examine whether the introduction of CDSs causes firms to change their financial reporting practices. My study is different from prior studies in that it evaluates the overall effects of CDSs. As such, my study is close to the prior papers by Narayanan and Uzmanoglu (2018b) and Danis and Gamb (2018), both of which examine the influence of CDSs on firm value. Interestingly, the two studies reach contradictory conclusions. Narayanan and Uzmanoglu (2018b) use Tobin's q to proxy firm values and observe a decline in firm value following the inception of CDS trading, while Danis and Gamb (2018) use simulated US corporation data and document an increase in firm value. My study will address this controversy by analyzing how CDSs affect firms' WACC. An increase in WACC will suggest a decrease in the firm's value and vice versa.

My research is related to studies that examine 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 my understanding of the mechanisms through which CDSs affect bond and loan costs. However, it is evident that bond and loan instruments are only a few methods that firms use to raise capital. Public companies generally employ various types of debt (e.g., syndicated facilities, term loans, revolving credits, and bonds) to attract investors (Rauh and Sufi, 2010; Colla et al., 2013). Therefore, it is important to examine the impact of CDSs on the overall cost of capital of a firm.

My empirical 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 referenced firms (hereafter, CDS firms). In terms of negative effects, they hypothesize that CDSs grant insured lenders[3] improved bargaining power over ex-post debt renegotiations. Thus, those lenders become less accommodating in out-of-court debt workouts. Furthermore, overly insured lenders may have less or even no interest in the continuation of distressed companies, because if the CDS firm goes bankrupt, they 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.

CDS trading lays a variety of costs on 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

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

[3] We use CDS protected lenders, insured lenders, lenders, creditors, or CDS buyers interactively. 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 of the CDS markets and facilitate transactions in the markets but may not alter the lender-borrower relations, hence they do not have a direct real effect on the referenced companies.

a heightened risk after CDS trading, capital suppliers will usually demand higher returns 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 CDS firms significantly increase cash holdings and conclude that such a conservative liquidity policy adopted by CDS firms results from the threatening effects of tougher lenders. Such 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 significant 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 engaging in distressed exchanges. The lower participation rate or holdout problem would eventually halt the debt workout. Ultimately, shareholders would bear these costs caused 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 increase the business 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 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 serve 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 increase the loan spread. Furthermore, Martin and Roychowdhury (2015) show that CDS trade initiation results in a decline in borrowing firms' reporting conservatism. Kim et al. (2018) demonstrate that the executives of CDS firms voluntarily disclose more public information (such as earning forecasts) after CDS trading because shareholders intend to make up for the reduced monitoring efforts of creditors and hence demand more information to monitor the firm. The decrease in reporting conservatism can increase business risks and the disclosure of firms' information can incur additional business costs as well.

I have discussed heretofore negative effects arising from CDS trading, but researchers have also found evidence of the positive effects of CDS trading. In their theoretical model, Bolton and Oehmke (2011) argue that CDSs could serve as a commitment device for borrowers to avoid strategically debt defaults. 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).

[4] A bank can purchase CDSs to protect its credit risk exposures to risky borrowers, and then the bank can replace the credit risk of borrowers (usually high) by the CDS seller's credit risk (usually pretty low). By doing so, the bank can shift assets from high-risk categories into zero-risk ones (e.g., the CDS seller, usually a triple A rated firms, could be

Such commitment and risk hedging functions of CDSs can reduce the frictions on credit supply sides and make insured lenders more willing to extend their credits, reduce the charged interest rate, and use fewer covenants and collaterals (Shan et al., 2019). Empirical studies find solid evidence to support these risk hedging and commitment effects. 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) reach a similar conclusion as 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 CDS firms' leverage over post-CDS periods.

While the above studies focus on the impact of CDS trading from the borrowers' perspective, other studies have examined the issue 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 referenced companies, implying an increased credit supply after CDS trading. Like Hirtle (2009), Shan et al. (2016) show that banks using CDS 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

deemed to have zero risk) and still comply with regulatory capital requirement. Therefore, the bank can have more available capital that was released from the risky borrowers.

can enhance the firms' financial flexibility and reduce their financial constraints, ultimately promoting economic growth.

CDSs also benefit firms by improving their information environment (Stulz, 2010; Berndt and Ostrovnaya, 2014). The major participants in CDS markets are banks and 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 significant information incrementally revealed in CDS markets flows into equity markets, implying the existence of private information in CDS markets. Batta et al. (2016) find that the quality of analysts' forecasts has been significantly improved after CDS trading. They conclude that CDS trading reveals the informed traders' privileged information to equity markets. 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 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 priorities. I test this hypothesis in this study.

While I illuminate both positive and negative effects of CDS trading on firms, I specify that the functions of CDSs are complex and need to be analyzed case by case. For instance, though I 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. They suggest that lenders use CDSs as a substitution for debt covenants and collaterals because their monitoring is costly to the lender. Using CDSs for strict covenants and collaterals may improve loan contract efficiency for both lenders and borrowers, and thus may have positive effects on CDS firms.

As a result, CDS trading gives rise to 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. On the contrary, the benefits arising from decreasing frictions in credit supply (as a consequence of risk shifting and commitment effects of CDSs), as well as 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.

To explore the effects of CDS trading on WACC, I construct a panel sample using the universe of US companies from Compustat from 2001 to 2018. I collect CDS data from Markit and then manually match CDS firms with Compustat firms according to Markit Reference Entity Database (RED) and LexisNexis. I obtain debt compositions from Capital IQ and the cost of capital data from Bloomberg. My final sample contains 48,850 firm-year observations from 5,575 firms. Using this large dataset, I find strong evidence that CDS trading causes a significant reduction in the WACC for CDS firms across samples and estimation measures. The estimated coefficient of -23.9 basis points (BPS) on CDS initiation based on the firm-year fixed framework is significant at the 1% level. This decrease in the WACC is not only statistically significant, but also economically meaningful. With the average capital provided by equity and debt holders ($9.143 billion), this decrease in WACC is equivalent to a decline of $21.85 million in firm costs. To substantiate my results, I use quantile regressions over various quantiles and find consistent results.

My finding on the cost of equity is not straightforward, as the estimation suggests that CDSs either increase or have no effects on the cost of equity. Prior 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 (Ashcraft and Santos, 2009; Hirtle, 2009). I conjecture that CDS trading has contrary effects on the shareholders of riskier and safer firms. To examine my hypothesis, I categorize firms with a rate of 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, but in the meantime their investors demand higher returns on the cost of equity after CDS trading. To substantiate my findings, I segment firms into three groups based on Bloomberg five-year predicted default probability. I re-estimate my baseline model with subsamples that have a low and high default probability, respectively. The results from subsamples with high and low default probability are consistent with those from subsamples with high and low credit quality.

To substantiate my conclusions, I re-estimate my baseline model with a dummy variable that indicates the termination of CDS trading. If the initiation of CDS trading can bring more positive effects on firms than negative effects so that I see a decrease in the WACC, then I should observe an increase in the WACC due to the cessation of CDSs. I find a significant and positive estimate on CDS reversal variable, validating my conjecture and conclusions from main sample. I further use an alternate of Bloomberg WACC, the empirical WACC (EWACC) which use rolling windows regression of net operating profit after taxes (NOPAT) on total capital, in my baseline model. The consistent estimates using EWACCs as dependent variable indicate that my results are not driven by Bloomberg WACCs.

I also use several standard econometric mechanisms to validate my results. To address sample selection bias and endogeneity concerns, I construct propensity score marching (PSM) samples. The results from various PSM samples are in line with my prior results. To fully eliminate the sample selection concerns, I estimate the baseline model with CDS firms only. I observe negative and significant estimates on the CDS initiation when using the cost of debt as the dependent variable, consistent with my main sample results. I further introduce variables to control 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.

My tests are subject to reverse causality concerns. It may be the case that investors anticipate the reduction in the cost of capital and consequently initiate CDSs to profit from the anticipated reduction of CDS spreads in the future. To address the reverse causality and further validate my results, I construct the first difference samples and test the baseline model on them. The results validate my main sample tests. I use the CDS initiation as the dependent variable and regress it on the changes in the various measures of the cost of capital. I find insignificant coefficients on the changes of various capital costs, indicating that there is no reverse causality in my tests.

The initiations of CDS in my sample have clustered before 2007, and such a cluster creates concerns that it is some grouped events that drive the results instead of CDS initiations. To address this concern, I follow Bekaert et al. (2005) and Chang et al. (2019) to use a Monte Carlo simulation. The results from the simulation indicate that CDS firms and their initiation dates must match. Therefore, my results are not subject to event clustering issues. I also use CDS trading liquidity variables to substitute for the CDS availability indicator variable. Estimates using CDS daily notional volume and number of clearing dealers further corroborate my findings.

After validating my results with a battery of tests, I 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. I test this conjecture with both firm-fixed effects model and quantile regressions. The estimate of regressions of debt weight on CDS initiation from firm-fixed effects models is positive and marginally significant at the 10% level, 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 capital mix. However, my 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, I 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 indicate 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. On the contrary, 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. In equilibrium, the contrary effects of CDSs on debt usage cause a marginal decrease in debt issuance on average.

By excluding the channel in changing the debt weight to reduce the WACC, managers can also reduce the cost of debt to lower 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 employed 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. Post-CDS trading, the cost of capital may increase (or decrease) even though the bond spreads reversely decrease (increase). 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, I 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 problems, bank debt become less attractive to firms than before. Furthermore, the monitoring benefits of bank debt are weakened as well. Therefore, I conjecture that firms may substitute public debt for bank debt. I borrow the definitions from Lin et al. (2013) for public debt, described as the sum of various bonds, notes, and commercial papers, and for bank debts, described as the sum of bank loans, term loans, and revolving credits. I test my conjecture by regressing the ratios of each debt category to the total debt on CDS initiation. I find negative and significant estimated coefficients for revolving credits. Meanwhile, CDS firms significantly increase the weight of arm-length debt, demonstrated by the positive and significant estimates. Finally, I test the relations between the measures of capital costs and various debt ratios and find evidence that the cost of debt is significantly and positively related to the cost of bonds but significantly and negatively related to bank debts. These findings suggest that it is the substitution of bonds or notes for bank sources of financing that causes a decrease in the cost of debt and hence the overall cost of capital.

Post-CDS trading, CDS firms alter their debt priority to capture the benefits induced by CDS trading and avert the costs associated with it. I conjecture that firms use more arm-length debt to replace revolving credits to avoid rollover risks. To substantiate my rollover risk explanation on the reduction of revolving credits, I re-examine the relation between ratios of revolving credits to total debt and CDS initiation with two groups of firms whose default probability lies above the 66% quantile and below the 33% quantile, respectively. Looking into the estimated coefficients under firm-fixed effects models, I find that the coefficient is significant at the 1% level and has a larger magnitude in the sample with higher default probability, compared to the corresponding estimate from the whole sample. More importantly, the corresponding estimate from the sample with low default probability is not significant at all. Such a sharp contrast in the estimates suggests that firms with high risk may run into more rollover risk after CDs trading because of the revolving credits. Therefore, firms adjust the usage of them when considering financing choices.

My study contributes to the growing literature on the effects of CDS trading. Different from 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), I consider the overall costs and benefits of CDS trading on the economy. My results robustly show that the costs of capital are significantly reduced after CDS trading. Furthermore, I 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 low credit quality require higher returns to compensate their increased risk associated with CDS trading. My study also contributes to the capital structure literature. I show that after CDS trading, CDS firms with improved information environment prefer arm-length debt to bank debt. Thus, financial market innovation, particularly CDS, can affect companies' debt compositions.

The rest of the paper is organised as follows. In section 2, I describe my data sample and summary statistics. I present the test methodology and baseline results in section 3, and robustness tests are conducted in section 4. I make extra analyses in section 5, and section 6 concludes.

2. Sample data, variables, and summary statistics

2.1 Data sources and sample construction

To construct my research sample, I 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.

I start with the universe of US public firms covered by Compustat from 2001 to 2018. Following prior studies (e.g., Saretto and Tookes, 2013), I exclude financial firms (such as banks and insurance companies, etc.) whose standard industrial classification (SIC) codes are within 6000-6999. I first merge Compustat and CRSP datasets and require firm-year observations to have nonmissing total assets and debt on Compustat. I also drop observations with missing book and market values of equity, resulting in a sample of 87,124 firm-year observations from 8,984 firms. I 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).

I start my sample period from 2001 to coincide with the availability of the Markit's CDS trading quotes. Following Subrahmanyam et al. (2014) and Amiram et al. (2017), I assign the first trading date of a CDS contract with five-year maturity denominated in the US dollar on the referenced company to the CDS initiation date. I manually match each CDS firm from Markit to Compustat firm by using Bloomberg RED tracking events database[5] and further validate CDS firms by exploring company events from LexisNexis[6]. Following Narayanan and Uzmanoglu (2018b), I trace a subsidiary that has been inferred by CDSs back to its parent company[7]. I follow studies (Kim et al., 2018; Amiram et al., 2017) to 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 that month onwards. Finally, I obtain 873 non-financial US public firms who have been referenced by CDSs sometimes over the period 2001 to 2017[8]. For all CDS firms whose trading dates fall in 2001, I further verify those dates using Bloomberg and do not find invalid ones (i.e., the trading dates start before 2001).

Next, I obtain debt structure variables from 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 fillings (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 up data, I first select data

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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 the Compustat database.

[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.

items with last filling or the only filling reports (i.e., *FILLINGFLAG_COMPANY* = 2 or 3). I also restrict reports to those that are the latest instance for the filling date and financial period (i.e., *LATESTFILINGFORINSTANCEFLAG* =1 and *LATESTFORFINANCIALPERIODFLAG* =1). I further remove duplicates by following Choi et al. (2018). For company-year observations, I require observations not to 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, I 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*), I 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. I 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 used one. Last, I aggregate all fined-grained debt components based on their type at an annual frequency. I then merge Capital IQ and Compustat/CRSP based on ISIN.

I extract stock analyst data from Bloomberg and I/B/E/S. Because Bloomberg has more extensive coverage than I/B/E/S over my sample period, I use data from the former for my analyses and data from the latter for robustness tests. I acquire top executives' (e.g., CEO, CFO, etc.) stock ownership from Execucomp, institutional ownership from Thomson Reuters Institutional Holdings

[9] Although we remove duplicated reports using the abovementioned approaches, duplicated reports in terms of unique debt issues 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.

(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), respectively. I integrate those data into Compustat sample based on ISIN and retain only the observations that have no missing control variables discussed in section 2.2. Besides, following prior studies (e.g., Fuller et al., 2018; Colonnello et al., 2019), I exclude firms with zero long-term debt and total assets of less than $10 million. My final sample contains 48,850 firm-year observations from 5,575 US public firms, of which 8,597 firm-year observations belong to 677 CDS firms and 40,253 firm-year observations come from 4,898 non-CDS firms[10]. Furthermore, 41,077 observations have Capital IQ debt structure data from 5,250 firms. In line with prior studies in capital structure, I winsorize all accounting variables at the bottom and top one percentile to reduce the influence of potential outliers.

2.2 Variables

2.2.1 Dependent variables

I draw WACC data from Bloomberg directly for two reasons: Bloomberg specialists evaluate the cost of debt for companies using fair market value (Bloomberg function FMV), and a multitude of institutional investors use the Bloomberg platform to refer to 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. In detail, I extract the following data as my dependent variables: WACC, cost of debt, cost of equity, weight of debt, and weight

[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 39,200 firm-years because Compustat provides tax rates until the 2016 fiscal year.

of equity[11]. The detailed definitions and computation of these variables can be found in Appendix 2.2.

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, I construct other explained variables from Capital IQ. Particularly, following Lin et al. (2013), I use the ratios of bank debt and public debt to total debt as two measures of the preference for debt financing. The bank debt is the sum of revolving credits and loans from banks, the public debt is the sum of commercial papers and bonds and notes, and the total debt is the sum of all seven types of financing mechanisms mentioned above. In addition, I follow Colla et al. (2013) to compute 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.

2.2.2 Independent variables

Following prior studies in the stream of CDS (e.g., Ashcraft and Santos, 2009; Martin and Roychowdhury, 2015; Chang et al., 2019), I 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. I 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

[11] We evaluate the changes of 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.

(i.e., never have traded CDSs on their debts over the sample period). Thus, this dummy variable would capture the time-invariant divergence from unobservable firms' characteristics between CDS and non-CDS companies.

Besides the dummy variable *CDSINIT*, which indicates the availability of CDSs, I employ two alternatives that measure the liquidity of CDS trading, the average daily trading notional scaled on total debt, 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, I conjecture that the more liquidy the CDS markets have, the more significant the effects of CDSs will be on referenced firms. I follow Narayanan and Uzmanoglu's method (2018c) to assign zeros to these two alternative measures of CDS trading activity, if DTCC did not report the trading data[12].

2.2.3 Control variables

A multiple of the firm's internal and external factors can affect the focal 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 (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-

[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 may not cause biased estimates.

length debt, less information asymmetry, or higher credit rating. Furthermore, the firms are not randomly selected to trade CDSs. The factors that contribute to the cost of capital may also the determinants of CDS trading. Therefore, I also control factors related to CDS firms' selection.

To isolate the effects of CDS trading on WACC, I 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. I use the logarithm of total assets[13] to control firm size effects. Saretto and Tookes (2013) argue that larger firms undergo less adverse selection when issuing equities than small or medium counterparts because these firms are more transparent and have a higher credit rating. Following Chang et al. (2019), I 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 the firms' maturity relates to the firms' borrowing costs because a mature firm has less information asymmetry than younger ones. Following Loderer and Waelchli (2010), I proxy firm maturity by a firm's age. I first select the earliest date of a firm's

[13] We substitute log of sales for log of 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.

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 (1997) theorizes that firms with high growth opportunities may use less debt to avoid suboptimal investment issues. I control the firm's growth prospects by using the market-to-book asset ratio. I also follow Titman and Wessels (1988) to use capital expenditures scaled by sales to capture the firms' future growths. According to the pecking order theory of Myers and Majluf (1984), profitability would be an important factor in determining capital structure. More profitable companies may use less external financing sources and thus may have less cost of capital. I define profitability by the ratio of earning before interest and tax (EBIT) divided by assets. Titman and Wessels (1988), 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 and hence increase 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, I control for the tax rate, product uniqueness, and liquidation cost. I proxy the firm's product uniqueness by the ratio of research and development expenses to sales. Following Almeida and Campello (2007) and Kim (2016), I 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, I use the marginal tax rate computed by Blouin et al. (2010). I 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, I 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 the cost of capital. I 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 claimholders 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. I use stock return volatility computed from the past five years weekly stock prices to proxy business risk. Additionally, I 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. I 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, I control for stock liquidity effects on the cost of capital. I define stock liquidity as stock trading turnover by volume scaled on the outstanding common shares. I present the sample statistics of controls in Table 2.1.

2.3 Sample characteristics

Panel A of Table 2.1 reports the distribution of CDS firms by the initiation year. I observe the clustering of CDS trade initiations, evidenced by 90 percent of CDS inceptions centralized in the period from 2001 to 2007. After that, the initiation significantly decreases in part due to my research design, i.e., I only identify new CDS firms for my research. Martin and Roychowdhury (2015) argue that the financial crisis may contribute to the decrease in CDS initiations as well. My sample shows a similar pattern to that of Kim et al. (2018). For example, Kim et al. (2018) record 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, my sample has 21.7, 15.4, 17.8, 15.1, and 6.2 percent of CDS initiations, respectively. The absolute numbers of CDS initiations are also close in these two studies. I show the distribution of CDS firms by one-digit SIC code in Panel B. As shown, firms in manufacturing industry (such as food, petroleum, paper, printing, rubber, stone, and computer) are more prone to trade CDSs, demonstrated by the high percentage of firms, 45.6% of the sample.

<Insert Table 2.1 about here>

Turning to Panel C of Table 2.1, which presents the means, medians, and mean differences between CDS and non-CDS firms across firm-level characteristics, the upper part of Panel C shows the summaries of explained variables, and I observe that the cost of debt and equity of CDS firms are significantly greater than the ones of non-CDS firms. Notably, though 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, which use more equity capital.

Debt priority 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 68.6 and 35.8 percent for CDS and non-CDS firms, respectively. Furthermore, 50.2 percent of total debt are from banks for non-CDS firms, while this percentage decreases to 18.2 for CDS firms. This divergence could be explained by the difference in firms' information environment as per Diamond (1991) and Rajan (1992). I find related evidence for such explanation. In my sample, a larger number of stock analysts follow CDS firms rather than non-CDS firms. On average, there are 13.93 analysts recommending CDS firms' stocks, while only 5.59 analysts for non-CDS firms.

I 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 S&P, and employ higher financial leverage than non-CDS firms. Those finding are consistent with prior literature regarding the properties of CDS firms (Subrahmanyam et al., 2014; Martin and Roychowdhury, 2015; Chang et al., 2019). Martin and Roychowdhury (2015) argue that to alleviate information disadvantages comparing to the CDS buyers who generally originate loans, CDS sellers are more inclined to write CDSs for larger and mature firms. I also observe that CDS firms pay higher dividends and have higher stock trading liquidity than non-CDS firms. Regarding institutional ownership (IO), institutional investors tend to hold more shares of CDS firms than non-CDS firms. On average, institutional investors hold about 70.4 percent of common shares of CDS firms. In contrast, institutional shareholders hold only about 43.0 percent of non-CDS firms' common shares. However, the HHI of IO indicates that CDS firms have more dispersed ownership (0.064 of HHI) than non-CDS firms (0.154 of HHI). In addition, CDS firms are more mature than non-CDS ones. The average firm's age is 32.77 and 18.08 years for CDS and non-CDS firms, respectively.

I present CDS trading activity in Panel D of Table 2.1. The mean of *CDSINIT* is 0.154, indicating that 15.4 percent of firm-year observations have CDS traded over the sample period. Last, I present the Pearson correlations matrix of variables in Panel E of Table 2.1. As shown in the table, the correlation between *CDSFIRM* and *CDSINIT* is 0.92[15] and significant at the 1% level. The high correlation is the result of the variable construction methodology, 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 0.56, between S&P rating and log of assets), implying that my tests will not suffer from multi-collinearity problems. Furthermore, the lower correlations among controls also indicate that these controls capture the different aspects of firms' 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) will use fewer bank debts than younger ones (e.g., non-CDS firms).

3. Methodology and empirical results

3.1. Baseline specification

I aim to explore the relationships 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), I use the difference in difference (DID) mechanism to investigate such relationships in a multivariate panel regression model. Specifically, I estimate the following baseline model with industry- or firm-year fixed effects[16]:

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

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

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

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

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

where $Cost\ of\ capital_{i,t}$ is one of the explained variables (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 would capture the DID 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 2.2. I lagged all controls one year because the initiation of CDS trading may not have affected 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. I 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, I incorporate year effects in my specification to capture aggregate time trends in the firms' cost of capital. Following the suggestion of Petersen (2009), I cluster the standard errors at the firm level, given that observations of the same firm are autocorrelated.

3.2. Empirical results

Table 2.2 reports the estimates of the baseline model (1). In columns (1) and (2) of Table 2.2, I 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 models, respectively. I repeat the test under firm-year fixed effects but control for marginal tax rate this time, as reported in column 3[17]. As shown in the first three columns of Table 2.2, the overall cost of capital significantly declines after the inception of CDS trading. The declines in WACCs range from 22.7 to 28.1 basis points and are significant minimally at the 1% level. This reduction is not only statistically significant, but also economically meaningful. Using the average capital ($9.42 billion) of CDS firms contributed by equity and debt holders, the declines in required return, when converted into monetary amount, are of $20.7 to $25.7 million. To examine whether my tests are vulnerable to potential outliers, I 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 1% level, substantiating my results in Table 2.2. The estimated results from quantile regressions are reported in Table 2.3.

Turning to the estimates of the cost of debt, I find consistent evidence of declines, significant at the 1% level across testing approaches and samples, in the cost of debt. Regarding results from the cost of equity tests, I observe positive estimates across samples, suggesting that investors required higher returns after CDS trading. This finding is consistent with Narayanan and Uzmanoglu (2018c) who ascribe the increase in equity returns to the increased bankruptcy risk after CDs trading. However, I find an insignificant estimate from the industry-fixed effects model. I observe contrary estimates between firm-fixed (0.242 with a *t*-statistic of 2.32) and industry-fixed (-0.245 with a t-statistic of -2.34) effects models, and both are significant at the 5% level. As per these controversial estimates, I hold my conclusions on the cost of equity and address this issue in section 3.3.

[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 48,850 to 36,388 observations. The tax rate data was computed by using a non-parametric procedure by Blouin et al. (2010).

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 2.2 about here>

<Insert Table 2.3 about here>

The coefficients on controls are in line with prior literature. For example, all coefficients on profitability are negative and significantly 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 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, I 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, the larger and significant coefficients on liquidity variables demonstrate that stock trading liquidity proxied by stock volume turnover, which is scaled by outstanding common shares, has more negative effects on equity holders than on debt holders. This situation reverses when examining leverage effects. Debt holders require higher compensation for highly levered firms, while high leverage ratios seem not to affect equity holders. In addition, shareholders value more dividend payments, demonstrated by significant negative coefficients on dividend payments, while debt holders frown on dividend payments and require higher returns. Lastly, firm size is positively related to the cost of debt and equity, suggesting that firm size is a risk factor to capital contributors.

Turning to estimates of quantile regressions in Table 2.3, I have several interesting findings. For instance, the estimated coefficients on profitability support both the trade-off and pecking order theories. In column (1) of Table 2.3, the positive coefficient on profitability (0.308) is significant at the 1% level, indicating a positive relation between profitability and cost of capital. This estimate implies that when a firm has a high earning capability but employs a conservative debt policy, i.e., using a very low financial leverage ratio, the firm loses value because of the wasting tax shield benefits of interest expenses. Likewise, looking at the estimate on riskiness in column (1) of Table 2.3, I note that the coefficient on volatility is negative and significant at the 1% level, suggesting that low levered firms could benefit more from increasing business risk. Similarly, I also observe contrary signs for the coefficients of firm's age for firms with lower and higher costs of capital.

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

The baseline test provides 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, the evidence on the cost of equity is not straightforward. I 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 relies 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, I hypothesize that CDSs may positively affect shareholders in high-rated firms while negatively influence equity holders in low- or non-rated firms. The insignificant estimates of regressions of the cost of equity may be due to the mixed sample firms, i.e., the sample includes both high- and low-rated firms. To test this conjecture, I 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, and zero otherwise. I re-estimate my baseline model (1) using the high- and low-rated sample firms and report the results in Table 2.4.

<Insert Table 2.4 about here>

Panel A of Table 2.4 shows the estimates using high-rated firms. Starting with the cost of equity, I find consistent evidence that CDSs reduce the cost of equity for high-rated firms. The coefficients are negative and significant at either the 5% or 10% level. Turning to Panel B, which shows estimates from low- and non-rated rated firms and sharply contrasts with the results of high-rated firms, I find positive coefficients of regressions, significant minimally at the 5% level, on the cost of equity. This evidence suggests that the mixed results before may be partially due to the mix samples. The positive effects on the cost of equity from high-graded firms are counteracted by the negative effects from low- and non-rated firms. Furthermore, I note that the estimated coefficients from regressions of the cost of debt in high-rated samples are not significant at the 10% level, suggesting that high-rated firms did not capture the benefits from debt financing after CDS trading. In contrast to high-rated firms, low-rated firms significantly reduced their cost of debt post-CDS trading.

To substantiate my results above, I proxy a company's credit quality, provided by Bloomberg, for a five-year predicted default probability and re-sample firms into high and low default groups. Particularly, I classify firms whose default probability lies above the high 66% percentile into the high-risk group, while firms with a default probability in the lower 33% percentile are sampled into the low-risk group. I estimate the baseline model using the high and low default risk samples and present the results in Table 2.5.

<Insert Table 2.5 about here>

The results in Table 2.5 support the findings based on credit quality samples. Starting from Panel A of Table 2.5, I observe negative coefficients of regressions on the cost of equity. Both estimates are significant at the 5% or 10% level, suggesting that CDS trading brings down the cost of equity. In contrast, the estimates from high default sample are positive and significant at the 1% or 5% level. These findings indicate that shareholders in high-risk firms demand higher returns after CDS trading. Interestingly, in Panel B, the estimates from the cost of debt are negative and significant at least at the 5% level. The positive effects on the cost of debt and negative effects on the cost of equity in high-risk firms cancel each other, resulting in less positive effects on the overall cost of capital. Turning back to Panel A, like with the high credit sample, I find estimates from the cost of debt that are insignificant, implying that firms with a low default probability did not capture benefits from channels related to debt financing. Different from high credit sample, I note that firms with a low default risk seize significant benefits by lowering the overall cost of capital, demonstrated by the negative and significant estimates from the cost of capital. These findings corroborate Ashcraft and Santos's (2009) arguments as well as my conjectures. The results from Tables 2.4 and 2.5 disclose that CDSs bring benefits to high-credit firms mainly through the channel of reducing equity cost[18], 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 2.2, 2.3, 2.4, and 2.5 suggest that equity investors hold diverse views regarding CDS trading. Shareholders in firms with a high default risk or low credit quality view negatively CDS trading and therefore require a higher return to compensate for the risk. Such an increase in the cost of equity complies with Bolton and Oehmke's (2011) threatening

[18] The overall cost of capital for investment graded firms is decreased but not significant at the 10% level. One reason is that the sample firms increases equity issuances, evidenced by the significant and positive estimated coefficient when regressing Equityweight on *CDSINIT* variable, i.e., firms in investment graded sample increase their equity weight after CDS trading on their debt.

effects of CDS. In contrast, shareholders in firms with a low default risk or a high credit quality 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 low credit or high default risk firms. This finding implies that high and low credit firms capture the benefits of CDS trading through different channels.

The decreased cost of debt may be due to external lenders. For example, Ivanov et al. (2015) argue that debt holders may pass some of the benefits of CDS trading to borrowers by requiring a lower interest rate. These benefits include decreased costs in monitoring, less contracting expenses, or easier hedging (Shan et al. 2019). However, I point out that 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 debt types, firms can also decrease the cost of debt and capital as well. I discuss the channels through which firms reduce WACC in Section 5. Furthermore, although the tax rate affects the cost of capital, it does not materially alter the results. To reduce sample attrition, I ignore the tax rate in the following tests. In the next section, I validate my results with some robustness tests.

4. Robustness tests

Prior studies (e.g., Subrahmanyam et al., 2014, 2017; Martin and Roychowdhury, 2015; Chang et al. 2019) find that CDS referenced companies are usually larger, have investment grade ratings, less information opacity, and relatively high credit. This finding is in compliance with the theory of adverse selection, i.e., CDS sellers desire to sell protection to trustworthy companies that are more visible (i.e., have less information asymmetry) and highly rated to lower their information disadvantage comparing 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 could 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, I follow the literature (Ashcraft and Santos, 2009; Subrahmanyam et al., 2014; Martin and Roychowdhury, 2015; Kim et al., 2018; Chang et al. 2019) to use various robustness tests, including the reversal of CDS test, empirical WACC test, propensity score matching sample, CDS samples only, Monte Carlo simulation, the first difference sample, and CDS liquidity variables to proxy CDS availability.

4.1 The reversal of CDS contracts

Following Narayanan and Uzmanoglu (2018b), I introduce a dummy variable, *CDS-reversal*, which has a value of one for CDS firms in the years immediately following the termination of CDSs, and zeroes otherwise. The rationality is that if the initiation of CDS trading can lower the WACC because of more benefits induced by CDS trading, the termination of CDSs may cause an increase in the WACC, since the accompanied benefits may be removed by the termination of CDS. For instance, the lenders may be unwilling to increase their credit supply to those past 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, I include *CDS-reversal* as another independent variable in the baseline equation (1).

I report the regression results in Online Table A1. Columns (1) of Online Table A1 reports estimates with industry-year fixed effects model. The coefficients of *CDSINIT* and *CDS-reversal* are -0.460 (t-value of -5.14) and 0.276 (t-value of2.57), respectively. Both estimates are significant at the 1% level. This evidence indicates that investors may charge a higher interest rate after the termination of CDSs, which causes an increase in the WACC. Another explanation is that CDS firms adjust their capital structure, using more equity financing when CDSs cease., Turning to column (2) which shows the estimates based on firm and year fixed effects model, I observe a negative coefficient of *CDSINIT* and significant at the 1% level as before. Still, I observe a positive estimate on *CDS-reversal* (0.049 with a *t*-value of 1.10), although it is not significant at the 10% level. Overall, those estimates support that the initiation of CDS trading would bring more benefits than costs to CDS firms, which cause a decrease in the WACC.

4.2 Alternate of Bloomberg WACC

I 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 my results because several approaches (e.g., the implied cost of capital, Fama-French three factors model, etc.) are used in practice to estimate the equity and debt returns (Frank and Shan, 2016; Olson and Pagano, 2017). To test whether my results are sensitive to BWACC, I use Olson and Pagano's (2017) approach to estimate an empirical WACC (EWACC) by using equation (2).

$$NOPAT_{i,t} = k_i\left(Total\_Capital_{i,t-1}\right) + \varepsilon_{i,t} \quad (2)$$

where $NOPAT_{i,t}$ is the net operating profit after taxes for frim *i* in the period *t*, $Total\_Capital_{i,t-1}$ is the average of the firm *i*'s book value and market value in the period *t-1*. The coefficient estimate represents an average WACC of a company over a period. Following Olson and Pagano (2017), I first compute the moving sums of four-quarter NOPATs for each firm, starting from the 1st quarter of 1993. I then use rolling windows analysis ranging from 16 to 22 quarters to regress *NOPAT*s on total capitals. The coefficients of regression (i.e., EWACCs) proxy the average cost of capital of a company over the rolling window period. I re-estimate my baseline equation (1) with EWACCs and report results in Online Table A2. I present EWACCs based on 16 and 20 rolling windows in the columns (1) and (2) of Online Table A2, respectively. Both coefficients of *CDSINIT* are negative and significant at the 5% level. This evidence corroborates my conclusions as per Bloomberg WACCs.

4.3 Propensity score matching (PSM) sample

I use the following probit model to assess the probability of CDS trading initiation.

$$\mathrm{Prob}\left(CDSINIT_{i,t} = 1\right) = \emptyset(\alpha + \theta X_{i,t-1} + \varphi \mathrm{Industry_k} + \omega \mathrm{Year_t}) \quad (3)$$

in which $\emptyset$ is the cumulative distribution function of standard normal distribution. *CDSINIT* is an indicator variable that has a value of one in and after CDS trading initiation, and zero before that. X is an array of firm level characteristics that are used to predict the inception of CDS trading. Following Chang et al. (2019), I 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), I 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 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, I 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.

Following Ashcraft and Santos (2009) and Subrahmanyam et al. (2014), I construct a probit sample by using all firm-year observations of non-CDS firms whose debts are never inferenced in CDS markets and firm-year observations of CDS firms up until the beginning of CDS trading, i.e.,

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

eliminating firm-year observations of CDS firms for the post-CDS trading periods. I estimate equation (2) with lagged one-year firm level characteristics over the period 2001 to 2017 and present the results in Table 2.6. The model (2) forecasts the onset of CDS trading reasonably well, as indicated by the high concordant percentage (96.4%) and pseudo-R^2 (44.6%). These statistics are comparable to 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 prior studies (Martin and Roychowdhury, 2015; Subrahmanyam et al., 2014, 2017; Chang et al., 2019). For instance, larger firms, firms with high leverage and less riskiness, and more 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 initiated 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 2.6 about here>

I generate control firms (non-CDS firms) for treated ones (CDS firms) by year. Specifically, I 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), I produce three control samples using different matching criteria to further verify my results and attenuate the constraints of the propensity score matching[20]. Specifically, I construct three control samples as follows: (1) the one non-CDS firm with the closest propensity score to the CDS firm; (2) the one non-CDS

[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.

firm with the closest propensity score to the CDS firm and within the same CDS firm's FF48 industry classification; and (3) the same rule as for sample 2 but using Fama-French 17 (FF17) instead of FF48 as exacting matching conditions. Furthermore, I allow a non-CDS firm to be matched to multiple CDS firms in control samples of 2 and 3 but not in sample 1 to produce diverse PSM samples. However, in samples 2 and 3, I require that the same non-CDS firm go into the control sample only once each year. In this way, I have unique firm-year observations throughout my samples, even though a non-CDS firm may serve as a control for several CDS firms. Finally, for all three control samples, I 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].

I present firm characteristics of the control-treated samples prior to the year of CDS trading initiation in Table 2.7. For brevity, I only present the statistics based on the matching criterion (1), which require no multiple matching when selecting the nearest matching non-CDS firm. By doing so, I have the exact number of treated and control firms in the sample. Under criterion (1), I successfully match 408 CDS firms from a total of 677 CDS firms. In Table 2.7, I observe that CDS firms and non-CDS firms are not significantly different in terms of *leverage, probability, growth, 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. Like prior studies (e.g., Martin and Roychowdhury, 2015; Subrahmanyam et al., 2014, 2017; Chang et al., 2019), in spite of carefully matching, I find that CDS firms remain different from non-CDS firms in size, firm age, riskiness,

[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 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.

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, I note that all explained variables, *WACC, cost of debt,* and *cost of equity*, are similar in statistics for both groups prior to the CDS trading. Therefore, there are no trends in the firm characteristics that may cause variances between CDS and non-CDS samples post-CDS trading.

<Insert Table 2.7 about here>

4.4. Multivariate estimation of PSM samples

I re-estimate the baseline model (1) with my three PSM samples. I present the estimates in Panel A, B, and C of Table 2.8. For brevity, I only report the estimated coefficient on *CDSINIT* and *CDSFIRM* across samples. Consistent with the results from the whole sample, I find that all coefficients of regressions of WACC and cost of debt on CDS initiation are significant and negative at the 5% or 1% level across three PSM samples. The magnitude of estimates is similar to that of the whole sample as well. Furthermore, I still observe the non-significant estimated coefficients when regressing the cost of equity on CDS initiation. To further substantiate my results, I reconstruct my PSM samples from the probit sample that contains firms with zero long-term debt and total assets of less than $10 million. I present estimates in Online Table A3. The results based on the expanded probit sample are the same as those in Table 2.8, confirming the validity of my PSM tests. Overall, this evidence supports my main findings from the whole sample test: the availability of CDSs reduces the cost of debt and the cost of capital.

<Insert Table 2.8 about here>

4.5. CDS sample test

The whole sample results are based on comparing outcomes of CDS firms and non-CDS peers by controlling a set of covariates. However, there may have some latent factors that drive CDS firms to behave differently from non-CDS firms, and those factors are absent in my model. While I have employed PSM procedure to mitigate sample selection concerns, i.e., making CDS and non-CDS more alike, another way to reduce such uncertainty is to use the CDS firms only. In contrast to non-CDS firms, which are the benchmarks when assessing the CDS effects, a CDS firm may be a more appropriate benchmark to another CDS firm. I follow Ashcraft and Santos (2009) to estimate the baseline model using the treated sample (CDS firms). Additionally, I introduce the *CDSLAG* to the equation, which is an indicator variable but lagged one year for *CDSINIT* to capture the potential dynamic effects of CDS trading over time. I present the estimates in Panel A of Table 2.9.

<Insert Table 2.9 about here>

The estimates from the cost of debt are in line with my estimates from the whole sample and various PSM samples. Both coefficients on *CDSINIT* and its lag, *CDSLAG*, are significant and negative at either the 5% or 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 increases effects over time. Furthermore, all estimates of regressions of cost of equity are non-significant, consistent with my main samples' estimation. Turning to the regressions of WACC, all estimates are negative, and one of the estimates on the *CDSLAG* is close to the 10% significance level, suggesting a reduction on the cost of capital after CDS trading.

Overall, the estimation from the cost of debt, which is highly congruent with all estimates from various samples so far, and the estimates on *WACC* in Panel A of Table 2.9 are weak in contrast to the estimates from the whole sample. One may conclude that the underlying variances between

CDS and non-CDS drive the results. To examine such possibilities, I follow Kim (2016) to use 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.

I 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. I present the estimated results in Panel B of Table 2.9. I 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. I 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. Furthermore, Martin and Roychowdhury (2015) and Subrahmanyam et al. (2014, 2017) also indicate that firms with higher leverage ratios attract more attention from lenders since high leverage ratios indicate high financial risk and default probability. I use the level of leverage ratios as another strategic variable to control for the level of CDS trading. Similarly, I assign a value of one for firms whose leverage ratios are above the sample median, and zero otherwise. The estimates are presented in Online Table A4. The results based on these two alternative strategic measures are consistent with the findings when using liquidation cost as a strategic variable, thus verifying the conclusions from CDS samples. Overall, the results from the CDS sample confirm my main sample results. Moreover, the strategic opportunity tests indicate that the reduction in the cost of debt led to a decline in the overall cost of capital. The effects of CDS trading on the cost of equity rely on the credit quality of the focal company.

4.6. 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 proxy liquidity 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. I follow these studies to use CDS trading activity variables as replacements to the indicator variable, *CDSINIT*, to verify my results. I obtain CDS trading activity data from DTCC over the period 2009 to 2018. Specifically, I 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. I scale the notional volume by the natural log as the original notional amounts are significantly skewed right[22].

<Insert Table 2.10 about here>

I present the estimated coefficients in Table 2.10. 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 substantially reduces the cost of debt financing. Turning to regressions of WACC, I observe that three out of four estimates are negative and significant at either 5% or 1% level. Last, the estimates of regressions of the cost of equity with the industry-fixed effects model are significant and

[22] Over the period 2009 to 2018, we have 4,734 firm-year observations from 570 CDS firms, of which 1,723 observations have trading data from 240 CDS firms.

negative, implying the positive effects of CDS trading on equity holders. On the contrary, the estimates from the firm-fixed effects model are non-significant, consistent with the whole sample results demonstrating that CDS trading has no effects on equity holders.

4.7 Monte Carlo simulation test

In this section, I analyze the CDS initiation events by Monte Carlo simulation. Chang et al. (2019) state that the clustered characteristics of CDS trading initiations may cause spurious regression results, i.e., the significant effects may be attributed to events clustering instead of CDS firms themselves. I follow Bekaert et al. (2005) and Chang et al. (2019) to construct samples with pseudo CDS trading years among CDS firms. Specifically, I first gather the real CDS trading initiation years from 677 CDS firms. Next, I randomly assign these true CDS initiation years to CDS firms. I then construct the sample by combing all non-CDS firms and the CDS firms with pseudo trade initiation years. I estimate the baseline model (1) using the constructed sample with firm-year fixed effects and record the coefficients of *CDSINIT*. I reiterate this procedure 1,000 times and report the distribution of coefficients of *CDSINIT* in Table 2.11 for the cost of debt as an example.

<Insert Table 2.11 about here>

The mean (-0.172) and median (-0.171) of coefficients on *CDSINIT* from the regressions of the cost of debt in Table 2.11 are significantly different from the estimated coefficient based on true sample (coefficient of -0.256 with *t* statistic of 3.86)[23]. The 95th percentile of the distribution shows a coefficient of negative -0.255 and a *t* statistic of -3.78, which is close to my estimate from the real sample. Thus, my estimate is located the left tail far out from the mean and median values. This evidence indicates that my results are not attributed to statistical artifacts or CDS initiation

[23] The difference between the mean coefficient and the true one is 0.084 with a t statistic of 1.91, which is significant at the 10% level.

events clustering because many replications with pseudo samples, which have the true distribution of CDS initiation dates, would produce coefficients close to the true one estimated from the original sample. Therefore, the impact of CDS trading on the cost of debt owes to the firm and its true time of CDS trading initiation, and not to time trends of CDS trading.

4.8 The first difference sample test

One issue I have not yet addressed is the reverse causality between the changes in the cost of capital and the inception of CDSs. It may be the case that investors forecast a company's successful prospect and are willing to provide CDSs on the company's debt to profit from the further lowered spreads. Such transactions can cause a decrease in the focal firm's CDS spreads as well as the 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 initiation and endogenous concerns of CDS trading, I regress the first differences of the cost of capital on the CDS initiation. Specifically, I estimate the following model with the first difference samples.

$$\Delta Cost\ of\ capital_{i,t} = \omega CDSINIT_{\mathrm{i,t-1}} + \gamma \Delta \mathrm{X}_{\mathrm{i,t-1}} + \rho \mathrm{Fixed_i} + \phi \mathrm{Year_t} + \varepsilon_{\mathrm{i,t}} \quad (3)$$

where $\Delta Cost\ of\ capital_{\mathrm{i,t}}$ is the first difference between the cost of capital (e.g., WACC, cost of debt, or cost of equity) in a fiscal year and its value in the prior year. Likewise, $\Delta \mathrm{X}_{\mathrm{i,t-1}}$ represents the first difference of control variables discussed in section 2.2.3. CDSINIT is an indicator variable that has a value of one in and after the year of CDS trading, and zero otherwise. $Fixed_i$ denotes firm-fixed effects. I control for year effects to attenuate the changes in the cost of capital. To investigate the reverse causality from the cost of capital to CDS initiation, I follow Kim et al. (2018) and use CDS initiation as the dependent variable and regress it on the lagged changes of the cost of capital and lagged changes of controls. I estimate the model (3) with or without firm-fixed effects and present the results in Panel A and B of Table 2.12, respectively. For brevity, I only present the coefficients of interested variables, CDS initiation, and various costs of capital. The full results are reported in Panel A and B of Online Table A5.

<Insert Table 2.12 about here>

Starting from Panel A of Table 2.12, I consistently observe negative and significant coefficients of regressions of the cost of debt on CDS initiation. Both coefficients are significant at the 1% level regardless of firm-fixed effects. The estimates from the cost of equity are negative and significant at the 5% or 10% level. Last, I find one out of two estimates from the regressions of WACC on CDS initiation to be significant at the 10% level. Turning to Panel B of Table 2.12, I 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 the CDS initiation causes the reduction of the cost of debt. There is no reverse causality from the cost of debt to the CDS initiation. Besides the test above, I also run a probit model and include the changes in the cost of capital as an input factor. I find no significant coefficients on the changes in the cost of capital. This evidence indicates that there is no causal relation between the changes in the cost of capital and the CDS initiation[24]. The results are presented in the Online Table A6.

Taken together, my 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

[24] Though the changes in the cost of equity have no anticipating power for CDs initiation, the cost of equity itself can predict the inception of CDSs. This is because the cost of equity can be a proxy of a firm's business risk, and therefore it can predict the inception of CDS trading.

firms in investment grade benefit from a reduction in the cost of equity. In the rest of the paper, I investigate the channels through which firms lower their cost of capital.

5. Debt structure and WACC

A firm's capital structure optimization and financing choices are the outcomes of interplaying between various factors, such as business risk, growth options, firm's information environment, cost of financing, and major stakeholders (e.g., shareholders, creditors, top executives) (Myers, 1977, 1984; Myers and Majluf, 1984; Diamond, 199; Hovakimian et al., 200; Frank and Goyal, 2003; Rauh and Sufi, 2010; Lemmon and Zender, 2010; Denis and McKeon, 2012). Post-CDS trading, many factors above have changed because CDSs alter the relationship between the lenders and borrowers (Bolton and Oehmke, 2011) and improve a firm's information environment as well. 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 everchanging milieus, firms may consequently amend their capital financing policies and adjust capital leverage to seize the benefits and avoid the costs associated with CDS trading.

A CDS company's cost of capital could change due to either external or internal channels. With respect to external channels, CDS protected lenders may encounter some benefits arising from CDS trading, hence lowering the required interest rate. For instance, Ivanon et al. (2016) state that the cost of bank financing was reduced because CDSs offered reduced monitoring costs. However, regarding the cost of bonds, empirical studies come to mixed conclusions. For example, Kim (2016) studies bond spreads of CDS firms using 1,506 US firm-quarter observations from 136 corporate bonds over the period 2001 to 2008. He finds that firms that are subject to strategic default concerns experience significant declines in their bond spreads post-CDS trading. In contrast, Narayanan and Uzmanoglu (2018c) find that CDSs intensify debt renegotiation discordance and actually increase bond spreads. Their study uses 2,940 corporate bonds issued by 303 US public firms over the period 2008 to 2016.

In this section, I focus on the internal channels and their consequences on the overall cost of capital. In this regard, managers have two channels to adjust a firm's cost of capital. They can substitute debt for equity or inversely do so. As the cost of debt is much lower than that of equity, a firm can, to some extent, reduce the overall cost of capital. Another channel is to adjust debt priority among various 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 have a distinct cost of interest and flexibility, managers may alter their debt financing orders and thus change the overall cost of capital.

Nonetheless, both channels significantly rely on the assumption of an improved firm's information environment after CDS trading. A firm's information environment plays an important role in the firm's selection of external financing sources. The pecking order theory of Myers and Majluf (1984) assumes that information asymmetry between internal managers and external investors causes adverse selection when obtaining funds from external sources. Consequently, firms prefer to use less information sensitive types of funding, like debt, instead of equity. It is reasonable to conclude that a company with an improved information environment, and consequently subject to less information asymmetry problems, may be more willing to issue equity rather than debt, especially when it already has high financial leverage ratios because a high leverage ratio not only increases a firm's default probability, but also causes overhang debt problems (Myers, 1977). Therefore, I first address whether the information environment of a CDS firm has changed after CDS trading, and then investigate the channels for reducing the cost of capital.

5.1 CDS firms' information environment

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 (Acharya and Johnson, 2007). This kind of insider information would generally be reflected in the quotes of CDSs and, therefore, CDS spreads reveal the true credit risk of referenced firms and play price discovery roles in other markets (Batta et al., 2016), such as stock and bond markets. 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). I follow Batta et al. (2016) for the number of stock analysts who recommend stock buying of a firm as the proxy of the firm information environment. Specifically, I use the number of analysts as the dependent variable and regress it on CDS initiation to measure the changes of CDS firms' information quality. Table 2.13 reports the regression of the number of analysts on CDS initiation.

<Insert Table 2.13 about here>

In Table 2.13, I observe that the coefficients on CDS initiation are positive and significant at the 1% level for both industry and firm-fixed effects model. The adjusted R-squared is 89.4% in the firm-fixed effects model, and 11 of the 14 estimated coefficients are significant minimally at the 5% level, indicating that my model effectively captures the factors that affect analysts to follow stocks. The evidence indicates that after CDS trading, 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. The information discovery and dissemination reduce the asymmetric information between the firm and external investors and may finally induce an alteration on the firms' financing choices and their capital structure. With more symmetric information between managers and investors, I explore whether managers adjust their capital mix and debt priority to seize the benefits of CDS trading.

5.2 Substitute debt for equity security

Through my tests, I find consistent evidence that CDS firms experience a decline in the cost of debt after CDS trading. Such decreases may cause a reduction of the overall cost of capital. However, I cannot rule out the possibility that managers alter financial leverage to capture the benefits from CDS trading, thus resulting in a decline in the WACC. The mean of after-tax cost of debt of CDS firms is 3.00%, which is substantially lower than the mean of the cost of equity, which is 10.93%. By adjusting the weight of debt to equity, CDS firms can reduce the WACC as well. To investigate this channel of changing WACC, I estimate the relations between the market weight of debt and equity and CDS initiation. I obtain the market weight of debt and equity from Bloomberg. The details regarding the computation of weights are provided in Table 1.

Table 2.14 presents the results of regressions of the weight of debt and equity on CDS initiation and a set of control variables. I present the results estimated with firm-fixed effects model in column (1) for weight of debt and equity. I also report estimates based on quantile regression in columns (2), (3), and (4) over quantiles of 0.15, 0.50, and 0.85, respectively. I employ quantile regressions because I observe that CDS trading exerts greater effects on firms with high book leverage ratios than firms on the other end. I conjecture that CDSs have contrary effects on firms with high and low weight of debt as well.

<Insert Table 2.14 about here>

Examining the left side of Table 2.14, I find two noteworthy results. First, CDS trading has contradictory effects on companies with low and high market leverage ratios. The estimate on CDS initiation over the quantile of 0.15 in column (2) is positive (1.18) and significant at the 1% level, suggesting that firms originally employing lower debt financing would substantially increase the use of debt. In contrast, the one in column (4) over the quantile of 0.85 is negative (-2.58) 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 access and flexibility to capital markets, thus leading to using more debt financing than before. The arguments above are supported by the results on the right side of Table 2.14 as well, which show the quantile estimates for the weight of equity.

Second, the estimate of regression of the weight of debt on CDS initiation with firm-fixed effects model is positive (1.43) and marginally significant at the 10%. Correspondingly, I observe a negative coefficient on the weight of equity (-1.53) and significant at the 10% level as well. To verify my estimates, I regress market and book leverage ratios on CDS initiation and report estimates in the Online Table A7. Both estimates on CDS initiation are positive and significant at the 5% level, indicating an increased proportion 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].

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 than equity financing, on average. Nonetheless, I point out that the increase in the 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 them. To further ascertain the channels that reduce the WACC, I estimate the relations between CDS trading and security issuance. I regress net debt and net equity issuance on CDS initiation and on an array of firm's controls used before. I present the results in Table 2.15. Starting from net debt issuance, I find negative estimates significant at the 5% or 10% level on CDS initiation with firm- and industry-year fixed effects, respectively. This evidence demonstrates that, on average, firms do not issue more debt after CDS trading. On the contrary, they reduce the issuance of debt. This finding is consistent with Batta and Yu (2019) who find a decrease in debt issuance as well. Turning to net equity issuance, I observe that one of the two estimates is negative and marginally significant at the 10% level, indicating less equity issuance after CDS trading. However, the negative effect on equity issuance is weaker than the effect on debt issuance, evidenced by the negative but insignificant estimate from firm-fixed effects model.

In summary, I find evidence that the firm's weight of debt increases on average. The firm's increasing issuance of debt financing is not a cause here, but rather the decreased required return on debt is. This finding reveals that debt value increases because of the hedging functions of CDSs.

[25] The weight of debt and equity we use in this study is the proportion 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.

Interestingly, I 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 capital mix. However, such benefits are not due to managers actively adjusting debt usage, but to the hedging function of CDS markets, which generally increase the values of debt.

<Insert Table 2.15 about here>

5.3 Debt placement structure post-CDS trading

To advance my understanding of how CDSs reduce the cost of debt, I follow Saretto and Tookes (2013) to analyze the relation between CDS initiation and various debt compositions. Because different types of debt have distinct interest costs and covenants, a firm can withdraw a high cost of debt with others that have lower required returns. For instance, 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 instead of bank loans as a result. Such a conversion would reduce the overall cost of debt financing. I follow Colla et al. (2013) to classify debts into seven categories: bank loans, revolving credits, bonds and notes, commercial papers, leases, others, and trusted preferred. Furthermore, I follow Lin et al. (2013) to construct public and bank debt categories. The public debt is the sum of commercial papers and senior and subordinated bonds and notes, while bank debt is the sum of bank loans, term loans, and drawn revolving credits. I scale those debt compositions by total debt and use the ratios in my analysis.

<Insert Table 2.16 about here>

I present the estimates of regressions of debt composition ratios on CDS initiation and a set of firm's characteristics used before in Table 2.16. Starting from the public debt, I notice positive and significant coefficients on CDS initiation across estimators. The estimates are close to the ones 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. My estimate is 0.036 and significant at the 1% level as well. Turning to its components, the estimates from bond are positive and significant at the 1% level, while the estimates from commercial papers are insignificant. This evidence indicates that CDS trading has no effects on the usage of commercial papers but stimulate firms to use substantially more arm-length debt, like bonds. The coefficient from column (2) of bond regression using firm-fixed effects model is 0.047, implying that CDS firms increase bond sources of financing by 4.7% on average after CDS trading. This percentage is equivalent to a $207 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 -0.046 (significant at the 1%) on CDS initiation from the firm-fixed effects model. Once again, this estimate is close to Chen et al. (2018) in which the corresponding estimate is negative (-0.05) and significant at the 5% level. When further examining estimates from bank loans and revolving credit regressions, I find that bank loans are negatively but not significantly affected by CDS trading, indicated by the negative *t* statistic of -1.30 from the firm-fixed effects model. This finding is consistent with Saretto and Tookes (2013). They posit that the insignificant impact of CDSs on bank loans may be ascribed to the fact that most CDSs are written on bonds, and not on bank loans.

Different from Saretto and Tookes (2013) and Chen et al. (2018) in which the authors do not separately examine the effects of CDSs on revolving credits and loans, I treat bank loans and draw revolving credits individually. On one hand, the revolving credits are material composition of bank debt, evidenced by the weight in bank debt. For example, the mean percentages of revolving credits to bank debt are 34% and 45% for CDS and non-CDS firms, respectively. On the other hand, the financing costs are different for these two financing vehicles. I find a substantial reduction in the usage of revolving credits post-CDS trading. When combining the estimates from bank loans, I see that the significant reduction in revolving credits causes the overall decrease in bank debt.

The reduction in revolving credits may stem from the threatening effects of CDS trading. Borrowers may use long-term bonds to facilitate their short-term sources of liquidity to avoid rollover risk of revolving credits. To substantiate my arguments, I re-examine the relation between debt compositions and CDS initiation, with one third of the firms showing a higher default probability. The firms in this group would generally have a higher rollover risk than firms with a low default probability. If CDS trading aggravates the banks' concerns of repayment for these firms, I would observe a more significantly negative effect on those firms in terms of the usage of revolving credits. I present estimates in Online Table A8. The coefficients of regressions of revolving credits on CDS initiation are negative and significant at the 1% level across models. Furthermore, the magnitude of coefficients (0.058) from firm-fixed effects model is almost double comparing to the corresponding one (0.031) from the whole sample. In contrast, the corresponding estimate from firms with a low default probability is not significant at the 10% level and has a smaller magnitude (-0.017). These findings support the rollover risk explanations for the reduction in revolving credits. However, I point out that the reduction in revolving credits may be also due to the increased costs associated with revolving credits. Because of an increased default probability after CDS trading, banks may demand higher commitment fees or set stricter covenants on short-term lending. Last, I also observe that CDS trading has positive and significant effects on other borrowings, suggesting that firms increasingly pay attention to other sources of financing.

To further shed light on the relations between bank loans and CDSs, I re-estimate the relation with quantile regressions over quantiles of 0.5 and 0.85 and report the results in Online Table A9. The estimates on CDS initiation are negative and significant at the 1% level, indicating that firms originally with high bank loans reduce the borrowing from banks after CDS trading. The evidence of panel and quantile tests indicates that firms substitute bonds or notes for bank sources of debt. If such substitution causes a reduction in the cost of capital or cost of debt, I should observe a relation between the capital costs and the corresponding debt compositions. Based on the decreased cost of debt, I conjecture that the cost of debt has a positive relation with bond/note financing. Consequently, the increased usage of bond/note results in a lowered cost of debt, since generally the cost of bond is less than the cost of bank financing. I test my conjecture and report the estimates in Table 2.17.

<Insert Table 2.17 about here>

In Table 2.17, I find strong evidence to support my conjecture. The estimates on bond are positive and significant at the 1% level across models. Particularly, all estimates of regressions of WACC on public debt or bond are negative and significant minimally at the 10% level, indicating that the increased usage of bond financing can significantly reduce the overall cost of capital of a firm. This finding is consistent with my general knowledge that bank loans are costlier than bonds/notes. I also observe positive and significant coefficients on bank loans; however, the magnitude of estimates is about one third of the ones on bonds, indicating that bonds/notes have stronger effects on the cost of debt than bank loans. In this regard, bank loans may serve special functions to a firm, such as producing information or building reputation. Cost may not be the main consideration when evaluating external debt financing. Turning to revolving credits, I observe negative estimates across estimations, significant at the 1% level. The magnitude of estimates is significantly larger than the one on bank loans, indicating that revolving credits hold a stronger influence on the cost of debt. Interestingly, though revolving credits can significantly reduce the cost of debt, firms significantly cut down their usage after CDS trading. One explanation for such a reduction is that post-CDS trading firms attempt to avoid rollover risk associated with revolving credits.

In summary, the weight of debt marginally increases, while the weight of equity marginally decreases after CDS trading. The increase in debt weight is not due to the issuance of more debt securities but to the increased values of debt instruments caused by CDS markets. I also find that CDS firms adjust their debt priority by substituting arm-length debts for bank debts over post-CDS trading. The substitution may be due to CDS threatening effects or simply because the firms would like to capture the advantages of CDSs, such as longer maturity or easier access to public debt. Because the cost of bond is generally lower than bank loans, such a substitution causes a reduction in the cost of capital.

6. Conclusions

The CDS market has attracted substantial controversies (Stulz, 2010). Some believe that CDSs are partially to blame for the subprime crisis in the US that led to the subsequent 2008-2009 financial crisis. As a result, opponents of CDS have called for a ban on CDS trading. At the same time, others have pointed out that CDS trading completes the financial markets by providing easy and cheap hedging vehicles. Researchers have examined various tangible effects of CDSs on firms and the economy by examining how CDSs affect corporate policies and activities. My 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. I construct a panel dataset using the universe of US public companies to examine whether CDSs change the WACC, cost of debt, and cost of equity.

My 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 highly rated firms after CDS trading, while most low-rated firms benefit from a reduced cost of debt financing. Compared to shareholders in highly 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.

I have explored the channels through which CDS firms reduce the cost of capital. Quantile regressions of different debt ratio levels show that CDS trading initiation has an opposing effect on high and low leverage firms. Firms with low leverage significantly increase their usage of debt and correspondingly reduce their equity weight, while firms with high and medium leverage significantly reduce the weight of debt in their capital structure and issue more equity. Both effects are consistent with the empty creditor hypothesis which posits that CDS exerts simultaneously two contrary functions on firms. On one hand, it increases the credit supply for borrowers; on the other hand, it introduces frictions into debt renegotiation. Furthermore, I 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 weight of debt is a channel that decreases the overall cost of capital.

Finally, I find strong evidence that CDS firms alter their debt placement structure. Post CDs trading, CDS firms use more arm-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-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. My findings suggest that financial market innovations, such as CDSs, affect a firm's financing decisions and consequently their capital structure.

CHAPTER THREE

Credit Default Swaps and Corporate Social Responsibility

1. Introduction

Corporate social responsibility (CSR) has been deeply ingrained in modern business practices and society[26]. Although CSR prevails in global societies, the motives and factors that lead corporations to engage in CSR initiatives are not well-understood (Carroll and *Shabana*, 2010). For instance, agency theorists blame CSR as a means for managers to seize their interests at the costs of shareholders (Friedman, 1962; Jensen, 2001), while institutional theorists argue that the institutional environment (e.g., social norms, legal systems, etc.) plays a pivotal role in shaping the corporations' CSR policies (Campbell, 2007; Lee, 2011; Brammer et al., 2012). Likewise, stakeholder theorists advocate the use of CSR for promoting stakeholders' relationships of a corporation (Freeman, 1984; Jones, 1995; Mitchell et al., 1997; Freeman et al., 2010), and by this means achieving competitive advantages and sustainability for the focal company. Consistent with the theories above, academics identify various empirical factors that affect a firms' CSR practices, e.g., research and development expenditure (Padgett and Galan, 2010), institutional shareholder (Dyck et al., 2019), governance (Jo and Harjoto, 2012), social milieus (Chih et al., 2010), and more. In this article, I explore whether the innovation of financial markets, specifically the credit default swaps, can impact companies' CSR practices.

[26] *The importance of CSR to businesses and communities can be inferred from the tremendous fund that uses CSR as investing metrics. For example, the total US-domiciled assets under the management using sustainable, responsible, and impact investing (SRI) strategies grew to 12 trillion at the start of 2018, an 18-fold increase comparing with the US SRI assets in 1995, of 0.639 trillion (The Forum for Sustainable and Responsible Investment, 2018 Facts).*

Credit default swaps (CDSs) are credit derivatives wherein the buyers of CDSs make periodic payments to CDS sellers during the contract period in exchange for protection against risky credit events (e.g., payment default, debt restructuring, etc.) of the CDS referenced firms. The initial purpose of CDSs was to allow holders of corporate bonds/loans to protect themselves from the risk of default. Nonetheless, because CDS materially alters the relationships among major corporate stakeholders (Hu and Black, 2008; Bolton and Oehmke 2011), CDSs practically not only function as vehicles of risk hedging but also have shown real effects on CDS firms' operation and investment strategies (Li and Tang, 2016; Danis and Gamba, 2018; Batta and Yu, 2019). For example, Martin and Roychowdhury (2015) show that CDS firms substantially adopt less conservative accounting standards over post-CDS periods. Kim et al. (2018) document that managers of CDS firms are more likely to voluntarily disclose the firm's earning forecasts. Chang et al. (2019) show that CDS trading significantly and positively promotes firms' technology innovations. Given the importance of CDS in the economy[27], it is necessary to fully understand and examine the externalities CDS trading induces on the economy.

My empirical analysis of CDS is grounded on the empty creditor hypothesis developed by Hu and Black (2008) and Bolton and Oehmke (2011). The empty creditor hypothesis posits that CDS insured lenders may become less accommodating in debt renegotiations because CDSs provide them with a valuable alternative option[28] as opposed to a compromise during debt renegotiations (Bolton and Oehmke, 2011). Furthermore, overly insured lenders who have negative economic exposure may prefer forcing distressed CDS firms into default to collect payments from CDS

[27] *For example, CDS transactions rank third among derivative products after interest rate and foreign exchange; its notional amount remained at $9.9 and $9.75 trillion at the end of 2016 and 2017, respectively (Bank for International Settlements, 2017 annual report).*

[28] *CDS protected lenders can claim reimbursement from CDS sellers if the referenced firm triggers credit events (such as payment default).*

sellers (Subrahmanyam et al., 2014, 2017; Denis, 2016). In this regard, CDS trading could increase the restructuring frictions of the distressed firms, which decreases the likelihood of success renegotiation and causes more inefficient bankruptcy than before.

Empirical studies have documented evidence validating this threatening effects of CDSs. For instance, Subrahmanyam et al. (2014) provide evidence that following CDS-trade-initiation, the probability of bankruptcy significantly increases. Danis (2016) finds that bondholders of CDS firms are less inclined to participate in out-of-court debt workouts than bondholders of non-CDS firms. Bedendo et al. (2016) show that distressed CDS firms tend to have higher recovery rates in exchange offers to surmount the boycott of CDS-protected creditors.

The threatening effects of CDS may negatively affect a firm's corporate environmental and social practices because CSR activities may only bring benefits to the focal firm in the long run but require vast investment outlay (Hong and Kostovetsky, 2012; Lins et al., 2017). For example, Giuli and Kostovetsky (2014) document that S&P 500 companies that are more CSR inclined will averagely spend $80 million more than those that are not CSR inclined, and US corporations spend hundreds of millions of dollars in CSR activities. Due to these high financial costs and the intensified stress from exacting CDS protected lenders, I conjecture that executives may become more conservative towards CSR activities when CDSs were traded on their debts. In contrast to the long-term implicit benefits arising from engaging in CSR initiatives, CDS firms may prefer to invest in projects with sizeable economic benefits for fulfilling their obligations to debtors or cut down on investments to preserve more cash (Subrahmanyam et al., 2017), hence avoiding negotiating with CDS protected lenders. Therefore, I hypothesize that CDS inception would induce a negative impact on firms' CSR performance.

On the other hand, the empty creditor hypothesis also implies that CDS can deter the borrowers' ex-ante strategic default incentives because CDSs enhance the lenders' bargaining position over the ex-post debt renegotiation. Consequently, CDS could act as a commitment device in debt contacts for borrowers, i.e., not to strategically default. Besides, by shifting the borrowers' credit risk to the CDS sellers, the CDS insured lenders can convert high risk-weighted loans into low risk-weighted ones in their balance sheets (Shan et al., 2015, 2016). These two functions of CDS, i.e., shifting risk and serving as a commitment device, reduce frictions on the credit supply sides and therefore increase the firms' debt capacity. Empirical studies verify this credit supply effect. For instance, Saretto and Tookes (2013) find that CDS firms maintain a higher level of leverage ratios and longer debt maturity in contrast to non-CDS firms after the introduction of CDSs. Consistent with Saretto and Tookes (2013), Subrahmanyam et al. (2014) also find that CDS firm's leverage increases significantly over post-CDS periods. Hirtle (2009) finds that CDS-hedged banks originate new term loans coupling with larger volumes and longer maturities.

Furthermore, CDS markets reduce the information asymmetry (Ashcraft and Santos, 2009) and enhance public information disclosure of CDS firms (Kim et al., 2018) because managers of CDS firms face more stress for information requirements from shareholders due to weakened monitoring effects of debt lenders. With more information disclosed, CDS firms become less opaque in terms of information transparency (Ashcraft and Santos, 2009) and thus may attract more public attention concerning CSR activities. Meanwhile, the informational role of CDS markets may facilitate ESG evaluators to collect corporate CSR data and hence improve CSR scores, even if the focal firm maintains its original CSR policies. Therefore, my second hypothesis is that the inception of CDS trading may be positively related to CSR performance. Ultimately, the interplay of positive and negative effects of CDS trading may lead companies to alter their

CSR policies. The net impact of CDS trading on a firm's CSR practices depends on the wrestling of the contrary tensions caused by CDSs and should be determined empirically.

To test my two contrary hypotheses, I construct a longitude sample of globally public companies from eleven countries and regions over the period from 2002 to 2017. These include the United States, the United Kingdom, France, Germany, Switzerland, Australia, Japan, Korea, Taiwan, Hong Kong, and Canada. I use Thomson Reuters ASSET4 environmental and social (E&S) scores to proxy a company's environmental and social performance, respectively. By employing both event study and multivariate panel regression while controlling for both firm and time trend effects, I explore the impact of CDS trading on the firms' CSR initiatives.

I find statistical evidence indicating that CDS trading significantly and negatively influences firms' environmental emission reduction activities. The coefficient of CDS trading for emission reduction test is -4.9% with a p-value of 0.065 based on my whole sample, indicating a significant reduction in the metric of environmental emission reduction following CDS trading. In the economic sense, this reduction is equivalent to a $35.94 million cut back on a firm's emission reduction expenses. Additionally, I observe weak but negative effects of CDS trading on firms' other CSR activities. These findings are consistent with the exacting effects of the empty creditor hypothesis. Over post-CDS periods, managers avert to negotiate with exacting CDS-protected lenders and thus employ more conservative policies on spending scarce corporate resources.

I run several robustness tests to corroborate my findings, including event study, the propensity scores matched sample, Monte Carlo simulation, and various subsample tests. Results based on those tests robustly substantiate my conclusions. I also compare the impact of CDS initiation over the financial crisis period (August 31, 2008-August 30, 2009) with the impact over non-crisis periods. The financial crisis provides us a natural experiment to examine CDS effects since it is an exogenous shock to all firms in the economy, and most firms face credit crunch (Stulz, 2010; Augustin et al., 2014). The tight credit supply would exacerbate firms' financial needs and induce managers to become further conservative over the crisis period than usual. My estimates indicate that the negative effects of CDS trading become more salient in the crisis period comparing to the effects over the non-crisis period.

Finally, I explore the motives that CDS firms significantly cut back expenses on emission reduction activities while not on other aspects of CSR. I follow Hillman and Keim (2001) to investigate the relationship between shareholder value creation proxied by MVA and stakeholder relationship management proxied by ASSET4 E&S scores. My results indicate that emission reduction activities have no statistical relation to shareholder value creation, while other activities of CSR significantly and positively enhance shareholder value generation.

My study contributes to the present literature in several ways. First, my paper contributes to the growing body of CDS literature. I reveal one of the downsides of CDSs. That is, CDS trading induces firms to shrink their efforts on environmental emission reduction activities. My paper helps policymakers to weigh the benefits and costs of CDSs. Second, my work contributes to CSR literature. A long-lasting dispute in CSR literature is whether there is a robust connection between CSR performance and firm value assessed by either financial or accounting terms (Margolis et al., 2007; Becchetti et al., 2008; Kruger, 2015; Buchanan et al., 2018). My results shed light on this issue by showing that good stakeholder relationship management, measured by high CSR scores, brings value to shareholders.

Third, my paper illuminates the relation between environmental activities and shareholder value creation. I show that shareholder value creation proxied by market value added (MVA) has no connection with emission reduction activities. In contrast, other environmental practices, such as resource management and eco-product innovation activities, could bring wealth to shareholders. This finding is consistent with Siegel's (2009) argument that green management matters unless it can realize the organization's goal and ultimately bring wealth to shareholders. My findings help policymakers ascertain which policies corporations are more inclined to undertake under the circumstance of curtailed spending.

Last, my study contributes to the literature on the relationship between corporate governance (CG) and CSR performance. As far as I know, this is the first study that uses longitudinal data to explore the supra relationship from the overall CG levels instead of from a single or several aspects of CG. My empirical tests suggest that the overall CG is a critical determinant of a firms' CSR quality. Research articles that do not control the overall CG quality may produce biased estimates.

The rest of the paper is organized as follows. In section 2, I describe my data sample and summary statistics. I present the test methodology and baseline results in section 3, and robustness tests are conducted in section 4. I analyze primary and secondary stakeholders in section 5, and section 6 concludes.

2. Sample Data, Variables, and Summary Statistics

2.1. Sample selection and data

I construct my longitudinal sample by merging several data sources: Markit Group, Bloomberg, Thomson Reuters ASSET4, Worldscope, Datastream, Compustat, and the Depository Trust and Clearing Corporation (DTCC). I obtain the CDS initiation dates from Markit Group and Bloomberg. Following Ashcraft and Santos (2009) and Amiram et al. (2017), I identify the first CDS trade date of the referenced firm covered by Markit as the CDS inception date. I identify 1,236 CDS firms across eleven countries and regions from January 2001 to December 2016. I start my sample from January 2001 because it is the first month that Markit begins to collect derivative quotes from key CDS trading dealers. As CDS transactions traded over the counter, I are unsure whether those dealers started quoting CDS spreads in January 2001 while these CDSs were actually traded before 2001. To reduce such ambiguity, I remove 189 CDS firms whose trading dates fall in the first quarter of 2001[29]. Following Kim et al. (2018), I verify the onset dates of CDS firms in 2001 by examining the early trading dates available in Bloomberg. I further require that there is at least one-year financial and corporate social and environmental data available immediately after the onset of CDS trading. As per this rule, 657 CDS firms are eliminated, resulting in 569 CDS firms and 7,567 firm-year observations in my CDS sample.

I obtain corporate environmental and social data from Thomson Reuters ASSET4 and use E&S metrics as the proxies of the corporations' CSR performance. My E&S metrics span from the 2002 fiscal year to the 2017 fiscal year. Following the previous literature in the realm of CDS (for instance, Saretto and Tookes, 2013; Guest et al., 2017; Chang et al., 2019), I exclude firms in the financial industry that are identified by four-digit Standard Industrial Classification (SIC) (SIC codes 6000-6999). The resulting sample includes 4,347 non-financial firms and 73,899 firm-year observations, respectively. I merge the E&S sample with Worldscope's fundamental financial data and Datastream's stock prices by matching the corporations' International Securities Identification Number (ISIN).

Additionally, I obtain the exchange rate, firm age, and SIC codes from COMPUSTAT. Precisely, I follow Shumway (2001) and Loderer and Waelchli (2010) to approximate a firm's age by first

[29] *Unlike Ashcraft and Santos (2009), Amiram et al. (2017), and Kim et al. (2018) who remove CDS firms whose trading dates fall in January 2001, we eliminate all CDS firms traded in the first quarter of 2001. This action will lessen concerns of ambiguous CDS initiation dates in non-US markets because, in contrast to US market, the non-US markets have relatively less market participants and CDS quotes.*

selecting the earlier of the firm's initial public offering (IPO) date and the first date when the firm was included in the Compustat database. The number of years elapsed since the earlier date is then used to approximate the firm's age. I then merge the CDS sample with E&S and accounting samples through ISIN. Finally, I exclude observations that missed any of E&S metrics and thirteen control variables (see Section 2.2.3 for controls). This exclusion results in a full sample of 23,901 firm-year observations from 3,383 firms. Specifically, my final sample is comprised of 2,844 non-CDS firms with 17,214 firm-year observations and 539 CDS firms with 6,687 firm-year observations.

Lastly, for US CDS firms, I collect the average daily CDS notional amount and the number of clearing dealers from DTCC over the period 2009 to 2017. DTCC provides weekly aggregate single-name CDS transaction data for the most active 1000 reference entities from October 2008 onwards. I use the average daily CDS notional amount and the total number of clearing dealers in the fiscal year as alternative predictors of the onset of CDS trading. After manually matching each US CDS firm with the DTCC data, I obtain 2,082 firm-year observations over the period 2009 to 2017. By combining this US CDS subsample with the corresponding US non-CDS observations in this period, I finally have 6,722 US firm-year observations spanning from 2009 to 2017.

2.2. Variables

2.2.1. Dependent variables

Academics have struggled to determine how to operationally measure CSR performance (Clarkson, 1995; Wood and Jones, 1995; Waddock and Graves, 1997; Margolis et al., 2007; Galant and Cadez, 2017). The task has been challenging because of the multidimensional characteristics of CSR, which encompass economic, legal, ethical, and philanthropic components (Carroll, 1979, 1991, 2016). At the same time, there is no universal definition of CSR, making the task of measuring it more complicated. Researchers A variety of measures of CSR performance has been employed by researchers. For example, reputation indexes, including Fortune magazine corporate reputations (McGuire et al., 1988), Dow Jones Sustainability World Index (Artiach et al., 2010; Chih et al., 2010), and Newsweek Green Rankings (Cordeiro and Tewari, 2015); questionnaires and surveys (Alexander and Buchholz, 1978; Aupperle et al., 1985; Rettab et al., 2009); content analysis (Abbott et al., 1979; Karagiorgos, 2010); and single dimension measure of CSR such as carbon cost (Cadez and Guilding, 2017). The variety of measurements of CSR is one of the major causes that leads to the ambiguous relationship of CSR and corporate financial performance (Wood, 1991; Margolis et al., 2007; Galant and Cadez, 2017).

I use Thomson Reuters ASSET4 E&S scores to measure corporate social and environmental performance for three reasons. Firstly, it has a relatively broader coverage of publicly listed firms across countries[30]. Secondly, it evaluates CSR from multidimensions. Thirdly, the ASSET4 dataset was widely adopted to quantify corporate E&S performance (e.g., Ioannou and Serafeim, 2012; Cheng et al., 2014; Shaukat et al., 2016; Dyck et al., 2019). Over 150 trained content research analysts across the globe publicly collect available sources of information, including annual reports, company websites, nongovernment organization (NGO) websites, stock exchange filings, CSR reports, and news (Thomson Reuters ESG Score, 2019). Indicatively, the usage of only publicly available information ensures the objective and transparent evaluation of CSR performance. Thomson Reuters ASSET4 data is available starting from the 2002 fiscal year, and it initially

[30] *Betty Moy Huber and Michael Comstock posted a summary of ESG providers, "ESG Reports and Ratings: What They Are, Why They Matter".*
https://corpgov.law.harvard.edu/2017/07/27/esg-reports-and-ratings-what-they-are-why-they-matter/

covers approximately 1000 large and publicly traded firms (such as constituents of S&P 500, Nasdaq 100, CAC 40, FTSE 100, etc.). As of 2017, Thomson Reuters maintained and evaluated the CSR performance of over 7000 publicly traded corporations across the world.

Thomson Reuters collects over 900 data points per firm dealing with CSR performances (Cheng et al., 2014; Shaukat et al., 2016). For example, 'Does the company make donations in cash or in-kind?' and 'Total CO2 and CO2 equivalents emission in tonnes' are two data points regarding the firms' social philanthropic and environmental performance, respectively. These data points are transformed into quantitative data by analysts and are employed to calculate 250 key performance indicators (KPIs) to be further aggregated into 18 categories within four pillars: (1) environmental (three categories: emissions reduction, resource reduction, and product innovation), (2) social (seven categories: employment quality, health and safety, training and development, diversity, human rights, community, and product responsibility), (3) governance (five categories: board structure, compensation policy, shareholder rights, and vision and strategy), and (4) economic (three categories: client loyalty, performance, shareholders, and loyalty). Categories and pillars are calculated with equal weight and then Z-scored by benchmarking ASSET4 universe. Therefore, ASSET4 E&S scores are a relative measure of the firms' CSR performance comparing to all companies within the ASSET4 dataset.

In my study, I focus on ten themes of CSR performance, including three environmental categories and seven social categories. Furthermore, I include environmental and social pillar scores as my dependent variable as well to evaluate the overall effects of CDS trading on environmental and social performance.

2.2.2. Independent variables

I construct a dummy variable denominated as *CDSINIT*, which has a value of one for the CDS firms in and after CDS initiation year and zero before that. *CDSINIT* is my main variable of interest, which captures the changes in CSR performance following CDS inception. A significant and positive (negative) coefficient on *CDSINIT* would indicate that the initiation of CDS strengthens (weakens) the firms' CSR activities. I also construct another dummy variable, *CDSFIRM*, which has a value of one for CDS firms and zero for non-CDS firms, to control the time-invariant unobservable difference between CDS firms and non-CDS firms. Therefore, *CDSINIT* captures the incremental effects of CDS trading on the firms' CSR behaviors.

Prior studies have extensively use the CDS trading notional or liquidity variables to proxy CDS activity (e.g., Oehmke and Zawadowski, 2016; Fuller et al., 2018; Narayanan and Uzmanoglu, 2018a, 2018b; Chang et al., 2019; Colonnello et al., 2019). Therefore, as an alternative to the *CDSINIT* dummy variable, I use CDS average daily trading notional amount and log of the total number of clearing dealers in the fiscal year to proxy CDS activity. I hypothesize that the more liquidity the CDS trading on a reference entity has, the stronger the influence of CDS effects on the focal firm's CSR performance.

2.2.3. Control variables

A large body of literature has examined the incentives and factors that drive corporations to engage in CSR activities (e.g., McGuire et al., 1988; Roberts, 1992; Campbell, 2007; Siegel and Vitaliano, 2007; Artiach et al., 2010; Carroll and *Shabana,* 2010; Chih et al., 2010; Padgett and Galan, 2010; Shaukat et al., 2016; Dyck et al., 2019). I rely extensively on this stream of literature to construct an array of control variables to isolate the impact of CDS trading on CSR activities. Lins et al. (2017) and Dyck et al. (2019) suggest that institutional ownerships may impact a firm's social responsibility, as institutional shareholders can affect the corporation's decision making. I use the ratio of the strategic holdings, which is the sum of all five percent and beyond share ownership to total outstanding common shares, as the *institutional ownership*.

Large firms attract more public attention and, thus, more scrutiny and pressure from the public (Waddock and Graves, 1997; Artiach et al., 2010; Chih et al., 2010). Furthermore, they can realize economic scales in CSR activities (Artiach et al., 2010). Following Artiach et al. (2010), I use total assets on a natural log scale (*log (assets)*) to control the effect of firm size on CSR performance[31]. Further, compared to small firms, large firms may experience less financial constraints; therefore, they may have more financial flexibility to deploy resources on CSR activities (Hong and Kostovetsky, 2012). Following Lins et al. (2017) and Dyck et al. (2019), I use *leverage*[32], defined as the ratio of total debt to total assets, *tangibility*, which is defined as the ratio of net property, plant, and equipment (PPE) to total assets, and *cash holdings*, defined as cash and equivalent divided by total assets, to control the firm's financial slacks.

Furthermore, a firm's financial performance may influence its CSR efforts (Ullmann, 1985; Roberts, 1992; Waddock and Graves, 1997; Clarkson et al., 2011;). Executives in firms with weak financial performance may face increasing pressure from shareholders; therefore, they may focus more on commercial activities rather than on CSR ones (Roberts, 1992; Artiach et al., 2010). Following Artiach et al. (2010) and Lins et al. (2017), I proxy the firms' financial performance (*profitability*) by the ratio of operating income to total assets[33]. Furthermore, a high market-to-

[31] *We also use the log of total sales to proxy the firm's size. There is no material influence on our results.*

[32] *Replacing leverage by market leverage has no statistic effects on our results.*

[33] *We also proxy the profitability by earnings before interest, tax, depreciation and amortization (EBITDA) scaled by total assets, return on assets (ROA), return on equity (ROE), and return on capital. All proxies produce the same level of statistics. Further, following Artiach et al. (2010), we construct free cash flow using free cash flow divided by total sales to proxy profitability and financial slacks. However, the Pearson correlation between free cash flow and capital intensity variable is -0.798 and significant at the 1% level. The high correlation may cause multicollinearity problem in baseline model. Therefore, we drop free cash variable in all regression tests.*

book ratio implies a firm's future growth opportunity and its investment opportunity. High growth firms may have more prospects of integrating CSR into their products (Artiach et al., 2010) and may have higher CSR performance. I use the market-to-book ratio (*MTBV*) to account for growth. Clarkson et al. (2011) argue that firms with higher capital expenditures are expected to have better CSR performance because newly designed machinery is more likely to lower the pollution and resource waste by employing cutting-edge technology. Following Clarkson et al. (2011), I use the ratio of capital expenditures to total sales (*CAPEX*) to control capital intensity effects.

Padgett and Galan (2010) test the direct relationship between research and development (R&D) expenditure and CSR performance. They found evidence of a significant, positive correlation between them. Other studies corroborate such a relation (e.g., McWilliams and Siegel, 2000). Technology innovation would lead to innovative products and processes, which in turn could use resources efficiently, enhance productivity, and thus may satisfy the firms' various groups of stakeholders (McWilliams and Siegel, 2000; Padgett and Galan, 2010). Following Padgett and Galan (2010), I proxy R&D spending (*R&D*) by the ratio of R&D expenditure to total sales[34].

Jo and Harjoto (2012) find evidence that corporate governance (CG) enhances the corporations' CSR engagement, because a high level of governance may restrict opportunistic managerial behaviors and thus increase the trustworthiness of stakeholders, ultimately improving corporate social performance and reputation. Further, Shaukat et al. (2016) report that corporate board attributes, such as board diversity, independence, board strategic vision, and so on, can affect corporate CSR performance. Because corporate governance is a holistic system; therefore, a single

[34] *We also use the ratio of R&D expenditure to total assets to control R&D effects, a measure used by King and Lenox (2001) and Chang et al. (2018). Both measures lead to the same level of statistical results. Following the conventions (see Koh and Reeb (2015) for statistics of coding missing R&D expenses), we assign a zero to all missing R&D expenses.*

aspect of governance mechanism would not be a valid measure of weaknesses and strengths of the focal firm's governance. Consequently, I employ the governance score from the ASSET4 database to control the influence of the overall corporate governance on CSR practices.

Orlitzky and Benjamin (2001) and Padgett and Galan (2010) argue that a firm's business risk and CSR performance have a negative causality. Managers tend to reassess and alter their planning activities when financial risk is heightened. Furthermore, high financial volatility may also put firms on the edge of decline and bankruptcy (Baird and Thomas, 1985; Subrahmanyam et al., 2014). I follow Chang et al. (2019) to use the stock volatility over the fiscal year to proxy a firm's riskiness[35].

Cochran and Wood (1984) point out that asset turnover could influence a firm's CSR performance because this ratio measures the capability of managers to efficiently use the firm's assets to invest—including CSR outlay—and generate profits. I define asset turnover as sales divided by total assets. Finally, I control the age of a corporation because Roberts (1992) documents evidence of a correlation between a firm's age and CSR performance. A mature corporation may have stable strategies regarding its CSR policies (Roberts, 1992) and more exposure in the media than a new corporation, and hence more public pressure for its involvement in CSR activities. Following Loderer and Waelchli (2010), I estimate a firm's age by selecting the earlier of its initial public offering (IPO) date and the first date when the firm was included in Compustat. The number of years elapsed since the earlier date is used to approximate a firm's age.

The thirteen factors supra are firm-level characteristics that may influence a firm's CSR performance. In contrast to these internal factors, institutions (such as laws and regulations,

[35] *We also use beta and stock volatility over three fiscal years to proxy a firm's risk. All measures show the same level of statistical results.*

policies, social norms, ethics, and cultures, etc.) also shape the corporations' CSR activities via framing incentive and punishment structures (Campbell, 2007; Lee, 2011). In addition, Siegel and Vitaliano (2007) argue that firms selling experience and credence goods (such as automobiles and appliances) may have higher CSR performances than firms selling search goods (such as clothing and furniture). I include firm-fixed effects in my specification to account for systematic differences caused by institutional factors and firm types on CSR activities across countries and industries. Furthermore, I follow Chang et al. (2019) to winsorize all control variables at the bottom and top one percentile to reduce the effects of potential extreme values.

2.3 Summary statistics

Panel A of Table 3.1 reports the statistics of environmental and social metrics for both CDS and non-CDS firms across eleven countries and regions. All E&S metrics of CDS firms are significantly higher than those of non-CDS firms. For instance, the means of the overall environmental score are 62.49 and 41.47 for CDS and non-CDS firms, respectively. The difference between them is significant at the 1% level.

Turning to Panel B, which describes the summary statistics of firm-level characteristics used as control variables in my analyses, I observe significant differences between CDS firms and non-CDS firms across all firm features. The CDS firms are more profitable and less risky in equity returns, have a large market capitalization, high asset tangibility and leverage, and low growth rate than their counterparts. These statistics are consistent with findings of the extant CDS literature, such as Martin and Roychowdhury (2015) and Chang et al. (2019). Further, CDS firms show higher governance quality and have a longer firm age. For example, the means of CDS firm age and governance are 28.67 years and 61.92, respectively, which are significantly greater than the ones of the non-CDS firm,17.88 years and 54.11, respectively.

<Insert Table 3.1 about here>

In Panel C, the environmental and social scores have notable variations across eleven countries and regions. The E&S scores range from the lowest ones, 38.12 and 38.58 (Hong Kong), to the highest ones, 77.97 and 78.67 (Germany). Most European countries show significantly higher E&S scores than Asian countries. Remarkably, firms from Japan, South Korea, and Taiwan have significantly higher environmental scores than social scores, while this situation reverses for firms from the United States, the United Kingdom, and Australia. My sample has relatively the same properties as Dyck et al. (2019).

In Panel D, I present the distribution of CDS firms by one-digit SIC code. As shown, CDS firms are selected mainly from the manufacturing industry (such as food, petroleum, paper, printing, rubber, stone, and computer) in my sample (51.76% of the sample), following by transportation business (18.55% of the sample). I report the distribution of CDS firms in Panel E by the inception year of CDS trading. Most of the CDS are initiated from 2001 to 2007, capturing 73.47% of the CDS sample.

I describe the Pearson correlation matrix of selected variables in Panel F. I observe that the highest correlation is 0.896, which is between *CDSFIRM* and *CDSINIT*. Such a high correlation is due to my variable construction methodology. I employ the firm-fixed model to counteract this possible multicollinearity concern. Except for this correlation, I do not observe high correlations between control variables, which indicates that multicollinearity is not likely to be a problem in my regression.

3. Methodology and Empirical Results

3.1. Baseline specification

To estimate the effects of CDS trading on CSR performance, I apply the difference in difference (DID) mechanism to all empirical tests. I estimate the following baseline regression model with firm-year fixed effects[36].

$$\log\,(Score_{\mathrm{i,t}}) = \alpha + \beta CDSINIT_{\mathrm{i,t-1}} + \gamma Y_{\mathrm{i,t-1}} + \omega Firm_{\mathrm{i}} + \phi Year_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \qquad (1)$$

where $Score_{i,t}$ is one of the twelve E&S scores for firm i at time t. The main variable of interest is *CDSINIT*, which is an indicator variable and has a value of one for the CDS firm in and after CDS initiation, and zero before the initiation year. Its coefficient β captures the percentage effect on E&S scores due to CDS trading. A significant and positive (negative) coefficient of *CDSINIT* would indicate that CDSs strengthen (weaken) a firm's CSR activities. $Y_{i,t-1}$ is the vector of firm-level control variables observed at the end of year $t-1$ defined in section 2.2.3. I follow Chang et al. (2019) to lag all control variables one year in contrast to dependent variables because the initiation of CDS trading is not expected to immediately affect a CDS firm's CSR activities. I include firm-fixed effects in my specification to control the effects of time-invariant, unobservable firm characteristics, and institutional differentials on CSR activities across countries and industries. Further, I incorporate year effects in my specification to capture the aggregate time variation in CSR performance. Given that the observations of the same firm are autocorrelated, I cluster the standard errors of coefficients at the firm level[37].

3.2. Empirical results

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[36] *With firm-fixed effects model, the DID regression specification (2) reduces to equation (1):*
$log\ (Score_{i,t}) = \alpha + \rho CDSFIRM_i + \beta CDSFIRM_i * CDSINIT_{i,t-1} + \gamma Y_{i,t-1} + \omega Firm_i + \phi Year_t + \varepsilon_{i,t}$ *(2)*

[37] *We also cluster the standard errors at both firm and year dimensions by following the suggestion by Petersen (2009). However, there is no material changes on our estimates.*

Table 3.2 reports the estimates of my baseline model (1). I regress each E&S score with and without controlling *Governance* and organize the results in pairs. I present estimates using all controls except *Governance* in the first column, while the second column uses all controls.

<Insert Table 3.2 about here>

As shown in Table 3.2, all coefficients of *CDSINIT* are negative, although most are not statistically significant at the 10% level. This finding suggests that the introduction of CDS trading negatively impact CSR performance. Across E&S measures, emission reduction metric (*ENER*) is the only one having a statistically significant coefficient. The coefficient of *CDSINIT* is -4.9%, statistically significant at the 6.82% level, indicating that compared with non-CDS firms, CDS firms experience, on average, a 4.9% reduction on emission reduction score after CDS trading initiation. This reduction is not only statistically significant but also economically meaningful. To examine its economic significance, I follow Giuli and Kostovetsky (2014) and Lins et al. (2017) to estimate the relation between Selling, General, and Administrative (SG&A) expenses and emission reduction score with my whole sample. Specifically, following Lins et al. (2017), I regress the log of SG&A expenses on the log of assets, equity book to market, cash and equivalent to total assets, total debt to total asset, cash dividend payment to total assets, and earnings before interest and taxes (EBIT) to total assets. The results are presented in Panel A of Table 3.3.

<Insert Table 3.3 about here>

Panel B of Table 3.3 reports the summary statistics of SG&A expenses based on CDS firms, non-CDS firms, and full sample. As per the estimated coefficient of *ENER* and mean and median values of SG&A expenses, the decline of a 4.9% in *ENER* score is approximately equivalent to $34.82

($15.81) million decrease in emission reduction expenses based on the mean (median) of CDS sample following the CDS trading initiation one year later[38].

I also find that governance quality plays a vital role in determining firms' CSR performance. All coefficients of *Governance* are statistically significant at the 1% level across regressions. Further, with the inclusion of governance control, the magnitude of all coefficients of *CDSINIT* is reduced significantly. Particularly, the coefficients of the social score (*SOCSCORE*), environmental score (*ENVSCORE*), resource reduction (*ENRR*), training and diversity (*SOTD*), and product responsibility (*SOPR*) are statistically significant at either the 5% or 10% level without controlling *Governance*. However, when including governance control, they all lose statistical significance. This evidence suggests that when analyzing CSR issues, the omission controlling governance would yield biased results.

The coefficients of control variables are, in general, conform to the extant literature of CSR. For instance, the coefficients of total assets and firm age are mostly positive and statistically significant. This result reflects that larger and more mature companies face more public pressure than small ones and thus have a relatively higher CSR performance. Risk is generally negatively related to CSR scores, consistent with the present CSR literature. In addition, I observe that asset turnover significantly and positively promotes a corporation's E&S performance, evidenced by most, though not all, positive and statistically significant estimates of coefficients on asset turnover. Furthermore, all coefficient estimates of R&D are positive, and most are close to or significant at

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[38] *Let* $log(y) = \alpha + \beta x + \varepsilon$, $\frac{dy}{dx} = y * \beta$, *so the* β **100% is approximately the percentage differential on dependent variable* y *due to a unit change in variable* x. *In our case, when CDSINIT changed from zero to one, ENER decreased by 4.9% approximately. The change in ENER from its mean, 62.43, is then: 4.9% *62.43=3.059. Likewise, one-unit change in ENER will cause 0.39% difference in SG&A expenses. Therefore, the total change of SG&A expenses due to CDS trading would be 0.39%*3.059=1.19%. The change of SG&A from its mean value of 291.907 million would be:1.193%*291.907=34.82 million.*

the 10% level. This result is in line with prior studies, such as Padgett and Galan (2010), who find a significantly positive relation between R&D expenses and CSR performance.

Taken together, the baseline results presented in Table 3.2 suggest that CDS trading adversely influences a firm's CSR efforts. Particularly, CDS trading significantly and negatively affects the firm's emission reduction activities. These findings indicate that the executives of CDS firms become more conservative towards the company's investment outlay related to CSR activities when they realize that CDSs were traded on their firm's debt. To reduce the potential of triggering credit events and consequently negotiating with tougher CDS protected lenders, the executive pays more attention to economic returns instead of social returns. Those results are consistent with the hypothesis that the CSR performance of CDS firms declines after the CDS trading initiation. The results corroborate the threatening effects of the empty creditor hypothesis. In the next section, I verify those results with several robustness tests.

4. Robustness Tests

4.1. Propensity Score Matched (PSM) sample

Prior literature in CDS stream (e.g., Subrahmanyam et al., 2014; Chang et al., 2019) documents that firms selected to be referred for CDS trading are generally larger and more mature, more informationally transparent, and possess better creditworthiness. This fact is consistent with lemon effects. Comparing with CDS buyers, CDS sellers face an information disadvantage regarding the referenced firms because CDS buyers are generally loan originators or bondholders, and thus hold private information of the borrowers. Therefore, CDS sellers prefer to trade trustworthy companies that are less opaque and larger in market value by way of reducing transaction risk. It is possible that some unobservable factors drive CDS trading and simultaneously negatively influence CSR performance. To address those concerns, I follow the literature (Ashcraft and Santos, 2009; Subrahmanyam et al., 2014; Martin and Roychowdhury, 2015; Chang et al. 2019) to form matched control firms that have never been selected to trade CDS throughout the whole sample period.

I use the following probit model to capture the likelihood of CDS trading each year.

$$Prob\left(CDSINIT_{i,t} = 1\right) = \emptyset(\alpha + \theta X_{i,t-1} + \varphi Industry_j + \beta Country_k + \omega Year_t) \quad (3)$$

in which $\emptyset$ is the cumulative distribution function of standard normal distribution. *CDSINIT* is an indicator variable that has a value of one in and after CDS trading initiation, and zero otherwise. X is a vector of firm-level characteristics that are used to predict the inception of CDS trading. Following Chang et al. (2019), I include all controls into vector X to mitigate the concern that the determinants of CSR performance may also be factors driving CDS trading initiation. Besides, following Subrahmanyam et al. (2014), I include the ratio of working capital to total assets and return on assets as well. Furthermore, I include Fama-French 48 industry classification to isolate industry fixed effects on CSR performance. I also include country- and year-fixed effects into my model to address country differential and aggregate time trends effects on CSR performance.

Following Ashcraft and Santos (2009), I use firm-year observations of CDS firms until the beginning of CDS trading, i.e., excluding CDS firm-year observations in post-CDS-initiation periods. I combine this traded CDS subsample with all firm-year observations in which firms are never traded in CDS markets (i.e., non-CDS firms) to construct my whole probit sample and use it to estimate equation (3). Table 3.4 reports the probit regression results. The model (3) predicts the onset of CDS trading reasonably well, as evidenced by the high concordant percentage (92.2%) and pseudo-R^2 (35.7%). These statistics are comparable to previous studies. For example, the pseudo-R^2 is 39% in Subrahmanyam et al. (2014), and the proportion of concordant pairs is 91.5%

in Martin and Roychowdhury (2015). The coefficients of predictors are in line with the extant literature (Subrahmanyam et al., 2014; Martin and Roychowdhury, 2015). For instance, larger firms, firms with high leverage, and more profitable firms attract more attention from CDS market participants. The coefficient of Governance is positive and significant at the 10% level, suggesting that firms with good governance are likely to have CDS trading originated in the sample period.

<Insert Table 3.4 about here>

Next, I use the estimates of equation (3) to generate control firms for each CDS firm by comparing the computed propensity of CDS initiation. Specifically, I compare the estimated likelihood of CDS initiation of non-CDS firms to that of CDS firms in the year prior to the CDS trading initiation. I follow Subrahmanyam et al. (2014) to produce three matched samples using different matching criteria to further verify my results and counter the limitations of propensity score matching methodology[39]: (1) the single non-CDS firm has the same Fama-French 48 industry as the CDS firm and has the closest propensity score to the CDS firm, (2) besides conditions of (1), the non-CDS firm and CDS firm come from the same country, (3) the two non-CDS firms have the same CDS firm's Fama-French 48 industry and have the closest propensity score to the CDS firms. Moreover, I require the distance of mean propensity scores between CDS and non-CDS samples not to be statistically significant at the 10% level. I employ Martin and Roychowdhury's (2015) approach to allow a non-CDS firm to match multiple CDS firms. However, the same non-CDS firm can go into the control sample only once for each year. This way, I have unique firm-year observations throughout my samples even though a non-CDS firm may serve as a control for several CDS firms.

[39] *For example, the propensity score matching method is based on the premise that the control unit is independent of treatment assignment, conditional on the propensity score. This assumption is untestable (Roberts and White, 2013).*

I tabulate the firms' characteristics of the control-treated sample before the year of CDS trading initiation in Table 3.5. For brevity, I only present the statistical results based on the matching criteria (1), which require the closest matched non-CDS firm to have the same Fama-French 48 industry classification as the one of CDS firm. Panel A compares the E&S performances of matched non-CDS and CDS firms, while Panel B assesses the thirteen firm characteristics and logit of propensity scores for both samples. In Panel A, I observe that all E&S scores are statistically the same for CDS and matched non-CDS samples. In Panel B, as shown, CAPEX is the only firm-level characteristic that is statistically significantly different between the control and treated samples. The high CAPEX suggests that CDS firms have higher capital intensity than non-CDS firms. Except for this firm characteristic, CDS firms statistically exhibit the same characteristics with the non-CDS firms prior to the initiation of CDS trading. These results suggest that these firm-level CSR determinants documented in extant CSR literature are unlikely the sources of differences in CSR performance after the inception of CDS trading.

<Insert Table 3.5 about here>

4.2. Multivariate test based on the control-treated samples

I now re-estimate the baseline model specified by equation (1) with my three PSM samples. Panels A, B, and C of Table 3.6 report the regression results. The coefficient of *CDSINIT* measures the treatment effect from the control-treated sample. For brevity, I only report the coefficients of *CDSINIT* across E&S scores and samples. Similar to the findings from the whole sample, all coefficients of *CDSINIT* are negative across three control-treated samples. In particular, the coefficient estimates of *CDSINIT* for emission reduction (*ENER*) are negative and statistically significant at the 5% level across samples, suggesting that in contrast to non-CDS firms, CDS firms' emission reduction scores decrease significantly, even after adjusting the likelihood of CDS trading. Further, I do not observe any of the coefficient estimates for social scores to be significant at the 10% level, although they are all negative. This evidence indicates that after the initiation of CDS trading, CDS firms reduce their CSR efforts in general and particularly in environmental emission reduction efforts.

<Insert Table 3.6 about here>

4.3. Event study

Following Chang et al. (2019), I conduct an event study to examine the differences in CDS firms' E&S performances surrounding the inception of CDS trading. I benchmark non-CDS firms against CDS firms and define the counterfactual event year (*t=0*) of a non-CDS firm as the trading initiation year of the corresponding CDS firm. I then compute the average cumulative differentials over various event windows between CDS and non-CDS firms. For brevity, I only present results of emission reduction based on propensity-matched sample created as per criterion (1) because I did not find statistically significant results for other E&S scores. I plot the mean cumulative differences for event windows (-1, 0), (0, 1), and (0, 2) in Figure 3.1 and report event study results of emission reduction in Table 3.7.

<Insert Figure 3.1 about here>

<Insert Table 3.7 about here>

As shown in Table 3.7, the largest average cumulative difference (ΔENER=-2.098, p-value of 0.126) occurs within the immediate year after the year of CDS trading initiation between control-treated samples. While this difference decreases within two years after the year of CDS initiation, it becomes significant at the 10% level, indicating that CDS trading significantly and negatively influence CDS firms' emission reduction performance within two years after CDS trading initiation. Further, the negative CDS effects fade out within three years after CDS trading, as evidenced by the non-significant mean cumulative differential difference (event window (0,3), p-value of 0.224) between CDS and non-CDS firms. Overall, the finding based on the event study is consistent with the one based on the whole sample, i.e., the initiation of CDS trading negatively affects firms' emission reduction activities.

4.4. CDS initiation during the financial crisis period

Results from both the whole sample and PSM samples support the hypothesis that CDS firms adopt more conservative investment policies, such as being more prudent with CSR investment after their debts have been referenced for CDSs. Consequently, CDS-trade-initiation negatively affects CDS firms' CSR performance. During the global financial crisis of 2008-2009, firms were confronted with more tightened bank lending and credit crunch because of the overall shaky financial markets (Campello et al., 2010). Therefore, the limitation of capital availability and a dramatic plunge in profits could strengthen the negative effects of CDS trading on a firm's CSR performance because survival is the managers' primary mission during the crisis. Thus, I expect to observe an increased coefficient of *CDSINIT* during the financial crisis period. I follow Dyck et al. (2019) to define the period of August 31, 2008, to August 30, 2009, as the crisis period. I construct an indicator variable, *CRISIS*, which equals one if a firm's fiscal year ends within this period and zero otherwise. I use the following equation with the PSM sample as per criterion (1) to investigate my supposition.

$$\log(Score_{i,t}) = \alpha + \beta_1 CDSINIT_{i,t-1} + \beta_2 CDSINIT_{i,t-1} * CRISIS + \beta_3 CRISIS + \gamma Y_{i,t-1} + \omega Firm_i + \phi Year_t + \varepsilon_{i,t} \quad (4)$$

I report the regression results in Table 3.8. Across E&S metrics, emission reduction (*ENER*) regression has the largest coefficient of *CDSINIT* (-0.096) and is statistically significant at the 5% level. The coefficient of interaction between *CDSINIT* and *CRISIS* from *ENER* regression is -0.085, with a p-value of 0.107. Also, the coefficient of *CRISIS* is -0.063 and has a p-value of 0.106. These coefficient estimates suggest that over the crisis period, the CDS-trade-initiation causes a reduction of about 14.8% in CDS firm's emission reduction score comparing to non-CDS firms. Moreover, I do not find any significant coefficient estimates for social scores. These results suggest that during the crisis period, the inception of CDS trade further intensifies the concern of managers of CDS firms to satisfy debt obligations.

<Insert Table 3.8 about here>

4.5 Monte Carlo simulation of CDS initiation events

In this section, I analyze the CDS initiation events by Monte Carlo simulation. Chang et al. (2019) state that the clustering feature of CDS trading initiation may cause spurious regression results, i.e., the significant effects may be attributed to CDS events clustering instead of CDS firms themselves. I follow Bekaert et al. (2005) and Chang et al. (2019) to construct CDS samples with pseudo CDS trading years. Specifically, I first gather the real CDS trading initiation years from 539 CDS firms. Next, I randomly assign these true CDS initiation years to CDS firms. I then construct the sample by combining all non-CDS firms with these CDS firms but with pseudo trade initiation years. I estimate baseline specification (1) using the constructed sample and record the coefficient of *CDSINIT*. I reiterate this procedure 2,000 times and report the distribution of coefficients of *CDSINIT* in Table 3.9. Because the coefficient estimate for the emission reduction (*ENER*) score is the sole statistically significant one at the 10% level, I, therefore, analyze the clustering issue of CDS initiation events in terms of *ENER* score.

<Insert Table 3.9 about here>

The mean and median of *CDSINIT* coefficients from emission reduction (*ENER*) regression reported in Table 3.9 are close to zero, and the estimated coefficient based on the true sample (coefficient of -0.049, with a p-value of 0.065) is far out in the left tail of the distribution. The 95th percentile of the distribution shows a coefficient of -0.042 with a t-statistic of 1.31, which is well above my estimated coefficient of -0.049 with a t-statistic of 1.82 reported in Table 3.2. This evidence indicates that my results are not attributed to statistical artifact or CDS initiation event clustering because many replications with pseudo samples, which have the true distribution of CDS initiation dates, would produce coefficients close to the true one estimated from the original sample. Therefore, the impact on CSR performance is indebted to the firm and its right time of CDS trading initiation, not to the time trends of CDS trading.

4.6 Subsample tests

In this section, I further alleviate the concerns of endogeneity and sample selection bias using various subsamples to estimate the baseline model (1). To mitigate sample selection concerns, I follow Ashcraft and Santos (2009) to estimate the baseline model using the treated sample (CDS firms) only. Besides, I partition my whole sample into a variety of subsamples and re-estimate the baseline model with these subsamples. First, I partition the whole sample into two subsamples based on the time of financial crisis, spanning from 2002 to 2007 and 2010 to 2017, respectively. Second, I estimate the baseline model with observations from developed countries by excluding firm-years from South Korea, Hong Kong, and Taiwan. Last, I partition observations into US and non-US subsamples. I do so because capital market financing dominates in the US, while bank financing dominates in European and Asian countries. Therefore, the impact of CDS trading may be different in the US and non-US markets. For the sake of brevity, in Table 3.10, I only report coefficients of *CDSINIT* from emission reduction regression across samples.

<Insert Table 3.10 about here>

Column (1) of Table 3.10 reports the estimated coefficient of *CDSINIT* (-0.059, p-value=0.039) from CDS samples. This estimate validates my full sample test in which the coefficient of *CDSINIT* from emission reduction regression is -0.49, with a p-value of 0.065. This evidence shows that sample selection bias is not likely an issue in my test. The coefficient of *CDSINIT* (-0.047, p-value=0.090) from the developed country sample presented in column (2) has relatively the same magnitude as the one in the whole sample (-0.049, p-value=0.068), indicating that CDS trading may affect firms' emission reduction performance similarly across countries and regions.

I present the estimated coefficients for sample spanning from 2002 to 2007 in column (3) and sample from 2010 to 2017 in column (4), respectively. The coefficient estimate from the prior financial crisis sample (-0.064, p-value=0.033) has a relatively larger magnitude than the one from the post-crisis period (-0.058, p-value=0.031). This evidence indicates that CDS-trade-initiation results in greater influence on firms' emission reduction activities in prior financial crisis period than in post-crisis periods. Finally, columns (5) and (6) report estimates for the non-US sample and the US sample, respectively. The estimated coefficient (-0.078, p-value=0.019) of non-US samples is significant at the 5% level and is greater than the one from the whole sample, while the estimate (-0.053, p-value=0.193) from US sample is not significant even at the 10% level. These results indicate that CDS trading has more significant effects in non-US countries and regions than in the US.

For the US subsample spanning from 2009 to 2017, I substitute CDS trading activity variables for the indicator variable, *CDSINIT*, to verify the results above. I report the estimated coefficients of the average daily trading notional and the log of the total number of clearing dealers in columns (7) and (8), respectively. Both coefficients are negative and significant at the 10% level, suggesting that CDS trading negatively affects CDS firms' emission reduction engagement in the US. This finding is consistent with prior studies, e.g., Narayanan and Uzmanoglu (2018a, b), that show that actively traded CDSs exert more effects on referenced firms. Furthermore, this evidence suggests that CDS trading activity has more capability to capture the effects of CDS trading on the CDS firms' CSR performance than the indicator variable, *CDSINIT*.

To summarize, I use various approaches to validate my main conclusions that CDS trading significantly and negatively influences firms' emission reduction performance and weakly but negatively affects other CSR efforts. Such negative effects of CDS trading on CSR performance are due to the threatening effects of empty creditors. The estimates of various PSM samples validate my conclusions by showing consistently estimated coefficients of *CDSINIT*. The event study also displays a significant and negative average cumulative difference of ENER between control and treated samples surrounding CDS initiation year. Furthermore, the regression analyses on financial crisis periods confirm the empty creditor hypothesis. Over the crisis periods, CDS firms' managers become more concerned about their debt obligations, evidenced by the estimated coefficient of the interaction term between *CDSINIT* and *CRISIS* (-0.085, p-value=0.107). My conclusions are resilient to a variety of subsample composition, including samples of CDS firms, firms from developed countries, firms from prior and post 2008-2009 financial crisis, and US and non-US firms. Finally, my results are also robust to alternative predictors of CDS activity.

5. Primary vs. secondary stakeholders

The baseline and various robustness test results suggest that the inception of CDS trading causes negative effects on the CDS firms' CSR performances. In particular, it significantly and negatively influences firms' emission reduction activities. In this section, I aim to justify the inclination of CDS firms to shrink their efforts on emission reduction rather than on other environmental and social aspects. I hypothesize that emission reduction activities have a close and high correlation with the corporations' expenses than other CSR activities. Consequently, when executives cope with increased concerns arising from fulfilling the debt obligations of exacting lenders, they prefer to cut back expenditures related to emission reduction activities. To test this hypothesis, I employ the same approach used in Table 3.3 to regress SG&A expenses on the rest of the E&S category scores. The results are reported in Table 3.11.

<Insert Table 3.11 about here>

The estimated coefficients of E&S scores range from the lowest one, 0.23% for health and safety (*SOHS*), to the highest one, 0.55% for production innovation (*ENPI*). All estimates are statistically significant at the 1% level. The estimated coefficient of emission reduction (*ENER*) is in the middle, with a value of 0.38%. This evidence is contrary to my supposition that emission reduction activities have the highest relation with corporate SG&A spending, and hence modifying in ENER activities would cause the most considerable change in SG&A expenses. Accordingly, cost-saving may not have a connection with the decline in firms' emission reduction activities.

To justify my findings, I resort to stakeholder theory, since stakeholder management is a practical mechanism to carry out corporate environmental and social responsibilities (Clarkson, 1995; Freeman et al., 2010). From the perspective of stakeholder management, stakeholders have different importance to the sustainability of the focal firm. Further, because of limited resources such as capital availability, managers must strategically balance competing stakeholders' claims on the corporation's resources and identify stakeholders whose resources are vital to the corporation's survival (primary stakeholders). According to Freeman et al. (2010), primary stakeholders usually include customers, employees, shareholders, creditors, local communities, and suppliers. In contrast, secondary stakeholders are not essential to the firm's survival, such as media, competitors, special interest groups, the surrounding society, and so on (Freeman et al., 2010). Therefore, post-CDS trading, I conjecture that the managers of CDS firms still uphold CSR initiatives intending to develop and manage primary stakeholder-firm relations (such as employees and local communities). At the same time, they may pay less attention to the secondary stakeholders' claims (such as the natural environment).

In Appendix 3.2, I replicate the descriptions of key performance indicators (KPI) of emission reduction from Thomson Reuters 2015 ESG data Glossary. Examining these definitions suggests that except for the emission reduction, most ESG assessments focus on primary stakeholders. For example, social/product responsibility (*SOPR*) and social/health and safety (*SOHS*) evaluate a firm's performance on customers and employees, respectively, while most emission reduction (*ENER*) criteria study the negative externalities incurred by corporate operations on the natural environment, a secondary stakeholder. For example, greenhouse gas emissions and the total amount of waste produced are two KPIs of emission reduction measures. Therefore, when facing economic uncertainties, CDS firms may cut back costs related to the secondary stakeholders. In this case, expenses associated with the natural environment may be the first to be cut. I hypothesize that emission reduction management has either no or negative relation to shareholder value creation in contrast to other stakeholder's management, such as employee, customer, and community relationship management.

To test the supra hypothesis, I employ the approach in Hillman and Keim (2001) to investigate the relation between a firm's market value creation and stakeholder relationship management. Following Hillman and Keim (2001), I proxy shareholder value creation by MVA, which is the firm's market value minus its total capital contributed by its equity and debt holders. I use the ASSET4 E&S scores as the proxies of the levels of stakeholder engagement. A high score indicates that the focal firm has built a healthy and positive relationship with the involved stakeholders. For example, a higher community score suggests that the managers sensitively attend to claims from the community in which the firm operates.

Furthermore, I compute an overall employee relationship score by equally weighting the four category scores associated with employees, i.e., health and safety (*SOHS*), training and development (*SOTD*), employment quality (*SOEQ*), and diversity and opportunity (*SODO*). I call it the workforce score. I also include control variables applied in the extant firm-value and CSR literature (such as Hillman and Keim, 2001; Lins et al., 2017; Buchanan et al., 2018) to isolate factors that could affect MVA. Specifically, I include the following firm-level characteristics as controls: *firm size*, *profitability*, *risk*, *leverage*, *growth opportunity*, *cash holdings*, *capital intensity*, *R&D*, and *cash dividend*. I estimate my whole sample using equation (5):

$$\log(MVA_{\mathrm{i,t}}) = \alpha + \beta E\&S\ Score_{\mathrm{i,t-1}} + \gamma X_{\mathrm{i,t-1}} + \omega Industry_{\mathrm{i}} + \rho Country_{j} + \phi Year_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \quad (5)$$

where $MVA_{i,t}$ is the market value-added of firm i at the end of fiscal year t, $E\&S\ Score_{i,t-1}$ is one of the environmental or social scores of firm i at the end of fiscal year $t-1$, $X_{i,t-1}$ is an array of firm-level control variables described supra at the end of year $t-1$, and $Industry_i$, $Country_j$, and $Year_t$ represents the industry-, country-, and year-fixed effects, respectively. As usual, I cluster standard errors at the firm level. I present the regression results of equation (5) in Table 3.12.

<Insert Table 3.12 about here>

Row (1) of Table 3.12 reports the estimated coefficient of *ENER* (0.041, with a p-value of 0.452). This non-significant coefficient suggests that the engagement in environmental emission reduction activities has no direct economic relation to shareholder value creation[40]. In contrast, the coefficients of resource reduction (0.092) in Row (2) and environmental product innovation (0.132) in Row (3) are significant at the 10% and 5% level, respectively. This evidence suggests that good management in resource control and eco-product innovation may generate value for shareholders.

Turning to Row (4) in which I report the relationship between MVA and employee relationship management, I find the largest magnitude (0.194, with a p-value of 0.006) of estimated coefficients across relationship measurement in Table 3.12. The estimate is significant at the 1% level, indicating that effective employee management plays an essential and decisive role in shareholder value creation. This finding is consistent with Edmans (2011) and Guiso et al. (2015), who document a positive relationship between employee management and shareholder's wealth. Rows (5) and (6) report estimates for human rights and community relationship management. Both estimated coefficients are significant at the 10% level, implying that maintaining a good relationship with the local community and respecting fundamental human rights are beneficial not only to the involved stakeholders but also to the shareholders. Finally, in Row (7), I find a non-

[40] *We also use Tobin' Q as the proxy of firms' value and regress it on emission reduction (ENER) score scaled on log. The estimated coefficient estimate of log (ENER) is -0.0371, with a p-value of 0.0234, which suggests that investment in emission reduction activities could transfer shareholders' wealth to other stakeholders.*

significant but positive relationship (0.0577, with a p-value of 0.24) between product responsibility and shareholder value creation. This result suggests that customer relationship management proxied by product responsibility score has a weak but positive influence on shareholder value creation.

Overall, my findings are in line with Hillman and Keim (2001), who document that investing in secondary stakeholder relations may not create value for shareholders while maintaining good relationships with primary stakeholders will bring value to shareholders. The estimates by regressing MVA on various proxies of stakeholder relationship management strongly support my conjecture that CDS firms mostly cut down costs related to environmental emission reduction activities when facing cost-savings. Managers opt for such policies because, in part, investment in emission reduction activities may not yield economic benefits to shareholders, evidenced by the non-significant estimated coefficient of *ENER*.

6. Conclusion

In this study, I examine the impact of CDS trading on the firms' CSR performance using firms from eleven countries and regions. I provide evidence that CDS trading leads to weak but negative effects on the firms' CSR performance in general, but holds a significant and negative influence on the firms' emission reduction activities. This conclusion is robust to various testing approaches, including event study, propensity score matching, Monte Carlo simulation, and various subsample examinations. By associating emission reduction scores to SG&A expenses, I find that CDS firms, on average, cut down their expenditure on environmental emission reduction activities to the amount of $35.94 ($15.41) million based on the mean (median) of SG&A expenses of CDS firms. A further examination of the connection of SG&A expenses and other E&S metrics indicates that reducing expenses seems not to be the sole reason to shrink efforts on emission reduction activities because other E&S metrics have a higher correlation with the firms' expenses than the emission reduction metric.

I justify my finding by examining the relationship between the firms' market value-added and the various stakeholder relationship management proxied by ASSET4 E&S scores. My results indicate that emission reduction activities have statistically no economic relation with shareholder value creation. In contrast, other activities, such as resource and employee management, have strong positive effects on shareholder value creation. Therefore, when the managers of CDS firms concern with debt obligations of CDS insured lenders, they may cut down investments on emission reduction activities. The results are consistent with instrumental stakeholder theory that managers pay more attention to primary stakeholders' interests, such as employees and customers, and pay less attention to secondary stakeholders, such as the natural environment, when managers need to resolve conflict interests among stakeholders. My results highlight the downside of CDSs arising from the threatening effects of empty creditors. After the inception of CDS trading, the managers of CDS firms adopt a more conservative stance towards CSR issues.

CHAPTER FOUR

CONCLUSIONS

While a stream of literature has explored the motives and factors that propel a firm's CSR activities, academics and practitioners still struggle to understand why and how a company engages in CSR activities. Given the increasing importance of CSR in businesses and societies, I add to the literature by addressing the question of whether financial market innovation, particularly CDSs, can impact a company's corporate social responsibility.

With more extensive sample data from eleven countries and regions across the globe, I find robust evidence that CDS trading significantly and negatively affects a company's emission reduction activities. Post-CDS trading, a CDS firm's ENER score decreases by 4.9% generally in contrast to non-CDS firms. To get an economic sense of this decrease, I associate the reduction in ENER scores with SG&A expenses and find the decline in ENER score to be equivalent to a cut of $35.94 million in a firm's emission reduction investment. However, although CDS negatively affects a firm's other CSR performance, I find no statistical evidence that the influences are significant. Furthermore, emission reduction activities seem to have no relation to shareholders' value creation, while other CSR activities, such as employee management and eco-product innovation, do positively correlate with shareholders' wealth.

I also explore the impact of CDS trading on the cost of capital and corporate capital structure. I assess the overall benefits and costs induced by CDS trading on a firm because previous studies have reached mixed conclusions on this topic. I construct a longitudinal sample with the universe of Compustat US public companies to conduct my tests. I find strong statistical evidence that CDS trading brings more benefits than costs to CDS firms, evidenced by a lowered WACC post-CDS trading. Furthermore, CDS trading affects firms with different leverage in a diverse manner.

Highly levered firms prefer to reduce their usage of debt, while firms with lower leverage desire to take the advantage of CDS trading by increasing their debt usage. Finally, I find that CDS firms adjust their debt placement. Post-CDS trading, they substitute arm-length debt for bank debt. Notably, they significantly reduce the usage of revolving credit and simultaneously increase bond issuance to avoid rollover risk. Overall, the changes in debt placement reflect that CDS trading increases debt renegotiation costs but simultaneously reduces capital supply-side frictions.

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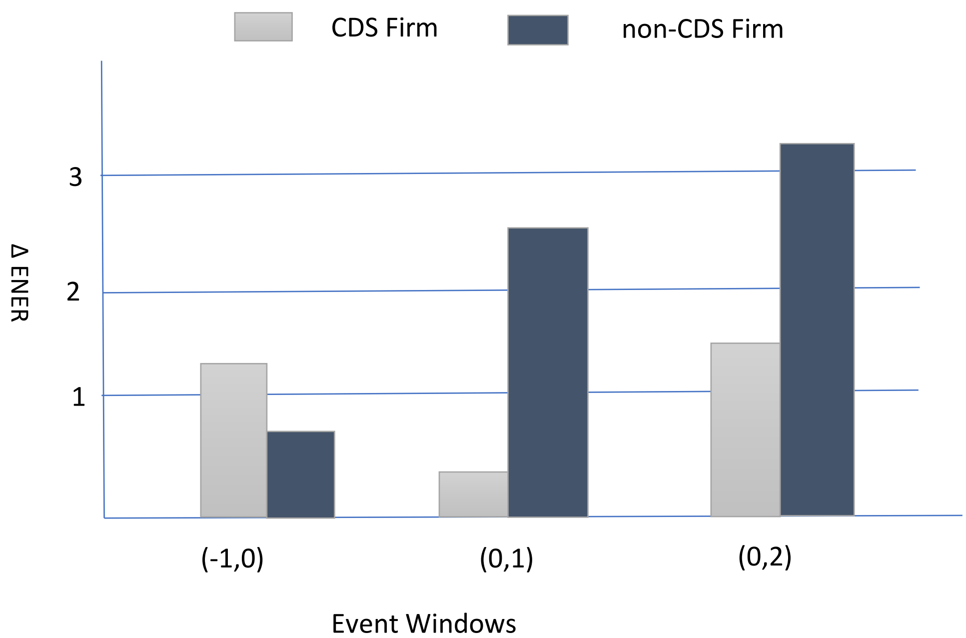
Figures

Figure 3.1. Average cumulative differentials of emission reduction score surrounding the inception of CDS trading



Appendix

Appendix 2.1. 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 2.2 Variable definitions

Variable Name	Definition	Source
WACC	The weighted average of cost of debt (after tax) and cost of capital, please see Appendix 2.1 for details.	Bloombrg
Cost of debt	The overall cost of debt, including all sources of debt financing, please see Appendix 2.1 for details.	Bloombrg
Cost of equity	The required rate of return of investors, computed from capital asset pricing model (CAPM), please see Appendix 2.1 for details.	Bloombrg
Weight of debt	The weight of debt evaluated on market values, please see Appendix 2.1 for details.	Bloombrg
Weight of equity	The weight of equity evaluated on market values, please see Appendix 2.1 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
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 2.2 Continued

Variable Name	Definition	Source
MTBV	The ratio of equity market value to its book value.	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
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

Appendix 3.1. Variable definitions

Dependent Variables

Variable Abbreviation	Variable Name	Definition	Source
ENVSCORE	Environmental performance score	The environmental pillar measures a company's impact on living and non-living natural systems, including the air, land, and water, as well as complete ecosystems.	Thomson Reuters ASSET4
SOCSCORE	Social performance score	The social pillar measures a company's capacity to generate trust and loyalty with its workforce, customers, and society, through its use of best management practices.	Thomson Reuters ASSET4
ENER	Emission reduction score	It measures a company's management commitment and effectiveness towards reducing environmental emissions in the production and operational processes.	Thomson Reuters ASSET4
ENRR	Resource reduction score	It measures a company's management commitment and effectiveness towards achieving efficient use of natural resources in the production process.	Thomson Reuters ASSET4
ENPI	Product innovation score	It measures a company's management commitment and effectiveness in supporting the research and development of eco-efficient products or services.	Thomson Reuters ASSET4
SOEQ	Employment quality score	It measures a company's management commitment and effectiveness in providing high-quality employment benefits and job conditions.	Thomson Reuters ASSET4
SOTD	Training and development score	It measures a company's management commitment and effectiveness towards providing training and development (education) for its workforce	Thomson Reuters ASSET4
SOCO	Community score	It measures a company's management commitment and effectiveness towards maintaining the company's reputation within the general community (local, national, and global).	Thomson Reuters ASSET4
SODO	Diversity and opportunity score	It measures a company's management commitment and effectiveness towards maintaining diversity and equal opportunities in its workforce.	Thomson Reuters ASSET4
SOHS	Health and security score	It measures a company's management commitment and effectiveness in providing a healthy and safe workplace.	Thomson Reuters ASSET4
SOHR	Human rights score	It measures a company's management commitment and effectiveness towards respecting the fundamental human rights conventions.	Thomson Reuters ASSET4
SOPR	Product responsibility score	measures a company's management commitment and effectiveness towards creating value-added products and services upholding the customer's security.	Thomson Reuters ASSET4

Appendix 3.1. Continued

Variable Abbreviation	Variable Name	Definitions	Source
		Independent Variables	
CDSINIT	CDS trade initiation	A dummy variable having a value of one for the CDS firms in and after CDS initiation year, and zero before that.	Constructed
CDSFIRM	CDS referenced firms	A dummy variable having a value of one for CDS firms, and zero for non-CDS firms.	Constructed
WORKFORCE	Employee workforce	The Workforce Score measures a company's effectiveness towards job satisfaction, the health and safety of the workplace, and the maintenance of diversity and equal opportunities and development opportunities for its workforce. This variable is computed from an equally weighted average of SOTD, SODO, SOEQ, and SOHS. All data is extracted from the Thomson Reuters ASSET4 database.	Constructed
Log (Assets):	The natural log of total assets	Total assets on the natural log scale.	Worldscope
Profitability	Financial profitability	Earnings before interest and taxes (EBIT) divided by total assets.	Worldscope
Tangibility	Asset tangibility	The ratio of net property, plant, and equipment (PPE) to total assets.	Worldscope
CAPEX	Capital expenditure	The ratio of capital expenditures to total sales.	Worldscope
Cash holdings	Cash and equivalent	Cash and equivalent divided by total assets.	Worldscope
MTBV	Market to book ratio	The ratio of equity market value to its book value	Worldscope
Log (Age):	The natural log of firm age	A firm's age is computed by selecting the earlier of its initial public offering (IPO) date and the first date when the firm was included in COMPUSTAT. The number of years elapsed since the earlier date is used to approximate a firm's age.	COMPUSTAT.
Risk	Business riskiness	The stock volatility over the fiscal year.	Datastream.
Turnover	Asset turnover	The ratio of total net sales to total assets.	Worldscope
R&D	Research and development expenses	The ratio of R&D expenditure to total sales.	Worldscope
Leverage	Book leverage	The ratio of total debt to total assets.	Worldscope
Institutional ownership	Institutional shareholder ownership	The ratio of the strategic holdings, which is the sum of all five percent and beyond share ownership to total outstanding common shares.	Worldscope
Governance	Corporate governance	The corporate governance pillar measures a company's systems and processes, which ensures that its board members and executives act in the best interests of its long-term shareholders.	Thomson Reuters ASSET4
Dividends	Cash dividends	Cash dividend payment divided total assets.	Worldscope
ROA	Return on assets	Net income divided by total assets.	Worldscope
WCAP	Working capital	The ratio of working capital to total assets.	Worldscope
CRISIS	Financial crisis	An indicator variable which equals one if a firms' fiscal year ends between August 31, 2008, to August 30, 2009, and zero otherwise.	Constructed
FF48	Fama-French 48	FF48 is the Fama-French 48 industry classification.	Fama-French
Notional	The average daily trading notional amount	The average of CDS daily trading notional amount.	DTCC
Dealer	The number of clearing dealer	The total number of clearing dealers in the fiscal year scaled on the log.	DTCC

Appendix 3.2. Key performance indicators of emission reduction

Emission reduction key performance indicators

Datastream Mnemonic	Name	Description
ENERD01V	Emission Reduction/Policy	Does the company have a policy for reducing environmental emissions or its impacts on biodiversity? And does the company have a policy for maintaining an environmental management system?
ENERD04V	Emission Reduction/Improvements	Does the company set specific objectives to achieve emission reduction?
ENERO01V	Emission Reduction/Biodiversity Impact	Does the company report on initiatives to protect, restore, or reduce its impact on native ecosystems and species, biodiversity, and protected and sensitive areas?
ENERO03V	Emission Reduction/Greenhouse Gas Emissions	Total CO2 and CO2 equivalent emissions in tonnes divided by net sales or revenue in US dollars.
ENERO04V	Emission Reduction/Cement CO2 Emissions	Total CO2 and CO2 equivalent emissions in kilograms per tonne of cement produced.
ENERO08V	Emission Reduction/NOx and SOx Emissions Reduction	Does the company report on initiatives to reduce, reuse, recycle, substitute, or phase out SOx (sulfur oxides) or NOx (nitrogen oxides) emissions?
ENERO09V	Emission Reduction/VOC Emissions Reduction	Does the company report on initiatives to reduce, substitute, or phase out volatile organic compounds (VOC) or particulate matter less than ten microns in diameter (PM10)?
ENERO10V	Emission Reduction/Waste	Total amount of waste produced in tonnes divided by net sales or revenue in US dollars.
ENERO11V	Emission Reduction/Waste Recycling Ratio	Total recycled and reused waste produced in tonnes divided by total waste produced in tonnes.
ENERO12V	Emission Reduction/Hazardous Waste	Total amount of hazardous waste produced in tonnes divided by net sales or revenue in US dollars.
ENERO13V	Emission Reduction/Discharge into Water System	Total weight of water pollutant emissions in tonnes divided by net sales or revenue in US dollars.
ENERO14V	Emission Reduction/Waste Reduction	Does the company report on initiatives to recycle, reduce, reuse, substitute, treat, or phase out total waste, hazardous waste, or wastewater?

Appendix 3.2. Continued.

ENERO15V	Emission Reduction/Innovative Production	Does the company report on the concentration of production locations to limit the environmental impact during the production process? OR Does the company report on its participation in any emissions trading initiative? OR Does the company report on new production techniques to improve the global environmental impact (all emissions) during the production process?
ENERO16V	Emission Reduction/Environmental Partnerships	Does the company report on partnerships or initiatives with specialized NGOs, industry organizations, or governmental or supra governmental organizations that focus on improving environmental issues?
ENERO17V	Emission Reduction/Environmental Management Systems	The percentage of company sites or subsidiaries that are certified with any environmental management system.
ENERO18V	Emission Reduction/Environmental Restoration Initiatives	Does the company report or provide information on company-generated initiatives to restore the environment?
ENERO19V	Emission Reduction/Transportation Impact Reduction	Does the company report on initiatives to reduce the environmental impact of transportation of its products or its staff?
ENERO22V	Emission Reduction/Climate Change Risks and Opportunities	Is the company aware that climate change can represent commercial risks and/or opportunities?
ENERO24V	Emission Reduction/Environmental Expenditures	Does the company report on its environmental expenditures or on proactive environmental investments to reduce future risks or increase future opportunities?

Table 2.1. 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	147	21.71	21.71
2002	104	15.36	37.08
2003	121	17.87	54.95
2004	102	15.07	70.01
2005	42	6.20	76.22
2006	44	6.50	82.72
2007	50	7.39	90.01
2008	7	1.03	91.14
2009	4	0.59	91.73
2010	5	0.74	92.47
2011	8	1.18	93.65
2012	10	1.48	95.13
2013	3	0.44	95.57
2014	7	1.03	96.60
2015	9	1.33	97.93
2016	3	0.44	98.38
2017	11	1.62	100
Total	677	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	29	0.34
Construction and mining (1)	66	747	8.69
Manufacturing (2,3)	309	4,122	47.94
Transportation (4)	125	1,555	18.09
Wholesale and retail (5)	71	915	10.64
Services (7,8,9)	104	1,229	14.30
Total	677	8,597	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 and long-term debts 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 2.2 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	8,597	8.492	8.358	2.405	40,253	9.005	8.784	3.145	-0.514***
Cost of debt	8,597	3.002	3.039	1.751	40,253	2.668	2.633	2.029	0.335***
Cost of equity	8,597	10.926	10.474	2.848	40,253	10.418	10.197	3.248	0.507***
Weight of debt	8,597	0.300	0.256	0.211	40,253	0.203	0.124	0.228	0.097***
Weight of equity	8,597	0.695	0.742	0.215	40,253	0.788	0.869	0.235	-0.092***
Debt decompositions									
Public debt	8,127	0.715	0.817	0.293	32,950	0.361	0.164	0.397	0.353***
CPs	8,127	0.022	0	0.051	32,950	0.002	0	0.018	0.019***
Bonds/Notes	8,127	0.686	0.775	0.292	32,950	0.358	0.160	0.396	0.327***
Bank debt	8,127	0.182	0.057	0.254	32,950	0.502	0.500	0.413	-0.320***
Drawn revolving credits	8,127	0.062	0	0.141	32,950	0.227	0.007	0.337	-0.165***
Bank loans	8,127	0.120	0	0.218	32,950	0.275	0.029	0.363	-0.155***
Capital leases	8,127	0.022	0	0.087	32,950	0.085	0	0.240	-0.063***
Trusted preferred	8,127	0.002	0	0.008	32,950	0.000	0	0.001	0.001***
Other debt	8,127	0.079	0.001	0.182	32,950	0.052	0	0.174	0.027***
Firm-level characteristics									
Assets ($ billion)	8,597	14.896	5.395	27.525	40,253	3.239	0.307	14.950	11.657***
Leverage	8,597	0.335	0.305	0.208	40,253	0.221	0.167	0.240	0.113***
Growth	8,597	2.906	2.100	5.317	40,253	2.694	1.820	5.306	0.213***
Profitability	8,597	0.080	0.082	0.117	40,253	-0.032	0.053	0.329	0.112***
IO concentration	8,597	0.064	0.041	0.091	40,253	0.154	0.068	0.209	-0.090***
IO ratio	8,597	0.704	0.772	0.259	40,253	0.430	0.393	0.359	0.274***
Age	8,597	32.776	30.000	18.780	40,253	18.088	14.000	13.027	14.688***
R&D	8,597	0.032	0	0.315	40,253	0.461	0.003	2.374	-0.429***
Liquidation	8,597	0.576	0.566	0.133	40,253	0.476	0.474	0.174	0.099***
Riskiness	8,597	0.395	0.337	0.209	40,253	0.585	0.514	0.341	-0.189***
CAPEX	8,597	0.101	0.042	0.195	40,253	0.129	0.034	0.374	-0.029***
Stock liquidity	8,597	2.482	1.890	2.129	40,253	1.655	1.037	1.961	0.826***
Tax rate	7,340	0.297	0.338	0.086	29,048	0.219	0.265	0.121	0.077***
Dividends	8,597	0.575	0.310	0.750	40,253	0.171	0	0.441	0.403***
Credit rating	8,597	0.821	1.000	0.384	40,253	0.155	0	0.362	0.666***
Analyst	8,597	13.926	13	9.049	40,253	5.594	4	6.160	8.035***
Long-term debt	8,597	4.224	1.462	9.117	40,253	0.783	0.019	4.092	3.272***

Panel D. Summary statistics of CDS activities

Variables	N	Mean	Median	STD
CDSINIT	48,850	0.154	0	0.361
CDSFIRM	48,850	0.175	0	0.381
Notional	26,580	0.017	0.002	0.222
Dealers	26,580	0.685	0	2.791

Panel E. Pearson correlation between selected variables

This table illustrates the Pearson correlations for firm-level characteristics. Variable definitions are listed in Appendix 2.2 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)	0.92***	1.00																	
WACC (3)	-0.07***	-0.06***	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***	-0.02*	0.30***	-0.26***	1.00													
Leverage (7)	0.18***	0.17***	-0.32***	0.22***	-0.08***	0.15***	1.00												
Profitability (8)	0.14***	0.13***	-0.05***	-0.00	0.03***	0.37***	-0.09***	1.00											
CAPEX (9)	-0.03***	-0.03***	0.02***	0.04***	-0.04***	-0.04***	0.05***	-0.21***	1.00										
Growth (10)	0.01***	0.01***	0.08***	0.01**	-0.03***	0.00	-0.08***	0.02**	0.02***	1.00									
Log (Age) (11)	0.36***	0.38***	-0.09***	0.20***	-0.17***	0.32***	0.02***	0.18***	-0.10***	-0.03***	1.00								
Riskiness (12)	-0.22***	-0.22***	0.12***	-0.09***	0.04***	-0.47***	0.04***	-0.39***	0.12***	-0.02***	-0.35***	1.00							
Dividends (13)	0.29***	0.30***	-0.11***	0.19***	-0.16***	0.43***	0.06***	0.16***	-0.03***	0.03***	0.37***	-0.33***	1.00						
Tax rate (14)	0.26***	0.24***	0.01**	0.06***	-0.02***	0.55***	-0.13***	0.50***	-0.13***	0.01**	0.29***	-0.53***	0.30***	1.00					
IO concentration (15)	-0.17***	-0.16***	-0.14***	-0.13***	0.13***	-0.47***	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***	0.28***	0.18***	-0.14***	-0.07***	0.16***	-0.22**	0.16***	0.25***	-0.07***	1.00			
R&D (17)	-0.07***	-0.07***	0.09***	-0.01**	-0.02***	-0.17***	-0.02***	-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***	-0.09***	0.37***	-0.31***	0.56***	0.25***	0.17***	-0.01*	-0.01**	0.27***	-0.24***	0.25***	0.29***	-0.22***	0.28***	-0.10***	1.00	
Stock liquidity (19)	0.15***	0.15***	0.24***	0.13***	-0.13***	0.12***	-0.00	-0.02***	0.04***	0.05***	-0.01**	0.10***	-0.07***	0.07***	-0.14***	-0.07***	0.05***	0.07***	1.00

Table 2.2. 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 2.2 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 from 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)
CSDFIRM	-0.097			-0.265***			-0.682***		
	(-1.07)			(-3.51)			(-6.55)		
CDSINIT	-0.281***	-0.239***	-0.227***	-0.260***	-0.256***	-0.282***	0.134	0.242**	0.321***
	(-3.57)	(-2.87)	(-2.59)	(-4.11)	(-3.86)	(-4.22)	(1.38)	(2. 32)	(2.94)
Controls									
Tax rate			0.635**			-1.197***			-0.648**
			(2.17)			(-6.52)			(-2.01)
Log(assets)	0.273***	0.309***	0.322***	0.110***	0.228***	0.197***	0.526 ***	0.648***	0.690***
	(13.08)	(7.82)	(6.83)	(8.12)	(9.10)	(6.74)	(24.15)	(15.02)	(13.22)
Leverage	-2.654***	-2.215***	-2.144***	1.520***	1.316***	1.278***	0.118	0.181	0.017
	(-24.18)	(-17.56)	(-14.82)	(24.15)	(17.99)	(14.73)	(1.02)	(1.28)	(0.11)
Profitability	-0.363***	-0.235***	-0.320***	-0.202***	-0.226***	-0.175***	-0.428***	-0.378***	-0.403***
	(-4.53)	(-2.69)	(-3.17)	(-4.98)	(-5.01)	(-3.32)	(-5.21)	(-4.19)	(-3.93)
CAPEX	-0.020	0.024	-0.075	0.128***	0.083*	0.082	0.072	0.068	-0.037
	(-0.29)	(0.30)	(-0.79)	(3.39)	(1.93)	(1.59)	(0.99)	(0.81)	(-0.37)
Growth	0.015***	0.011***	0.009***	0.003**	0.003**	0.002	0.009***	0.008***	0.007**
	(5.32)	(3.95)	(2.77)	(2.03)	(2.13)	(1.39)	(3.24)	(2.90)	(2.15)
Log (Age)	-0.044	0.016	-0.545***	-0.061***	0.044	-0.059	0.058	0.321***	-0.366***
	(-1.26)	(0.18)	(-4.49)	(-2.71)	(0. 71)	(-0.71)	(1.50)	(3.18)	(-2.74)
Riskiness	1.258***	1.531***	1.729***	0.281***	0.244***	0.163**	1.853***	2.042***	2.139***
	(11.96)	(11.96)	(11.94)	(5.99)	(4.05)	(2.29)	(14.32)	(12.98)	(11.47)
Dividends	-0.001	0.095**	0.062	-0.016	0.060*	0.086**	-0.255***	-0.106*	-0.175***
	(-0.03)	(2.04)	(1.00)	(-0.52)	(1.66)	(2.16)	(-5.53)	(-1.94)	(-2.79)
IO concentration	-0.805***	-0.540***	-0.589***	0.252***	0.194***	0.074	-0.299**	-0.181	-0.284*
	(-7.03)	(-4.15)	(-3.95)	(4.40)	(2.94)	(0.98)	(-2.37)	(-1.27)	(-1.79)
Liquidation	-1.295***	-1.077***	-1.348***	0.958***	0.839***	0.836***	-0.773***	-0.703***	-1.073***
	(-9.15)	(-6.03)	(-6.69)	(10.19)	(7.10)	(6.18)	(-5.13)	(-3.64)	(-4.96)
R&D	0.025*	0.007	0.007	-0.004	0.005	-0.007	0.017	-0.003	-0.006
	(1.94)	(0.46)	(0.41)	(-0.58)	(0.06)	(-0.64)	(1.33)	(-0.20)	(-0.34)
S&P rated	-0.181***	-0.225***	-0.453***	0.573***	0.560***	0.842***	0.059	0.029	0.068
	(-3.37)	(-3.62)	(-5.41)	(13.78)	(11.69)	(11.88)	(0.94)	(0.39)	(0.64)
Stock liquidity	0.166***	0.126***	0.155***	0.003	0.001	0.014*	0.242***	0.203***	0.230***
	(14.75)	(10.17)	(11.21)	(0.56)	(0.15)	(1.84)	(20.08)	(15.24)	(15.50)
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	48,850	48,850	36,388	48,850	48,850	36,388	48,850	48,850	36,388
#Firms	5,575	5,575	4,613	5,575	5,575	4,613	5,575	5,575	4,613
Adjusted R^2	0.298	0.584	0.613	0.327	0.631	0.645	0.279	0.547	0.586

Table 2.3. 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 2.2 All accounting variables are winsorized at the top and bottom 1%. Column 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	0.133 (2.00) **	0.028 (0.53)	0.016(0.32)	-0.055 (-0.84)
CDSINIT	-0.282 (-4.34) ***	-0.313 (-5.44) ***	-0.348 (-6.49) ***	-0.572 (-8,23) ***
Controls				
Log(assets)	0.206 (22.05) ***	0.221 (20.57) ***	0.208 (20.63) ***	0.186 (12.21) ***
Leverage	-3.814 (-39.40) ***	-3.857 (-50.10) ***	-3.737 (-54.56) ***	-3.421 (-51.01) ***
Profitability	0.308 (3.45) ***	-0.221 (-2.46) **	-0.427 (-5.42) ***	-1.002 (-9.08) ***
CAPEX	-0.140 (-2.27) **	-0.194 (-3.09) ***	-0.219 (-4.37) ***	-0.124 (-1.71) *
Growth	0.037 (13.91) ***	0.037 (12.28) ***	0.035 (12.50) ***	0.020 (8.20) ***
Log (Age)	0.073 (3.62) ***	0.064 (3.96) ***	0.033 (1. 99) **	-0.098 (-4.31) ***
Riskiness	-0.178 (-2.38) **	0.777 (9.17) ***	1.317 (17.79) ***	3.101 (22.14) ***
Dividends	-0.193 (-7.07) ***	-0.207 (-8.13) ***	-0.239 (-12.22) ***	-0.195 (-6.35) ***
IO concentration	-1.661 (-16.93) ***	-1.712 (-20.21) ***	-1.803 (-22.28) ***	-1.655 (-14.47) ***
Liquidation	-0.470 (-4.27) ***	-0.705 (-8.31) ***	-1.099 (-14.34) ***	-1.951 (-17.19) ***
R&D	0.070 (5.69) ***	0.077 (6.57) ***	0.081 (8.53) ***	0.065 (3.65) ***
S&P rated	0.084 (2.22) **	-0.062 (-1.75) *	-0.088 (-2.59) ***	-0.220(-4.66) ***
Stock liquidity	0.224 (31.67) ***	0.258 (35.24) ***	0.262 (28.64) ***	0.252 (19.10) ***
Industry-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
# Observations	48,850	48,850	48,850	48,850

Table 2.4. 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 2.2. 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)
CSDFIRM	0.218		0.024		-0.016	
	(1.19)		(0.13)		(-0.09)	
CDSINIT	-0.106	-0.123	0.132	0.137	-0.312**	-0.290*
	(-0.84)	(-0.88)	(1.22)	(1.24)	(-2.14)	(-1.79)
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	2,534	2,534	2,534	2,534	2,534	2,534
Adjusted R^2	0.553	0.71	0.394	0.761	0.475	0.608

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)
CSDFIRM	-0.121		-0.192**		-0.750***	P=10.9
	(-1.24)		(-2.49)		(-6.62)	
CDSINIT	-0.296***	-0.245**	-0.323***	-0.328***	0.231**	0.355***
	(-3.31)	(-2.55)	(-4.67)	(-4.47)	(2.08)	(2.94)
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	46,316	46,316	46,316	46,316	46,316	46,316
Adjusted R^2	0.292	0.619	0.335	0.631	0.282	0.549

Table 2.5. 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 2.2 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 firms whose default probability lies below 33% quantile, while Panel B reports estimates using observations firms whose default probability lies above 66% quantile. 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 firms with low default probability

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CSDFIRM	-0.087		-0.225*		-0.161	
	(-0.70)		(-1.75)		(-1.31)	
CDSINIT	-0.435***	-0.325**	-0.059	-0.015	-0.335***	-0.196*
	(-4.04)	(-2.86)	(-0.54)	(-0.13)	(-3.08)	(-1.69)
Industry-fixed effects	Yes		Yes			Yes
Firm-fixed effects		Yes		Yes	Yes	
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	13,581	13,581	13,581	13,581	13,581	13,581
Adjusted R^2	0.343	0.657	0.335	0.684	0.269	0.618

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)
CSDFIRM	-0.023		-0.146		-0.554**	
	(-0.14)		(-1.09)		(-2.48)	
CDSINIT	-0.408**	-0.259	-0.420***	-0.336**	0.488**	0.819***
	(-2.49)	(-1.31)	(-3.22)	(-2.14)	(2.00)	(2.67)
Industry-fixed effects	Yes		Yes			Yes
Firm-fixed effects		Yes		Yes	Yes	
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	13,995	13,995	13,995	13,995	13,995	13,995
Adjusted R^2	0.253	0.594	0.393	0.682	0.301	0.596

Table 2.6. 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 2001-2017. 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 2.2. 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	-10.932 (-2.20) **
Log (Assets)	0.328 (13.34) ***
Growth	0.007 (1.49)
Risk	-0.429 (-2.41) **
Profitability	0.400 (1.65) *
PPE ratio	0.684 (2.75) ***
CAPEX	0.199 (1.81) *
Dividends	-0.005 (-0.10)
IO concentration	0.559 (1.94) *
Leverage	0.798 (5.49) ***
Log (Age)	0.283 (7.86) ***
Cash	0.481 (1.22)
Turnover	0.051 (4.59) ***
Liquidation	1.808 (4.32) ***
R&D	-0.069 (-1.08)
WCAP	0.869 (3.08) ***
Excess return	0.096 (1.76) **
S&P rated	1.119 (13.25) ***
Stock liquidity	0.151 (11.26) ***
Likelihood Ratio	2,464.932***
Industry- and year-fixed effects	Yes
Pseudo R^2	44.67%
Percent Concordant /C	96.4%
C	0.964
#Observations	42,352

Table 2.7. Comparison of control-treated firms' 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 2.2. 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	8.304	8.319	-0.014 (-0.09)
Cost of debt	4.184	4.303	-0.120 (-0.94)
Cost of equity	10.006	10.056	-0.050 (-0.27)
Log (Assets)	15.095	14.742	0.353 (3.77) ***
Leverage	0.337	0.352	-0.015 (-1.08)
Profitability	0.079	0.072	0.006 (0.85)
CAPEX	0.118	0.165	-0.046 (-1.90) *
Growth	2.973	2.918	0.054 (0.13)
Log (Age)	2.954	2.722	0.231 (4.23) ***
Riskiness	0.441	0.479	-0.037 (-2.51) **
Dividends	0.366	0.222	0.144 (3.96) ***
IO concentration	0.057	0.066	-0.008 (-1.25)
Liquidation	0.568	0.560	0.008 (-0.33)
R&D	0.037	0.067	-0.029 (-1.01)
S&P rated	0.917	0.906	0.005 (0.24)
Stock liquidity	1.86	2.227	-0.422 (-2.64) ***
Logit of Propensity of initiation	-2.259	-2.395	0.135 (1.18)
#Observations	408	408	

Table 2.8. 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 4.1. 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 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.

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	0.302***		0.092		0.045	
	(2.94)		(1.01)		(0.41)	
CDSINIT	-0.229**	-0.233**	-0.240***	-0.234***	-0.185	-0.119
	(-2.20)	(-2.03)	(-2.93)	(-2.74)	(-1.53)	(-0.90)
Industry-fixed effects	Yes		Yes			
Firm-fixed effects		Yes		Yes	Yes	Yes
Adjusted R^2	0.469	0.629	0.415	0.659	0.472	0.601
#Observations	10,157	10,157	10,157	10,157	10,157	10,157
#Firms	804	804	804	804	804	804

Panel B. Regression results using nearest-one matching sample with exact FF48 industry classification

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.219**		0.122		0.042	
	(2.01)		(1.21)		(0.35)	
CDSINIT	-0.248**	-0.252**	-0.240***	-0.252***	-0.166	-0.089
	(-2.49)	(-2.32)	(-2.98)	(-2.99)	(-1.38)	(-0.68)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Adjusted R^2	0.472	0.630	0.448	0.667	0.473	0.601
#Observations	8,648	8,648	8,648	8,648	8,648	8,648
#Firms	672	672	672	672	672	672

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	0.148		0.138		-0.084	
	(1.37)		(1.38)		(-0.71)	
CDSINIT	-0.178*	-0.317***	-0.179**	-0.202**	-0.118	-0.057
	(-1.86)	(-3.03)	(-2.32)	(-2.50)	(-1.03)	(-0.46)
Industry-fixed effects	Yes		Yes			
Firm-fixed effects		Yes		Yes	Yes	Yes
Adjusted R^2	0.484	0.619	0.422	0.663	0.477	0.603
#Observations	9,319	9,319	9,319	9,319	9,319	9,319
#Firms	721	721	721	721	721	721

Table 2.9. The impact of CDS trading on the cost of capital using CDS firms

Panels A and B present regression results based on CDS (treatment) firms. Dependent variables are the cost of capital, cost of debt, and cost of equity. Independent variables are CDSINIT and CDSLAG, respectively. We introduce an interaction item between CDSINIT and High_liquidation in Panel B to capture shareholders' strategic incentives. High_liquidation is an indicator variable that has a value of one if the liquidation cost is above the sample median, and zero otherwise. All controls are included but not reported. 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 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. Cost of capital and CDS trading

	WACC				Cost of debt				Cost of equity			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDSINIT	-0.077	-0.505			-0.132*	-0.122*			0.145	0.190		
	(-0.83)	(-0.54)			(-1.92)	(-1.69)			(1.43)	(1.62)		
CDSLAG			-0.140	-0.137			-0.184***	-0.163**			-0.013	0.041
			(-1.62)	(-1.44)			(-2.82)	(-2.38)			(-0.14)	(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	0.509	0.666	0.510	0.667	0.494	0.682	0.495	0.683	0.569	0.675	0.575	0.680
#Observations	8,597	8,597	8,597	8,597	8,597	8,597	8,597	8,597	8,597	8,597	8,597	8,597
#Firms	677	677	677	677	677	677	677	677	677	677	677	677

Panel B. Cost of capital and CDS trading with controlling strategic incentive

	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	8,597	8,597	8,597
#Firms	677	677	677

Table 2.10. 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 is zero for 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	-0.440***		-0.452***		-0.287***		-0.298***		-0.661***		-0.726	
	(-4.38)		(-4.57)		(-4.36)		(-4.65)		(-5.88)		(-6.62)	
Notional	-0.017***	0.001			-0.018***	-0.017***			-0.028***	-0.011		
	(-3.24)	(0.12)			(-5.06)	(-3.54)			(-4.55)	(-1.29)		
Dealers			-0.025***	-0.015**			-0.028***	-0.029***			-0.027***	-0.014
			(-3.59)	(-1.99)			(-6.58)	(-5.59)			(-3.29)	(-1.57)
Controls												
Industry-fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Adjusted R^2	0.279	0.510	0.277	0.681	0.220	0.729	0.201	0.730	0.290	0.651	0.296	0.656
#Observations	26,580	26,580	26,580	26,580	26,580	26,580	26,580	26,580	26,580	26,580	26,580	26,580
#Firms	4,045	4,045	4,045	4,045	4,045	4,045	4,045	4,045	4,045	4,045	4,045	4,045

Table 2.11. The distribution of coefficient estimates of *CDSINIT* with randomized CDS-trade-initiation events (1,000 replications)

This table reports the distribution of estimated coefficients of *CDSINIT* from 1,000 samples constructed by randomizing CDS-trade-initiation dates among 677 CDS firms. The dependent variable is cost of debt. The estimates are from pseudo samples in which the CDS trading initiation dates are randomly assigned but based on the real CDS trading dates. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are used to compute var-covariances, and *t* statistics are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	Coefficient	*P* values
Mean	-0.172 (-3.43) ***	0.001
Median	-0.171 (-2.64) **	0.008
1st percentile	0.060 (-0.85)	0.394
5th percentile	-0.087 (-1.46)	0.144
10th percentile	-0.108 (-1.66) *	0.096
90th percentile	-0.234 (-3.62) ***	0.001
95th percentile	-0.255 (-3.78) ***	0.001
99th percentile	-0.291 (-4.28) ***	0.000

Table 2.12. 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 2.2. 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	0.007	-0.079*	0.032***	-0.102***	-0.039**	-0.100*
	(0.48)	(-1.74)	(-2.86)	(-2.80)	(-2.15)	(-1.80)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,216	47,216	47,216	47,216	47,216	47,216
#Firms	5,416	5,416	5,416	5,416	5,416	5,416
Adjusted R^2	0.108	0.176	0.186	0.238	0.119	0.185

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				
	(0.69)	(-1.42)				
ΔCost of debt			-0.001	-0.001		
			(-1.49)	(-1.46)		
ΔCost of equity					-0.000	-0.000
					(-1.29)	(-1.16)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,216	47,216	47,216	47,216	47,216	47,216
#Firms	5,416	5,416	5,416	5,416	5,416	5,416
Adjusted R^2	0.308	0.910	0.309	0.911	0.306	0.912

Table 2.13. 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 2.2. 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)
CSDFIRM	2.942 (8.17) ***	
CDSINIT	1.094 (4.29) ***	1.075 (4.09) ***
Controls		
Log(assets)	2.083 (28.27) ***	2.208 (25.10) ***
Leverage	-0.824 (-4.03) ***	-0.622 (-2.79) ***
Profitability	0.075 (0.66)	0.058 (0.48)
CAPEX	0.230 (1.98) **	0.138 (1.13)
Growth	0.049 (10.19) ***	0.043 (9.12) ***
Log (Age)	-0.982 (-9.65) ***	-1.176 (-5.64) ***
Riskiness	-0.764 (-4.74) ***	-0.569 (-3.19) ***
Dividends	0.616 (5.10) ***	0.767 (6.22) ***
IO concentration	-0.916 (-5.75) ***	-0.865 (-5.15) ***
Liquidation	-1.743 (-6.18) ***	-1.684 (-5.42) ***
R&D	-0.016 (-0.98)	-0.015 (-0.89)
S&P rated	0.224 (1.74) *	0.316 (2.32) **
Stock liquidity	0.324 (15.65) ***	0.262 (12.21) ***
Industry-fixed effects	Yes	
Firm-fixed effects		Yes
Year-fixed effects	Yes	Yes
#Observations	41,844	41,844
#Firms	4,866	4,866
Adjusted R^2	0.498	0.894

Table 2.14. 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 weight of debt and equity in percentage are from 2002 to 2018. Constants are ignored for brevity. Variable definitions are listed in Appendix 2.2. 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)
CSDFIRM		-0.986***	0.025	-1.783**		1.511**	-0.170	1.018***
		(-4.61)	(0.04)	(-2.41)		(2.03)	(-0.27)	(4.13)
CDSINIT	1.427*	1.182***	-1.694***	-2.583***	-1.531*	2.269***	1.812***	-1.236***
	(1.74)	(5.24)	(-2.94)	(-3.01)	(-1.81)	(2.93)	(2.98)	(-4.49)
Controls								
Log(assets)	3.499***	0.382***	1.694***	2.368***	-3.355***	-2.078 ***	-1.704***	-0.420***
	(12.75)	(16.39)	(28.16)	(19.80)	(-11.74)	(-16.42)	(-23.12)	(-17.93)
Profitability	-6.554***	-0.415***	-3.497***	-10.929***	7.319***	13.855***	5.080***	0.705***
	(-12.99)	(-6.21)	(-10.21)	(-9.08)	(13.22)	(12.16)	(10.37)	(7.41)
CAPEX	-0.132	0.022	2.180***	7.095***	0.095	-8.006***	-2.535***	-0.032***
	(-0.27)	(0.28)	(5.76)	(7.80)	(0.19)	(-8.32)	(-5.61)	(-0.32)
Growth	-0.103***	-0.044***	-0.260***	-0.457***	0.114***	0.481***	0.293***	0.052***
	(-6.40)	(-7.07)	(-15.57)	(-23.15)	(6.60)	(23.64)	(17.60)	(6.66)
Log (Age)	4.788***	-0.212***	-0.945***	-0.994***	-4.965***	0.651***	0.819***	0.206***
	(7.37)	(-5.31)	(-8.17)	(-4.25)	(-7.45)	(2.93)	(6.43)	(4.68)
Riskiness	1.717**	0.731***	8.056***	26.553***	-2.579***	-30.035***	-10.246***	-0.985***
	(2.44)	(7.66)	(15.56)	(23.89)	(-3.49)	(-30.78)	(-18.21)	(-8.93)
Dividends	-1.402***	-0.177**	-2.726 ***	-3.789***	1. 550***	3.790***	2.724***	0.243***
	(-3.30)	(-2.02)	(-14.21)	(-13.43)	(3.75)	(13.72)	(14.27)	(2.63)
IO	6.395***	1.708***	14.144***	28.925***	-6.754***	-30.527***	-105.969***	-2.041***
Concentration	(7.08)	(12.25)	(22.89)	(22.48)	(-7.16)	(-23.21)	(-20.49)	(-12.51)
Liquidation	14.755***	4.057***	22.391***	38.231***	-15.280***	-39.068***	-23.917***	-4.786***
	(12.33)	(20.40)	(46.89)	(32.82)	(-12.38)	(-32.19)	(-46.48)	(-20.78)
R&D	-0.143*	-0.003	-0.239***	-0.863***	0.159*	1.006***	0.349***	0.011
	(-1.78)	(-0.30)	(-5.26)	(-9.97)	(1.90)	(11.79)	(6.49)	(0.94)
S&P rated	5.029***	7.844***	10.054***	9.251***	-5.332***	-9.641***	-10.020***	-7.722***
	(9.63)	(42.99)	(35.16)	(20.67)	(-10.02)	(-20.17)	(-35.96)	(-43.59)
Stock liquidity	0.282***	-0.075***	-0.202***	-0.362***	-0.259***	0.509***	0.232***	0.078***
	(3.71)	(-5.56)	(-4.02)	(-3.89)	(-3.32)	(5.26)	(4.78)	(5.45)
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	48,850	48,385	48,385	48,385	48,850	48,360	48,360	48,360
Adjusted R^2	0.742				0.734			

Table 2.15. 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 2.2. 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	0.012 (2.48) **		0.041 (9.00) ***	
CDSINIT	-0.013 (-2.69) ***	-0.010 (-1.70) *	-0.005 (-1.65) *	-0.001 (-0.42)
Controls				
Log(assets)	-0.004 (-3.58) ***	-0.029 (-4.87) ***	-0.029 (-16.81) ***	-0.047 (-14.60) ***
Profitability	-0.068 (-5.05) ***	-0.048 (-3.57) ***	-0.136 (-11.17) ***	-0.111 (-8.72) ***
CAPEX	0.013 (2.18) **	0.004 (0.50)	0.002 (0.27)	0.005 (0.61)
Growth	0.000 (1.06)	-0.000 (-0.30)	0.000 (0.28)	0.000 (0.31)
Log (Age)	-0.006 (-2.84) ***	-0.006 (-0.75) *	-0.021 (-9.43) ***	-0.012 (-2.38) **
Riskiness	0.002 (0.85)	0.002 (0.19)	0.005 (0.56)	0.011 (1.41)
Dividends	0.010 (5.13) ***	0.015 (4.89) ***	0.009 (5.74) ***	0.009 (5.26) ***
IO concentration	-0.032 (-4.08) ***	-0.028 (-2.80) ***	-0.009 (-1.25)	-0.004 (-0.56)
Liquidation	0.065 (3.11) ***	0.149 (3.23) ***	0.076 (7.00) ***	0.131 (9.30) ***
R&D	0.000 (0.12)	0.001 (0.12)	0.011 (5.15) ***	0.008 (3.29) ***
S&P rated	0.017 (5.08) ***	0.026 (4.84) ***	0.014 (6.16) ***	0.011 (4.52) ***
Stock liquidity	0.001 (0.85)	0.004 (1.18)	0.001 (1.77) *	0.002 (1.92) *
Industry-fixed effects	Yes		Yes	
Firm-fixed effects		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes
#Observations	22,683	22,683	43,520	43,520
#Firms	3,918	3,918	5,303	5,303
Adjusted R^2	0.026	0.262	0.328	0.570

Table 2.16. 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 2.2. 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		Lease	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CSDFIRM	0.143***		0.120***		0.010***		-0.005	
	(8.17)		(6.88)		(5.42)		(0.74)	
CDSINIT	0.038**	0.036***	0.048***	0.047***	0.001	-0.001	0.007	0.004
	(2.57)	(2.34)	(3.20)	(3.02)	(0.25)	(-0.68)	(1.18)	(0.69)
Controls								
Log(assets)	0.030	0.037***	0.029***	0.036***	0.001***	0.001*	-0.005***	-0.004
	(9.15) ***	(5.86)	(8.77)	(3.02)	(7.24)	(1.66)	(-2.78)	(-1.18)
Leverage	0.268***	0.270***	0.245***	0.273***	-0.002***	-0.001	-0.131***	-0.116***
	(18.04)	(15.63)	(18.61)	(15.13)	(-3.73)	(-1.16)	(-16.11)	(-12.65)
Profitability	-0.048***	-0.030***	-0.048***	-0.031***	-0.001**	0.001	-0.003	0.009
	(-4.86)	(-2.75)	(-4.83)	(-2.79)	(-3.38)	(0.85)	(-0.42)	(0.13)
CAPEX	0.015*	0.006	0.015*	0.006	0.001	0.001	0.000	0.002
	(1.68)	(0.65)	(1.68)	(0.63)	(0.70)	(0.38)	(0.02)	(0.40)
Growth	0.002	0.000	0.001	-0.000	0.001***	0.001*	-0.001**	-0.001**
	(0.82)	(0.04)	(0.60)	(-0.18)	(3.00)	(1.69)	(-2.27)	(-2.19)
Log (Age)	0.025***	-0.006	0.023***	-0.007	0.001***	-0.001	-0.005*	-0.005
	(4.28)	(-0.48)	(3.98)	(-0.45)	(4.36)	(-0.35)	(-1.66)	(-0.77)
Riskiness	0.034	0.028**	0.035***	0.030**	-0.000	-0.001**	0.018**	0.015*
	(3.04)	(2.13)	(3.12)	(2.22)	(-1.41)	(-2.54)	(2.47)	(1.71)
Dividends	0.040***	0.037***	0.036***	0.034***	0.005***	0.003***	-0.002	-0.001
	(4.97)	(4.17)	(4.40)	(3.77)	(6.03)	(3.22)	(-0.77)	(-0.32)
IO concentration	0.030**	0.039**	0.031**	0.041**	-0.000	-0.001**	-0.011	-0.004
	(2.02)	(2.40)	(2.08)	(2.48)	(-0.42)	(-2.45)	(-1.39)	(-0.45)
Liquidation	-0.082***	-0.094***	-0.083***	-0.094***	0.001	0.002	-0.152***	-0.136***
	(-3.45)	(-3.18)	(-3.47)	(-3.22)	(0.87)	(1.23)	(-10.56)	(-7.17)
R&D	-0.001	-0.001	-0.002	-0.001	0.000	0.000	-0.001	-0.002
	(-0.83)	(-0.54)	(-0.83)	(-0.36)	(0.02)	(0.45)	(-0.65)	(-1.19)
S&P rated	0.084***	0.071***	0.086***	0.069***	0.001**	0.001	-0.028***	-0.027***
	(8.80)	(6.34)	(8.60)	(6.22)	(2.02)	(0.11)	(-5.86)	(-5.18)
Stock liquidity	0.009 ***	0.007***	0.010***	0.007***	-0.001***	-0.001**	0.000	0.001
	(6.47)	(4.43)	(6.96)	(4.78)	(-7.18)	(-1.99)	(0.25)	(0.05)
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	41,077	41,077	41,077	41,077	41,077	41,077	41,077	41,077
#Firms	5,250	5,250	5,250	5,250	5,250	5,250	5,250	5,250
Adjusted R^2	0.252	0.690	0.233	0.682	0.169	0.592	0.119	0.648

Table 2.16. Continued

	Bank debt		Bank loan		Revolving credit		Other	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CSDFIRM	-0.149***		-0.102***		-0.046***		-0.007	
	(-9.41)		(-7.31)		(-4.34)		(-1.01)	
CDSINIT	-0.053***	-0.046***	-0.021*	-0.015	-0.032***	-0.031***	0.015**	0.011*
	(-4.14)	(-3.47)	(-1.89)	(-1.30)	(-4.10)	(-3.81)	(2.41)	(1.66)
Controls								
Log(assets)	-0.031***	-0.033***	-0.005	-0.005	-0.026***	-0.028 ***	0.010***	0.001
	(-9.21)	(-5.24)	(-1.53)	(-0.89)	(-11.29)	(-3.81)	(7.82)	(0.21)
Leverage	-0.101***	-0.126***	0.018	0.004	-0.119***	-0.130***	-0.038***	-0.026***
	(6.78)	(-7.35)	(1.37)	(0.27)	(-12.25)	(-11.21)	(-6.81)	(-4.15)
Profitability	0.064***	0.038***	0.042***	0.032***	0.023***	0.007	-0.018***	-0.008*
	(6.44)	(3.54)	(4.87)	(3.34)	(3.41)	(0.82)	(-4.39)	(-1.86)
CAPEX	-0.010	-0.007	-0.006	-0.001	-0.004	-0.007	-0.005	0.001
	(-1.21)	(-0.78)	(-0.73)	(-0.12)	(-0.53)	(-0.73)	(-1.54)	(0.07)
Growth	0.000	0.001	0.001*	0.001**	-0.003	-0.000	0.000	-0.000
	(0.81)	(1.44)	(1.80)	(2.00)	(-1.43)	(-0.66)	(0.04)	(-0.29)
Log (Age)	-0.026 ***	-0.001	-0.054***	-0.026**	0.027***	0.025**	0.006***	0.014*
	(-4.41)	(-0.05)	(-9.32)	(-2.06)	(6.16)	(2.42)	(2.77)	(1.88)
Riskiness	-0.062***	-0.053***	-0.019**	-0.015	-0.042***	-0.037***	0.010**	0.009*
	(-5.26)	(-3.83)	(-2.02)	(-1.34)	(-5.29)	(-3.86)	(2.38)	(1.67)
Dividends	-0.024***	-0.018**	-0.024***	-0.022***	-0.001	0.004	-0.008**	-0.016***
	(-3.28)	(-2.27)	(-3.48)	(-2.85)	(-0.03)	(0.71)	(-2.15)	(-3.03)
IO	-0.014	-0.029*	0.018	0.006	-0.031***	-0.035***	0.033	-0.003
concentration	(-0.90)	(-1.75)	(1.18)	(0.35)	(-2.57)	(-2.59)	(0.42)	(-0.43)
Liquidation	0.267***	0.246***	0.092***	0.081***	0.176***	0.165***	-0.025***	-0.021
	(10.90)	(8.39)	(4.31)	(3.18)	(10.84)	(8.27)	(-2.69)	(-1.61)
R&D	0.004	0.003	0.003*	0.003	-0.002*	0.001	-0.001	-0.000
	(1.13)	(1.03)	(1.93)	(1.23)	(-1.71)	(0.11)	(-0.15)	(-0.11)
S&P rated	-0.059***	-0.044***	0.019**	0.022**	-0.080***	-0.067***	-0.004	-0.004
	(-6.15)	(-4.06)	(2.30)	(2.51)	(-11.21)	(-8.07)	(-1.01)	(-0.96)
Stock liquidity	-0.008 ***	-0.006***	-0.004***	-0.003*	-0.004***	-0.004***	-0.002***	-0.001
	(-5.81)	(-4.15)	(-3.27)	(-1.89)	(-3.93)	(-3.33)	(-2.95)	(-0.68)
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	41,077	41,077	41,077	41,077	41,077	41,077	41,077	41,077
#Firms	5,250	5,250	5,250	5,250	5,250	5,250	5,250	5,250
Adjusted R^2	0.224	0.681	0.115	0.633	0.168	0.631	0.058	0.411

Table 2.17. Cost of capital and debt compositions

This table reports regression results of costs of capital on debt compositions and a set of firm-level explanatory variables. The dependent variables span from 2001 to 2017, while independent variables lag one year than dependent ones. Variable definitions are listed in Appendix 2.2. 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)
Public debt	-0.094*	-0.151**	0.268	0.265	-0.093	-0.067
	(-1.80)	(-2.52)	(8.71) ***	(7.33) ***	(-1.66) *	(-1.02)
Adjusted R^2	0.294	0.618	0.386	0.649	0.301	0.591
Bond	-0.093*	-0.155***	0.288	0.278	-0.082	-0.017
	(-1.79)	(-2.57)	(9.29) ***	(7.66) ***	(-1.45)	(-0.25)
Adjusted R^2	0.293	0.619	0.385	0.694	0.301	0.591
Commercials	-1.254***	-0.775	-1.821***	-0.772*	-2.596	-1.277 **
	(-2.96)	(-1.69) *	(-5.01)	(-1.96)	(4.99) ***	(-2.18)
Adjusted R^2	0.294	0.619	0.386	0.646	0.303	0.591
Bank debt	-0.075	0.029	-0.062**	-0.084**	0.064	0.075
	(-1.43)	(0.48)	(-2.09)	(-2.41)	(1.17)	(1.17)
Adjusted R^2	0.295	0.619	0.382	0.694	0.301	0.591
Bank loan	-0.058	0.005	0.097***	0.075*	0.093	0.118*
	(-1.00)	(0.08)	(2.97)	(1.96)	(1.54)	(1.68)
Adjusted R^2	0.294	0.617	0.383	0.694	0.300	0.591
Revolving credit	-0.041	0.036	-0.213***	-0.212***	-0.017	-0.031
	(-0.66)	(0.52)	(-5.96)	(-5.23)	(-0.27)	(-0.43)
Adjusted R^2	0.294	0.620	0.383	0.694	0.301	0.591
Other	-0.042	-0.043	-0.276***	-0.188**	-0.125	-0.078
	(-0.47)	(-0.46)	(-4.67)	(-3.07)	(-1.30)	(-0.76)
Adjusted R^2	0.293	0.618	0.383	0.694	0.301	0.591
Lease	0.536***	0.413***	-0.331***	-0.318***	0.163*	0.022
	(5.72)	(3.75)	(-6.22)	(-5.04)	(1.71)	(0.19)
Adjusted R^2	0.294	0.619	0.383	0.694	0.300	0.590
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
#Observations	41,077	41,077	41,077	41,077	41,077	41,077
#Firms	5,250	5,250	5,250	5,250	5,250	5,250

Online Table A1. 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	
	(1)	(2)
CSDFIRM	-0.063 (-0.71)	
CDSINIT	-0.460 (-5.14) ***	-0.239 (-2.73) ***
CDSREVERSAL	0.276 (2.57) ***	0.049 (1.10)
Controls		
Log(assets)	0.226 (11.66) ***	0.326 8.25) ***
Leverage	-3.546 (-29.21) ***	-2.219 (-17.56) ***
Profitability	-0.635 (-7.58) ***	-0.264 (-3.16) ***
CAPEX	-0.129 (-1.75) *	0.017 (0.22)
Growth	0.026 (7.98) ***	0.010 (3.67) ***
Log (Age)	-0.011 (-0.31)	0.023 (0.25) ***
Riskiness	0.979 (9.36) ***	1.512 (11.93) ***
Dividends	-0.260 (5.68) ***	0.108 (2.38) **
IO concentration	-1.701 (-13.83) ***	-0.543 (-4.07) ***
Liquidation	-1.230 (-9.19) ***	-0.996 (-5.76) ***
R&D	0.055 (4.71) ***	0.009 (0.63)
S&P rated	-0.121 (-1.95) *	-0.203(-3.27) **
Stock liquidity	0.250 (19.41) ***	0.131 (10.75) ***
Industry-fixed effects	Yes	
Firm-fixed effects		Yes
Year-fixed effects	Yes	Yes
#Observations	48,850	48,850
#Firms	5,575	5,575
Adjusted R^2	0.301	0.553

Online Table A2. 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 Table A3. 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 includes all firms without limiting debt and minimum assets and has 46, 045 observations 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%. 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	0.267**		0.122		0.062	
	(2.68)		(1.33)		(0.57)	
CDSINIT	-0.223**	-0.241**	-0.224***	-0.236***	-0.184	-0.120
	(-2.18)	(-2.12)	(-2.68)	(-2.71)	(-1.55)	(-0.91)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Adjusted R^2	0.463	0.625	0.405	0.660	0.462	0.598
#Observations	10,315	10,315	10,315	10,315	10,315	10,315
#Firms	809	809	809	809	809	809

Panel B. Regression results using nearest-one matching sample with exact FF48 industry classification

	WACC		Cost of debt		Cost of equity	
	(1)	(2)	(1)	(2)	(1)	(2)
CDSFIRM	0.234**		0.083		-0.005	
	(2.28)		(0.89)		(-0.05)	
CDSINIT	-0.205**	-0.224**	-0.147*	-0.159**	-0.141	-0.124
	(-2.23)	(-2.10)	(-1.94)	(-2.02)	(-1.61)	(-1.05)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Adjusted R^2	0.486	0.636	0.498	0.672	0.463	0.606
#Observations	10,483	10,483	10,483	10,483	10,483	10,483
#Firms	797	797	797	797	797	797

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	0.276**		0.094		-0.012	
	(2.54)		(0.94)		(-0.11)	
CDSINIT	-0.222**	-0.236**	-0.133*	-0.142*	-0.151	-0.114
	(-2.31)	(-2.24)	(-1.74)	(-1.79)	(-1.58)	(-0.92)
Industry-fixed effects	Yes		Yes			
Firm-fixed effects		Yes		Yes	Yes	Yes
Adjusted R^2	0.474	0.628	0.432	0.676	0.482	0.600
#Observations	9,398	9,398	9,398	9,398	9,398	9,398
#Firms	724	724	724	724	724	724

Online Table A4. 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 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 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.

Panel A. 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	677	677	677

Panel B. The cost of capital and CDS trading controlling leverage

	WACC	Cost of debt	Cost of equity
CDSINIT	-0.307 (-2.67) ***	0.078 (0.93)	-0.098 (0.81)
CDSINIT*High leverage	-0.767 (-6.30) ***	-0.180 (-1.99) **	-0.276 (-1.86) *
High leverage	-0.792 (-5.20) ***	0.300 (2.83) ***	-0.051 (-0.51)
Industry-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Adjusted R^2	0.458	0.493	0.570
#Observations	8,419	8,419	8,419
#Firms	677	677	677

Online Table 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	0.007	-0.079*	0.032***	-0.102***	-0.039**	-0.100*
	(0.48)	(-1.74)	(-2.86)	(-2.80)	(-2.15)	(-1.80)
Controls						
ΔLog(assets)	-0.147***	-0.311***	0.339***	0.338***	0.285***	0.150**
	(-2.70)	(-4.97)	(12.34)	(10.37)	(5.43)	(2.52)
ΔLeverage	-2.725***	-2.664 ***	1.361***	1.304***	0.167	0.237*
	(-17.66)	(-15.99)	(17.43)	(15.20)	(1.27)	(1.68)
ΔProfitability	0.216 ***	0.314 ***	-0.255***	-0.277***	-0.155**	-0.084
	(2.80)	(3.82)	(-6.98)	(-7.13)	(-2.10)	(-1.04)
ΔCAPEX	0.0061	-0.016	0..033	0.013	-0.008	-0.003
	(0.01)	(-0.21)	(1.20)	(0.45)	(-0.11)	(-0.03)
ΔGrowth	-0.004	-0.004*	0.001	0.000	-0.003	-0.003
	(-1.55)	(-1.72)	(0.94)	(0.66)	(-1.11)	(-1.01)
ΔLog (Age)	0.768 ***	0.643	-0.156**	-0.050	0.907 ***	0.122
	(4.22)	(1.50)	(-2.19)	(-0.28)	(4.65)	(0.27)
ΔRiskiness	1.118***	1.215***	0.017	0.031	2.107***	2.212 ***
	(7.79)	(7.52)	(0.27)	(0.44)	(12.08)	(11.56)
ΔDividends	-0.098**	-0.134 ***	0.047*	0.059 *	-0.163***	-0.170***
	(-2.04)	(-2.57)	(1.66)	(1.91)	(-3.01)	(-2.94)
ΔIO concentration	-1.058***	-1.007***	0.079	0.074	-0.924***	-0.886***
	(-7.00)	(-6.23)	(1.04)	(0.89)	(-5.73)	(-5.14)
ΔLiquidation	-0.543***	-0.519***	0.619***	0.603***	-0.611**	-0.617***
	(-2.91)	(-2.65)	(6.05)	(5.56)	(-3.47)	(-3.35)
ΔR&D	0.000	0.001*	-0.000	0.000	0.000	0.001**
	(0.58)	(1.73)	(-1.29)	(0.06)	(0.80)	(2.40)
S&P rated	0.038**	-0.059	0.019 *	0.068 ***	0.114***	0.015
	(2.51)	(-1.49)	(1.80)	(2.62)	(6.59)	(0.33)
ΔStock liquidity	0.000	0.000	-0.000	0.001***	0.000	-0.001***
	(0.13)	(0.14)	(-0.32)	(5.40)	(0.24)	(-2.70)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,216	47,216	47,216	47,216	47,216	47,216
#Firms	5,416	5,416	5,416	5,416	5,416	5,416
Adjusted R^2	0.108	0.176	0.186	0.238	0.119	0.185

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				
	(0.69)	(-1.42)				
ΔCost of debt			-0.001	-0.001		
			(-1.49)	(-1.46)		
ΔCost of equity					-0.000	-0.000
					(-1.29)	(-1.16)
Controls						
ΔLog(assets)	-0.033	-0.023	-0.022	-0.023	-0.022	-0.023
	(-4.47) ***	(-5.86) ***	(-5.68) ***	(-5.79) ***	(-5.72) ***	(-5.83) **
ΔLeverage	-0.020	-0.004	-0.008	-0.003	-0.008	0.004
	(-1.57)	(-0.61)	(-1.15)	(-0.45)	(-1.18)	(-0.48)
ΔProfitability	0.017	0.010	0.011	0.009	0.011	0.010
	(3.65) ***	(3.30) ***	(3.51) ***	(3.14) ***	(3.62) ***	(3.26) ***
ΔCAPEX	-0.003	-0.004	-0.003	-0.004	-0.003	-0.004
	(-1.14)	(-1.38)	(-1.15)	(-1.39)	(-1.14)	(-1.38)
ΔGrowth	-0.000	0.001	0.000	0.000	0.000	0.000
	(-1.14)	(0.53)	(0.46)	(0.52)	(0.47)	(0.53)
ΔLog (Age)	-0.134	0.059	-0.134	0.059	-0.134	0.059
	(-4.36) ***	(1.41)	(-4.38) ***	(1.41)	(-4.36) ***	(1.41)
ΔRiskiness	-0.011	-0.013	-0.011	-0.014	-0.010	-0.013
	(-1.60)	(-1.91) *	(-1.62)	(-1.94) *	(-1.55)	(-1.88) *
ΔDividends	0.002	-0.002	0.003	-0.001	0.002	-0.002
	(0.83)	(-0.49)	(0.86)	(-0.46)	(0.83)	(-0.48)
ΔIO concentration	-0.000	-0.005	-0.000	-0.008	-0.000	-0.005
	(-0.05)	(-1.04)	(-0.01)	(-0.98)	(-0.03)	(-1.01)
ΔLiquidation	-0.001	0.003	-0.000	0.003	-0.000	0.003
	(-0.07)	(0.36)	(-0.03)	(0.41)	(-0.06)	(0.38)
ΔR&D	0.000	0.001	0.000	0.000	0.000	0.000
	(0.80)	(3.15) ***	(0.76)	(3.01) ***	(0.79)	(3.09) ***
S&P rated	0.047	-0.004	0.047	-0.004	0.047	-0.004
	(8.01) ***	(-0.71)	(8.02) ***	(-0.69)	(8.01) ***	(-0.70)
ΔStock liquidity	-0.000	0.000	0.000	0.000	-0.000	0.000
	(-2.30) **	(0.24)	(-2.26) **	(0.23)	(-2.32) **	(0.22)
Industry-fixed effects	Yes		Yes		Yes	
Firm-fixed effects		Yes		Yes		Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	47,216	47,216	47,216	47,216	47,216	47,216
#Firms	5,416	5,416	5,416	5,416	5,416	5,416
Adjusted R^2	0.308	0.910	0.309	0.911	0.306	0.912

Online Table A6. Probit regression with the cost 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., eliminate all observations in the post-CDS period). The sample period is from 2001-2017. 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 (-0.36)		
ΔCost of debt		0.023 (1.27)	
ΔCost of equity			0.002 (0.10)
Control variables	Yes	Yes	Yes
Likelihood Ratio	2,148.264***	2149.711***	2143.841***
Industry- and year-fixed effects	Yes	Yes	Yes
Pseudo R^2	42.84%	42.87%	42.82%
Percent Concordant /C	95.5%	95.5%	95.5%
C	0.955	0.955	
#Observations	42,352	42,352	42,352

Online Table A7. 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**	0.021**
	(2.12)	(2.52)
Controls		
Log(assets)	0.004	0.038***
	(0.92)	(14.12)
Profitability	-0.084***	-0.048***
	(-9.05)	(-10.34)
CAPEX	-0.008	0.003
	(-1.15)	(0.63)
Growth	-0.001***	-0.001***
	(-2.76)	(-6.04)
Log (Age)	0.036***	0.029***
	(4.29)	(4.19)
Riskiness	0.037***	0.025***
	(4.04)	(3.61)
Dividends	0.011***	-0.007
	(2.60)	(-1.33)
IO concentration	0.027**	0.061***
	(2.33)	(6.85)
Liquidation	0.150***	0.125***
	(8.16)	(10.89)
R&D	-0.003	-0.001*
	(-1.50)	(-1.86)
S&P rated	0.071***	0.057***
	(11.72)	(10.47)
Stock liquidity	0.002*	0.002***
	(1.76)	(2.75)
Firm-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
#Observations	48,572	42,772
Adjusted R^2	0.728	0.731

Online Table A8. CDS trading and debt heterogeneity as per high and low default probability subsamples

This table reports regression results of debt compositions on CDS initiation and a set of firm-level explanatory variables for high and low default risk samples. 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: low default risk sample

	Public debt		Bond		Commercial		Bank debt		Bank loan		Revolving credit	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)				
CSDFIRM	0.129***		0.082**		0.014***		-0.143***		-0.085***		-0.057***	
	(3.74)		(2.51)		(2.97)		(-5.13)		(-3.42)		(-3.23)	
CDSINIT	0.068**	0.057*	0.087***	0.077**	0.006	0.001	-0.062***	-0.051**	-0.036*	-0.033	-0.027**	-0.017
	(2.21)	(1.69)	(3.01)	(2.43)	(1.17)	(0.23)	(-2.74)	(-2.11)	(-1.79)	(-1.54)	(-2.06)	(-1.26)
							(1.74)					
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	13,384	13,384	13,384	13,384	13,384	13,384	13,384	13,384	13,384	13,384	13,384	13,384
Adjusted R^2	0.288	0.646	0.257	0.737	0.227	0.637	0.267	0.755	0.125	0.695	0.183	0.692

Panel B. The relationship between CDS trading and debt heterogeneity: high default risk sample

	Public debt		Bond		Commercial		Bank debt		Bank loan		Revolving credit	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)				
CSDFIRM	0.047		0.045		0.001		-0.036		-0.024		-0.013	
	(1.55)		(1.48)		(0.71)		(-1.30)		(-0.98)		(-0.64)	
CDSINIT	0.049	0.054	0.047	0.054	0.001	0.001	-0.076***	-0.077**	-0.021	-0.019	-0.055***	-0.058***
	(1.64)	(1.57)	(1.58)	(1.57)	(0.69)	(0.31)	(-2.80)	(-2.46)	(-0.85)	(-0.67)	(-3.10)	(-2.88)
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	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906
Adjusted R^2	0.210	0.757	0.208	0.757	0.068	0.731	0.176	0.743	0.126	0.722	0.195	0.774

Online Table A9. The relationships between CDS trading and bank loans

This table reports quantile regression results of bank loan ratios on the CDS trading activity and a set of firm-level explanatory variables. Columns (1) and (2) are quantile regression over 0.5 and 0.85 percentiles, respectively. CDS activity and firm-level controls are from 2001 to 2017, and bank loan 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.

	Bank Loan	
	(1)	(2)
CDSFIRM	-0.014 (-4.31) ***	-0.171 -9.62) ***
CDSINIT	-0.024 (-7.42) ***	-0.057 (-4.01) ***
Controls		
Log(assets)	0.005 (5.34) ***	-0.026 (-11.27) ***
Profitability	0.030 (6.28) ***	0.100 (5.93) ***
CAPEX	-0.022 (-5.38) ***	-0.046 (-5.00) ***
Growth	-0.001 (-3.19) ***	0.000 (0.27)
Log (Age)	-0.031 (-20.30) ***	-0.097 (-20.10) ***
Riskiness	0.024 (4.39) ***	-0.007 (0.68)
Dividends	-0.013 (-7.53) ***	-0.031 (-6.10) ***
IO concentration	0.091 (6.79) ***	-0.001 (-0.05)
Liquidation	0.097 (10.78) ***	0.066 (2.75) ***
R&D	0.004 (2.54) **	0.010 (7.02) ***
S&P rated	0.029 (0.92)	-0.093 (-8.33)
Stock liquidity	-0.003 (-15.51) ***	-0.014 (-5.94) ***
Industry-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
#Observations	41,077	41,077

Online Table A10. The relationships between CDS trading and weight of capital controlling leverage

This table reports regression results of the weight of debt and equity 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 weights of capital 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 effects 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)
CSDFIRM		-0.938***	-1.270***	-1.871**		2.155**	1.244***	-0.895***
		(3.43)	(-3.68)	(-2.43)		(2.93)	(3.39)	(-3.14)
CDSINIT	0.405	0.253	-0.736**	-3.002***	-0.519	2.739***	0.782**	-0.290
	(0.60)	(0.87)	(-2.02)	(-3.94)	(-0.74)	(3.59)	(2.21)	(-1.04)
Controls								
Log(assets)	3.831***	0.670***	0.955***	0.823***	-3.685***	-0.739***	-0.940***	-0.639***
	(16.70)	(16.13)	(17.83)	(7.63)	(-14.98)	(-7.24)	(-17.74)	(-15.39)
Leverage	32.190***	33.942***	63.523***	81.603***	-32.000***	-81.360***	-64.374***	-34.900***
	(32.46)	(94.09)	(125.59)	(80.58)	(-31.19)	(-86.19)	(-111.11)	(-98.30)
Profitability	-4.842***	0.227***	-4.175*	-11.580***	5.897***	15.795***	5.765***	0.228
	(-6.95)	(0.91)	(-7.19)	(-6.99)	(7.36)	(10.87)	(10.42)	(0.83)
CAPEX	0.743	0.989***	1.921***	3.261***	-0.668	-3.213***	-2.057***	-0.912***
	(1.30)	(3.72)	(5.80)	(6.52)	(-1.11)	(-4.98)	(-4.48)	(-3.20)
Growth	-0.069***	-0.227***	-0.546***	-0.663***	0.079***	0.697***	0.585***	0.243***
	(-3.96)	(-23.43)	(-27.07)	(-26.19)	(4.36)	(22.17)	(25.98)	(22.14)
Log (Age)	3.526***	0.051***	-0.002	-0.003	-3.585***	-0.233	-0.082	-0.066
	(5.46)	(0.68)	(-0.02)	(-0.01)	(-5.34)	(-1.20)	(-0.75)	(-090)
Riskiness	0.362	1.445***	5.757***	13.870***	-1.218	-16.350***	-7.072***	-1.681***
	(0.47)	(7.27)	(11.28)	(15.19)	(-1.53)	(-14.28)	(-13.64)	(-7.73)
Dividends	-1.373***	-0.818***	-1.477***	-1.735***	1. 565***	1.728***	1.454***	0.808***
	(-3.56)	(-7.92)	(-11.65)	(-7.32)	(5.10)	(7.28)	(11.28)	(6.80)
IO concentration	6.282***	4.052***	10.086***	14.431***	-6.417***	-16.686***	-11.187***	-4.337***
	(6.61)	(10.52)	(15.97)	(13.35)	(-6.24)	(-12.64)	(-15.98)	(-11.47)
Liquidation	8.754***	5.861***	2.468***	6.697***	-9.250***	-7.952***	-5.689***	-5.910***
	(6.67)	(16.46)	(10.23)	(6.01)	(-6.67)	(-7.13)	(-10.02)	(-16.94)
R&D	-0.077	-0.123*	-0.326***	-0.554***	0.096	0.683***	0.392***	0.134*
	(-0.69)	(-1.79)	(-6.38)	(-7.24)	(0.86)	(8.60)	(5.65)	(1.78)
S&P rated	2.872**	2.471***	2.465***	2.625***	-3.090***	-2.675***	-2.502***	-2.410***
	(6.17)	(15.16)	(11.72)	(6.50)	(-6.46)	(-6.46)	(-11.40)	(-14.40)
Stock liquidity	0.277***	-0.075***	-0.197***	-0.105	-0.255***	0.179**	0.254***	0.089***
	(3.44)	(-2.62)	(-4.34)	(-1.30)	(-3.06)	(2.24)	(6.22)	(2.96)
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	38,645	38,645	38,645	38,645	38,627	38,627	38,627	38,627
Adjusted R^2	0.772				0.773			

Table 3.1. Summary statistics

The definitions of variables are listed in Appendix 1. All control variables are winsorized at the top and bottom 1%. ***, **, and * indicate significance level at the 1%, 5%, and 10%, respectively.

Panel A. Summary statistics: Environmental and social scores

	CDS firms		non-CDS firms		
Items	Mean	Standard deviation	Mean	Standard deviation	Mean difference
Environmental	62.489	31.215	41.471	29.039	21.018***
Emission reduction	62.423	31.493	41.668	29.247	20.755***
Product innovation	57.556	31.878	41.166	28.180	16.389***
Resource reduction	61.821	30.818	42.562	29.992	19.259***
Social	61.790	30.023	42.343	28.466	19.447***
Employment quality	57.727	29.968	43.629	29.817	14.098***
Health and safety	57.137	31.193	45.205	28.715	11.932***
Training and development	56.827	31.029	43.074	30.528	13.757***
Human rights	56.980	31.898	41.596	28.248	15.385***
Community	61.387	29.173	42.973	29.849	18.414***
Product responsibility	57.219	29.585	45.345	29.906	11.874***
Diversity	60.377	30.500	43.443	28.864	16.933***
Observations	6,687	6,687	17,214	17,214	

Panel B. Summary statistics: Firm-level characteristics

	CDS firms		non-CDS firms		
Items	Mean	Standard deviation	Mean	Standard deviation	Mean difference
Log (assets)	16.177	1.100	14.407	1.312	1.770***
Leverage	0.276	0.159	0.207	0.179	0.069***
Profitability	0.079	0.090	0.072	0.131	0.006***
Tangibility	0.324	0.235	0.312	0.251	0.013***
CAPEX	0.101	0.199	0.199	0.573	-0.098***
Institutional ownership	0.146	0.169	0.244	0.209	-0.098***
MTBV	2.808	3.476	3.001	3.613	-0.193***
Age	28.669	19.708	17.885	11.204	10.784***
Governance	61.920	31.178	54.106	29.179	7.818***
Risk	0.335	0.163	0.391	0.184	-0.055***
R&D	0.031	0.057	0.038	0.102	-0.007***
Cash holdings	0.121	0.116	0.173	0.170	-0.052***
Turnover	0.878	0.553	0.917	0.669	-0.019***
Observations	6,687	6,687	17,214	17,214	

Panel C. Summary statistics: Environmental and social scores by countries and regions

Country	Environmental	Social	Number of firms	Number of observations
United States	39.831	42.591	1,620	9,108
Canada	38.584	40.543	279	1,933
United Kingdom	59.145	64.434	332	3,116
France	65.525	66.341	72	708
Germany	77.977	78.666	79	934
Switzerland	63.334	63.139	52	619
Japan	56.189	41.875	231	2,673
Australia	36.076	40.765	399	2,482
South Korea	60.160	52.879	94	600
Hong Kong	38.123	38.585	130	1,039
Taiwan	52.571	44.362	95	689
Total			3,383	23,901

Panel D. Distribution of CDS firms by one-digit SIC industry

SIC Industry	Number of CDS firms	Number of CDS observations	Percentage of all CDS firms
Agriculture, Forest and fishing (0)	1	14	0.19%
Construction and mining (1)	47	608	8.72%
Manufacturing (2,3)	279	3,463	51.76%
Transportation (4)	100	1,207	18.55%
Wholesale and retail (5)	40	533	7.42%
Services (7,8)	72	862	13.36%
Total	539	6,687	100%

Panel E. Distribution of CDS firms by inception year

Year	Number of new CDS firms	Percentage of all CDS firms
2001	86	15.96%
2002	82	15.21%
2003	52	9.65%
2004	62	11.50%
2005	34	6.31%
2006	47	8.72%
2007	33	6.12%
2008	23	4.27%
2009	8	1.48%
2010	16	2.97%
2011	21	3.90%
2012	23	4.27%
2013	12	2.23%
2014	11	2.04%
2015	21	3.90%
2016	8	1.48%
Total	539	100%

Panel F. Pearson correlation between selected variables

variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CDSFIRM (1)	1.000														
CDSINIT (2)	0.896***	1.000													
MTBV (3)	-0.019***	-0.016***	1.000												
Log (assets) (4)	0.532***	0.497***	-0.113***	1.000											
Profitable (5)	0.020***	0.026***	0.198***	0.073***	1.000										
Tangibility (6)	0.018***	0.014**	-0.151***	0.075***	-0.127***	1.000									
CAPEX (7)	-0.087***	-0.084***	-0.035***	-0.191***	-0.264***	0.347***	1.000								
Institutional Ownership (8)	-0.220***	-0.218***	0.028***	-0.098***	-0.000	-0.039***	0.001	1.000							
Leverage (9)	0.178***	0.170***	-0.012*	0.248***	-0.130***	0.231***	-0.007	-0.022***	1.000						
Log (Age) (10)	0.279***	0.304***	-0.071***	0.289***	0.075***	0.031***	-0.122***	-0.214***	0.016**	1.000					
Governance (11)	0.069***	0.067***	0.096**	0.042***	-0.011	0.048***	0.058***	-0.151***	0.093***	0.049***	1.000				
Risk (12)	-0.132***	-0.142***	-0.064***	-0.317***	-0.337***	0.074***	0.252***	0.096***	-0.044***	-0.247***	0.007	1.000			
Turnover (13)	-0.027***	-0.016***	0.115***	-0.086***	0.261***	-0.247***	-0.304***	-0.005	-0.167***	0.054***	-0.006	-0.111***	1.000		
Cash holdings (14)	-0.142***	-0.133***	0.172***	-0.277***	-0.007***	-0.355***	0.040***	0.115***	-0.347***	-0.163***	-0.129***	0.217***	-0.056***	1.000	
R&D (15)	-0.025***	-0.025***	0.153***	-0.138***	-0.246***	-0.263***	0.009	-0.011	-0.149***	-0.087***	0.025***	0.025***	-0.186***	0.476***	1.000

Table 3.2. The effects of CDS trading on environmental and social performance

This table reports the results from regressing environmental and social (E&S) scores on CDS trading and firm-level controls over the period 2002 to 2017. The dependent variables include the following: *ENVSCORE* is the overall environmental score and reflects the equally weighted average of *ENER, ENRR*, and *ENPI* scores, where *ENER* is the emission reduction score, *ENRR* is the resource reduction score, and *ENPI* is the production innovation score; *SOCCORE* is the overall social score, computed as the equally weighted average of the *SOEQ, SOTD, SOCO, SODO, SOHS, SOHR*, and *SOPR* scores. *SOEQ* is the employment quality score; *SOTD* is the training and development score; *SOCO* is the community score; *SODO* is the diversity and opportunity score; *SOHS* is the health and safety score; *SOHR* is the human rights score; and *SOPR* is the product responsibility score. In each pair of dependent variables, the first column uses all controls except *Governance*, while the second column uses all controls. *CDSINIT* has a value of one for CDS firms in and after the CDS initiation year, and zero before that. *Governance* is the pillar score of a firm's overall governance quality extracted from Thomas Reuters's ASSET4 database. All control variables are winsorized at the top and bottom 1%. Variable definitions are found in Appendix 1. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. All regressions use a firm-year fixed effects model. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	ENVSCORE		ENER		ENRR		ENPI		SOCSCORE		SOEQ	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	-0.051*	-0.036	-0.063**	**-0.049***	-0.054*	-0.038	-0.017	-0.009	-0.049**	-0.032	-0.052	-0.043
	(0.029)	(0.028)	(0.028)	**(0.027)**	(0.031)	(0.030)	(0.030)	(0.029)	(0.030)	(0.029)	(0.037)	(0.036)
Governance		0.235***		0.231***		0.262***		0.118***		0.278***		0.146***
		(0.014)		(0.013)		(0.015)		(0.014)		(0.015)		(0.018)
Log (Assets)	0.134***	0.123***	0.125***	0.113***	0.156***	0.143***	0.038**	0.032**	0.119***	0.106***	0.022	0.015
	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)	(0.020)	(0.020)
MTBV	0.001	0.000	0.002*	0.001	0.000	-0.000	0.000	0.000	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Profitability	-0.085**	-0.087**	-0.049	-0.061	-0.076	-0.079*	-0.008	-0.009	-0.001	-0.002	0.135**	0.133**
	(0.041)	(0.040)	(0.042)	(0.041)	(0.048)	(0.047)	(0.041)	(0.040)	(0.045)	(0.044)	(0.059)	(0.060)
Tangibility	-0.023	0.0124	-0.014	-0.003	-0.059	-0.048	-0.093	-0.088	0.002	0.014	0.028	0.035
	(0.066)	(0.064)	(0.062)	(0.061)	(0.072)	(0.075)	(0.068)	(0.068)	(0.068)	(0.066)	(0.086)	(0.087)
CAPEX	-0.011	-0.012	-0.016	-0.016	-0.011	-0.012	0.014*	0.014*	-0.062***	-0.063***	-0.033*	-0.033*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)	(0.008)	(0.008)	(0.015)	(0.014)	(0.019)	(0.019)
Institutional ownership	-0.030	-0.026	-0.021	-0.017	-0.025	-0.020	-0.005	-0.002	0.031	0.037	0.011	0.014
	(0.037)	(0.036)	(0.037)	(0.037)	(0.042)	(0.042)	(0.040)	(0.039)	(0.039)	(0.040)	(0.050)	(0.050)
Leverage	0.022	0.028	0.048	0.051	0.026	0.032	-0.021	-0.019	-0.081	-0.075	-0.119*	-0.115*
	(0.047)	(0.046)	(0.048)	(0.048)	(0.052)	(0.051)	(0.050)	(0.049)	(0.053)	(0.051)	(0.067)	(0.067)
Log (Age)	0.124***	0.056	0.142***	0.075*	0.134***	0.059	-0.013	-0.047	0.166***	0.086**	0.075*	0.032
	(0.039)	(0.038)	(0.038)	(0.038)	(0.042)	(0.041)	(0.040)	(0.041)	(0.039)	(0.038)	(0.047)	(0.047)
Risk	-0.067*	-0.054	-0.044	-0.032	-0.071*	-0.057	-0.057*	-0.051	-0.109***	-0.095***	0.018	0.026
	(0.035)	(0.035)	(0.034)	(0.034)	(0.039)	(0.039)	(0.038)	(0.038)	(0.037)	(0.037)	(0.047)	(0.048)
Turnover	0.067***	0.073***	0.057**	0.063***	0.034	0.041	0.031	0.034	0.085***	0.093***	0.005	0.009
	(0.024)	(0.023)	(0.024)	(0.023)	(0.028)	(0.026)	(0.026)	(0.026)	(0.027)	(0.025)	(0.031	(0.031)
Cash holdings	0.051	0.036	0.029	0.014	0.055	0.037	0.066	0.058	-0.010	-0.028	0.207***	0.198**
	(0.061)	(0.061)	(0.062)	(0.062)	(0.071)	(0.071)	(0.058)	(0.058)	(0.065)	(0.063)	(0.079)	(0.079)
R&D	0.219	0.194	0.207	0.183	0.157	0.129	0.164	0.151	0.318**	0.288*	0.138	0.198
	(0.143)	(0.140)	(0.138)	(0.136)	(0.174)	(0.170)	(0.122)	(0.124)	(0.156)	(0.155)	(0.170)	(0.17)
Adjusted R^2	0.834	0.842	0.823	0.831	0.793	0.802	0.766	0.779	0.830	0.840	0.703	0.706
Observations	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901

Table 3.2. Continued

	SOTD		SOCO		SOHS		SOHR		SODO		SOPR	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CDSINIT	-0.065**	-0.051	-0.005	-0.012	-0.015	-0.003	-0.001	-0.007	-0.017	-0.003	-0.057*	-0.048
	(0.033)	(0.032)	(0.037)	(0.036)	(0.028)	(0.027)	(0.029)	(0.029)	(0.031)	(0.029)	(0.032)	(0.031)
Governance		0.240***		0.278***		0.210***		0.117***		0.231***		0.144***
		(0.018)		(0.018)		(0.016)		(0.014)		(0.016)		(0.016)
Log (Assets)	0.125***	0.113***	0.135***	0.121***	0.093**	0.083***	0.029*	0.024	0.049***	0.038**	0.013	0.006
	(0.002)	(0.017)	(0.019)	(0.019)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
MTBV	0.000	0.001	-0.000	-0.001	0.000	0.000	0.002	0.001	-0.001	-0.002*	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Profitability	0.013	0.010	0.063	0.060	0.011	0.008	0.129***	0.127***	-0.047	-0.050	-0.032	-0.034
	(0.059)	(0.059)	(0.058)	(0.058)	(0.043)	(0.042)	(0.046)	(0.045)	(0.047)	(0.047)	(0.055)	(0.080)
Tangibility	0.010	0.021	0.078	0.091	0.002	0.011	-0.148*	-0.143*	-0.020	-0.010	-0.068	-0.062
	(0.088)	(0.087)	(0.084)	(0.082)	(0.066)	(0.065)	(0.076)	(0.075)	(0.066)	(0.069)	(0.081)	(0.080)
CAPEX	-0.046**	-0.046**	-0.048**	-0.048***	-0.021	-0.022	0.024**	0.024**	-0.043***	-0.044***	-0.038**	-0.038**
	(0.022)	(0.022)	(0.021)	(0.021)	(0.015)	(0.014)	(0.012)	(0.012)	(0.017)	(0.017)	(0.016)	(0.016)
Institutional ownership	-0.046	-0.041	0.121**	0.127**	-0.011	-0.007	-0.018	-0.016	0.012	0.016	0.001	0.004
	(0.047)	(0.046)	(0.052)	(0.052)	(0.039)	(0.039)	(0.041)	(0.041)	(0.045)	(0.044)	(0.048)	(0.047)
Leverage	-0.043	-0.037	-0.135**	-0.128**	0.003	0.008	0.087	0.089*	-0.002	0.003	-0.054	-0.051
	(0.065)	(0.064)	(0.066)	(0.064)	(0.049)	(0.049)	(0.053)	(0.053)	(0.053)	(0.052)	(0.060)	(0.059)
Log (Age)	0.073	0.003	0.187***	0.106**	0.071*	0.011	-0.084**	-0.118***	0.160***	0.094**	0.095**	0.053
	(0.046)	(0.046)	(0.047)	(0.046)	(0.036)	(0.036)	(0.042)	(0.042)	(0.039)	(0.039)	(0.043)	(0.043)
Risk	-0.009	0.003	-0.112***	-0.098**	-0.066**	-0.056	-0.083**	-0.076**	-0.051	-0.038	-0.003	0.004
	(0.045)	(0.044)	(0.049)	(0.049)	(0.035)	(0.035)	(0.035)	(0.035)	(0.038)	(0.037)	(0.041)	(0.042)
Turnover	0.037	0.043	0.074*	0.081**	0.048*	0.053**	0.014	0.017	0.051**	0.057**	0.029	0.032
	(0.031)	(0.029)	(0.032)	(0.030)	(0.026)	(0.026)	(0.025)	(0.024)	(0.025)	(0.025)	(0.026)	(0.025)
Cash holdings	-0.010	-0.025	0.059	0.041	0.055	0.042	-0.047	-0.055	-0.018	-0.033	-0.078	-0.088
	(0.077)	(0.075)	(0.086)	(0.085)	(0.060)	(0.059)	(0.066)	(0.066)	(0.065)	(0.064)	(0.068)	(0.068)
R&D	0.274	0.248	0.190	0.160	0.213	0.191	0.368**	0.356**	0.127	0.102	0.199	0.184
	(0.175)	(0.170)	(0.241)	(0.241)	(0.133)	(0.127)	(0.151)	(0.148)	(0.160)	(0.155)	(0.158)	(0.158)
Adjusted R^2	0.765	0.771	0.728	0.736	0.771	0.780	0.702	0.706	0.781	0.789	0.757	0.760
Observations	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901	23,901

Table 3.3. Emission reductions and SG&A expenses

Panel A reports the regression results of the log of SG&A expenses on the emission reduction (*ENER*) score. Definitions for control variables can be found in Appendix 1. We present summary statistics of SG&A expenses for CDS and non-CDS firms in Panel B. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively. SG&A expenses are expressed in thousand in panel B.

Panel A Regression of the log of SG&A expenses on the emission reduction (*ENER*) score

Variables	Log of SG&A expenses
ENER	0.0039 (0.0005) ***
Log (Assets)	0.8103 (0.0162) ***
MTBV	0.0199 (0.0031) ***
Cash holdings	0.3378 (0.0996) ***
Leverage	-0.6473 (0.0984) ***
Dividends	1.9631(0.5227) ***
Profitability	-0.1103 (0.1031)
Intercept	1.040 (0.2485) ***
Year dummies	Yes
Industry dummies (FF48)	Yes
Country dummies	Yes
Adjusted R-squared	0.806
Number of observations	16,978

Panel B. Summary statistics of SG&A expenses

	All firms			CDS firms			Non-CDS firms		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
SG&A	1,291,750	419,851	2,826,640	2,919,068	1,325,382	4,292,613	633,354	260,247	1,504,417
Observations	21,670	21,670	21,670	6,242	6,242	6,242	15,428	15,428	15,428

Table 3.4. Probit regression results on probability of CDS trading initiation

This table presents the coefficients of the probit model specified by equation (3), which is used to predict the inception of CDS trading. The sample includes all non-CDS firm-year observations and CDS firm-year observations until the CDS trading beginning during the period 2002-2017. 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 1. *Governance* is the pillar score of a firm's overall governance quality extracted from ASSET4 dataset. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level 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
Intercept	-8.418 (23.698)
Log (Assets)	0.342 (0.026)***
Governance	0.084 (0.044)*
Risk	-0.199 (0.214)
Profitability	0.482 (0.632)
Tangibility	-0.017 (0.172)
CAPEX	0.110 (0.098)
MTBV	-0.003 (0.007)
Institutional Ownership	-0.461 (0.143) ***
Leverage	1.014 (0.166)***
Log (Age)	0.025 (0.038)
Cash holdings	0.057 (0.285)
Turnover	0.107 (0.052)**
R&D	0.426 (0.492)
ROA	-0.121 (0.471)
WCAP	-0.388 (0.230)*
Likelihood Ratio	1,526.465***
Industry and year fixed effects	Yes
Pseudo R^2	35.57%
Percent Concordant /C	92.2%
C	0.922
Number of observations	18,939

Table 3.5. Comparison of control-treated firms' characteristics prior to the inception of CDS trading

Panel A Comparison of control-treated firms' E&S performances

This table compares CDS and matched non-CDS firms' characteristics in the year prior to the CDS trading initiation. A matched non-CDS firm is selected from the same FF 48 industry of the CDS firm and has the closest propensity score of CDS initiation. The definitions of variables can be read in the legend of Table 2, and further details are listed in Appendix 1. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Variables		Mean of CDS firm	Mean of non-CDS firm	Difference	P-value
ENVSCORE		49.544	48.152	1.392	0.583
	ENER	50.963	48.570	2.393	0.346
	ENRR	48.257	47.327	0.929	0.708
	ENPI	46.445	47.760	-1.314	0.580
SOCSCORE		47.840	46.581	1.259	0.611
	SOEQ	47.424	45.318	2.106	0.391
	SOTD	45.174	46.669	-1.495	0.535
	SOCO	46.899	47.673	0.773	0.748
	SODO	49.329	46.307	3.022	0.218
	SOHS	47.115	47.227	0.112	0.962
	SOHR	47.174	44.497	2.676	0.212
	SOPR	48.112	48.401	0.289	0.903
Observations		307	307		

Panel B. Comparison of control-treated firms' characteristics

This table reports the comparisons between samples of CDS and matched non-CDS firms. A matched non-CDS firm is selected from the same FF 48 industry of the CDS firm and has the closest propensity score of CDS initiation. The definitions of control variables are listed in Appendix 1. All control variables are winsorized at the top and bottom 1%. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Variables	Mean of CDS firm	Mean of non-CDS firm	Difference	P-value
Log (Assets)	15.615	15.551	0.064	0.424
Leverage	0.273	0.266	0.007	0.634
Governance	51.305	53.707	-2.403	0.337
Tangibility	0.353	0.341	0.012	0.545
CAPEX	0.062	0.051	0.011***	0.005
Institutional ownership	0.179	0.169	0.011	0.506
Risk	0.373	0.372	0.001	0.932
Profitability	0.078	0.079	-0.001	0.943
MTBV	2.679	2.791	-0.112	0.714
Log (Age)	2.829	2.812	0.017	0.771
Cash holdings	0.131	0.123	0.008	0.432
Turnover	0.925	0.920	0.005	0.931
R&D	0.021	0.022	-0.001	0.685
Logit of Propensity Score	-2.601	-2.687	0.087	0.385
Observations	307	307		

Table 3.6. The impact of CDS trading on E&S performance using PSM samples

This table presents the regression results using the propensity score matching samples constructed as per the three criteria listed in section 4.1. Dependent variables include all ten categories and two pillar scores and are provided in the legend of Table 2. Panel A presents the coefficients of *CDSINIT* using one matched non-CDS firm with the same FF48 industry as the CDS firm. Panel B reports the coefficients of *CDSINIT* using one matched non-CDS firm with the same FF48 industry and country as the CDS firm. Panel C reports the coefficients of *CDSINIT* using two matched non-CDS firms with the same FF48 industry as the CDS firm. All regressions include firm- and year-fixed effects. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Panel A. Regression results using the nearest one matching sample based on the same Fama-French 48 industry

Variables	ENVSCORE	ENER	ENRR	ENPI	SOCSCORE	SOEQ
CDSINIT	-0.054	-0.078**	-0.053	-0.048	-0.048	-0.075
	(0.037)	(0.035)	(0.038)	(0.038)	(0.037)	(0.049)
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.791	0.778	0.738	0.715	0.781	0.617
Observations	5,839	5,839	5,839	5,839	5,839	5,839

Variables	SOTD	SOCO	SOHS	SOHR	SODO	SOPR
CDSINIT	-0.063	-0.007	-0.014	-0.039	-0.002	-0.039
	(0.042)	(0.045)	(0.035)	(0.035)	(0.037)	(0.040)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.693	0.657	0.712	0.625	0.751	0.634
Observations	5,839	5,839	5,839	5,839	5,839	5,839

Panel B. Regression results using the nearest one matching sample based on the same country and Fama-French 48 industry

Variables	ENVSCORE	ENER	ENRR	ENPI	SOCSCORE	SOEQ
CDSINIT	-0.073*	-0.084**	-0.038	-0.107***	-0.042	-0.044
	(0.042)	(0.040)	(0.046)	(0.042)	(0.044)	(0.056)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.792	0.780	0.738	0.706	0.778	0.608
Observations	4,359	4,359	4,359	4,359	4,359	4,359

Variables	SOTD	SOCO	SOHS	SOHR	SODO	SOPR
CDSINIT	-0.079	-0.022	-0.010	-0.012	-0.036	-0.058
	(0.049)	(0.054)	(0.041)	(0.041)	(0.045)	(0.048)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.694	0.662	0.708	0.633	0.735	0.658
Observations	4,359	4,359	4,359	4,359	4,359	4,359

Panel C. Regression results using the nearest two matching sample based on the same Fama-French 48 industry

Variables	ENVSCORE	ENER	ENRR	ENPI	SOCSCORE	SOEQ
CDSINIT	-0.053	-0.067**	-0.049	-0.032	-0.044	-0.066
	(0.033)	(0.032)	(0.035)	(0.036)	(0.033)	(0.043)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.79	0.786	0.745	0.719	0.781	0.622
Observations	7,745	7,745	7,745	7,745	7,745	7,745

Variables	SOTD	SOCO	SOHS	SOHR	SODO	SOPR
CDSINIT	-0.044	-0.001	-0.011	-0.018	-0.020	-0.043
	(0.037)	(0.042)	(0.032)	(0.032)	(0.034)	(0.036)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.701	0.652	0.719	0.637	0.745	0.652
Observations	7,745	7,745	7,745	7,745	7,745	7,745

Table 3.7. Average cumulative differentials of ENER surrounding CDS initiation with different event windows.

Columns 2 and 3 are the average cumulative differences of *ENER* for CDS and non-CDS firms across event windows, respectively. Column 4 is the difference between the cumulative mean differentials of CDS and non-CDS firms in each event window. t=-1 indicates the year before the year of CDS initiation, and t=0 is the year of CDS trade initiation. P values are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	Mean differential		
Event Windows	CDS firms	Non-CDS firms	difference
[t=-1 t=0]	1.253	0.803	0.450 (0.767)
[t=-1 t=1]	0.754	1.712	-0.958 (0.346)
[t=-1 t=2]	1.341	2.407	-1.065 (0.183)
[t=-1 t=3]	1.509	2.149	-0.639 (0.356)
[t=0 t=1]	0.342	2.441	-2.098 (0.126)
[t=0 t=2]	1.378	3.063	-1.685 (0.074) *
[t=0 t=3]	1.584	2.529	-0.945 (0.224)

Table 3.8. The effects of CDS trade initiation over the crisis period

This table presents the coefficients of *CDSINIT* across E&S scores using the propensity score matching sample constructed as per criteria (1) of section 4.1. Dependent variables include ten categories and two pillar scores and are provided in the legend of Table 2. *CRISIS* is an indicator variable which equals one from August 31, 2008, to August 30, 2009, and zeroes otherwise. All control variables are included. For brevity, we only present the three interesting variables. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

Variables	ENVSCORE	ENER	ENRR	ENPI	SOCSCORE	SOEQ
CDSINIT	-0.065*	-0.096***	-0.059	-0.052	-0.050	-0.075
	(0.037)	(0.035)	(0.038)	(0.038)	(0.038)	(0.049)
CDSINIT* CRISIS	-0.047	-0.085	-0.024	-0.021	-0.058	0.027
	(0.055)	(0.052)	(0.058)	(0.055)	(0.049)	(0.076)
CRISIS	-0.064	-0.063	-0.036	-0.064	-0.015	-0.004
	(0.037)	(0.039)	0.039	(0.045)	(0.034)	(0.072)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.794	0.780	0.742	0.719	0.784	0.624
Observations	5,597	5,597	5,597	5,597	5,597	5,597

Variables	SOTD	SOCO	SOHS	SOHR	SODO	SOPR
CDSINIT	-0.059	0.018	-0.028	-0.040	-0.005	-0.043
	(0.040)	(0.463)	(0.035)	(0.036)	(0.037)	(0.041)
CDSINIT* CRISIS	-0.010	0.093	0.413	-0.058	0.069	0.058
	(0.064)	(0.066)	(0.049)	(0.049)	(0.053)	(0.061)
CRISIS	-0.031	-0.052	-0.006	-0.015	0.051	-0.057
	(0.053)	(0.056)	(0.035)	(0.040)	(0.032)	(0.039)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.703	0.659	0.629	0.625	0.756	0.637
Observations	5,597	5,597	5,597	5,597	5,597	5,597

Table 3.9. The distribution of estimated coefficients of *CDSINIT* with randomized CDS trade initiation events (2,000 replications)

This table reports the distribution of estimated coefficients of *CDSINIT* from 2,000 samples constructed by randomizing CDS-trade-initiation dates among 539 CDS firms. The dependent variable is emission reduction (*ENER*) score, and the independent variables include all controls and *CDSINIT*, a dummy variable indicating a pseudo CDS trading initiation year for CDS firms. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

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	Coefficient of CDSINIT	Standard errors
Mean	-0.0002	0.0251
Median	-0.0003	0.0292
1st percentile	0.0603	0.0282
5th percentile	0.0409	0.0295
10th percentile	0.0316	0.0271
90th percentile	-0.0318	0.0297
95th percentile	-0.0416	0.0319
97.5th percentile	-0.0507	0.0310
99th percentile	-0.0596*	0.0307

Table 3.10. Regression results of various subsamples

This table presents the coefficients of *CDSINIT* across subsamples. Column (1) reports results for the CDS sample. Column (2) shows results from the sample, excluding firm-year observations from South Korea, Hong Kong, and Taiwan. Columns (3) and column (4) present the results for subsample spanning from 2002 to 2007 and from 2010 to 2017, respectively. Columns (5) and (6) report the results for non-US and US samples, respectively. Column (7) presents results when the CDS notional amount is used to substitute for *CDSINIT*. The notional amount of CDS trading is a daily average of trading volume over the fiscal year in the unit of 1 million. Column (8) reports the estimates using the log of the total number of clearing dealers in a fiscal year to substitute for *CDSINIT*. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

variables				ENER				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDSINIT	-0.059**	-0.047*	-0.064**	-0.058**	-0.078**	-0.053		
	(0.028)	(0.028)	(0.030)	(0.027)	(0.033)	(0.041)		
Notional							-0.001*	
							(0.0006)	
Log (Dealer)								-0.021*
								(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.771	0.829	0.786	0.917	0.834	0.809	0.908	0.910
Observations	6,687	21,573	4,619	16,561	14,793	9,108	6,772	6,772

Table 3.11. Regressions of SG&A expenses on various E&S scores and controls

This table presents the results of regressing SG&A expenses on a multiple of E&S scores, including emission reduction (*ENER*), resource reduction (*ENRR*), product innovation (*ENPI*), employment quality (*SOEQ*), health and security (*SOHS*), training and development (*SOTD*), diversity and opportunity (*SODO*), community (*SOCO*), human rights (*SOHR*), and product responsibility (*SOPR*). The definition of each E&S variable are provided in the legend of Table 2 and further details can be referred in Appendix 1. To easily compare the magnitude of coefficients, we repeat the coefficients of *ENER* from Table 3 in this table. The sample is comprised of all CDS and non-CDS firms over the period 2002 to 2017, amounting to 16,688 firm-year observations. All regressions include control variables used in Table 3 and use industry-, country-, and year-fixed effects. For brevity, we only present the coefficients of *CDSINIT* in percentages. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parentheses. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	Log of SG&A	
Variables	Coefficients	Adjusted R-squared
(1) ENER	0.3988 (0.041) ***	0.806
(2) ENRR	0.4549 (0.052) ***	0.807
(3) ENPI	0.5551 (0.050) ***	0.809
(4) SOEQ	0.2638 (0.043) ***	0.804
(5) SOHR	0.3936 (0.051) ***	0.807
(6) SOCO	0.4242 (0.057) ***	0.805
(7) SOPR	0.3159 (0.061) ***	0.805
(8) SOTD	0.4364 (0.051) ***	0.808
(9) SOHS	0.2320 (0.055) ***	0.804
(10) SODO	0.5037 (0.054) ***	0.809

Table 3.12. Regressions of market value-added on stakeholder management

This table reports the results of regressing market value-added (MVA) on a multiple of stakeholder relationship management proxied by E&S scores, including emission reduction (*ENER*), resource reduction (*ENRR*), product innovation (*ENPI*), workforce (equally weighted average of *SOEQ, SOHS, SOTD*, and *SODO*), community (*SOCO*), human rights (*SOHR*), and product responsibility (*SOPR*). The sample is comprised of all CDS and non-CDS firms over the period 2002-2017, amounting to 15,359 firm-year observations. All regressions include the following control variables: *log (assets), profitability, risk, MTBV, leverage, cash holdings, capital intensity, R&D*, and *tangibility*. The definitions of control variables are listed in Appendix 1 ,and E&S variables are provided in the legend of Table 2 and Appendix 1. For brevity, we only present the coefficients of each E&S score. All coefficients are reported in percentages. The dependent variable is market value-added, which is the firm's market value minus total capital contributed by equity and debt holders. All regressions include industry-, country-, and year-fixed effects. All control variables are winsorized at the top and bottom 1%. The heteroskedasticity consistent errors (Wooldridge, 2002, p. 152) clustered at the firm level are reported in parenthesis. ***, **, and * indicate the significance of estimates at the 1%, 5%, and 10% level, respectively.

	Log of MVA	
Variables	Coefficients and Standard errors	Adjusted R-squared
(1) ENER	0.0414 (0.0551)	0.624
(2) ENRR	0.0924 (0.0520) *	0.625
(3) ENPI	0. 1323 (0.0556) **	0.652
(4) WORKFORCE	0.1935 (0.0717) ***	0.624
(5) SOHR	0.0963(0.0499) *	0.623
(6) SOCO	0.0828 (0.0487) *	0.624
(7) SOPR	0.0577 (0. 0502)	0.622