Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Half-full or Half-empty? Financial Institutions, CDS Use, and Corporate Credit Risk

Cecilia Caglio, R. Matt Darst, and Eric Parolin

2018-047

Please cite this paper as:
Caglio, Cecilia, R. Matt Darst, and Eric Parolin (2018). "Half-full or Half-empty? Financial Institutions, CDS Use, and Corporate Credit Risk," Finance and Economics Discussion Series 2018-047. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.047.

Half-full or Half-empty?
Financial Institutions, CDS Use, and Corporate Credit Risk *

Cecilia Caglio[†] R. Matthew Darst[‡] Eric Parolin[§]

Current version: January 31, 2018

Abstract

We construct a novel U.S. data set that matches bank holding company credit default swap (CDS) positions to detailed U.S. credit registry data containing both loan and corporate bond holdings to study the effects of banks' CDS use on corporate credit quality. Banks may use CDS to mitigate agency frictions and not renegotiate loans with solvent but illiquid borrowers resulting in poorer measures of credit risk. Alternatively, banks may lay off the credit risk of high quality borrowers through the CDS market to comply with risk-based capital requirements, which does not impact corporate credit risk. We find new evidence that corporate default probabilities and downgrade likelihoods, if anything, are slightly *lower* when banks purchase CDS against their borrowers. The results are consistent with banks using CDS to efficiently lay off credit risk rather than inefficiently liquidate firms.

Keywords: risk management, bank lending, credit risk, credit default swaps

JEL Classification: G2, G21, G23

*We thank Bill Bassett, Sergio Correia, Philipp Hartmann, Sarah Wang and conference participants at the Federal Reserve Board of Governors, Bocconi-Carefin Banking and Financial Institutions Conference, University of Warwick Frontiers of Finance Conference 2017, The Risk, Banking, and Finance Society Annual Meeting 2017, 25th Barcelona Finance Forum, IFABS 2017 and European Economic Association meetings.

[†]Federal Reserve Board of Governors: cecilia.r.caglio@frb.gov.

[‡]Federal Reserve Board of Governors: matt.darst@frb.gov.

[§]Office of Financial Research: eric.parolin@ofr.treasury.gov.

1 Introduction

The credit default swap (CDS) market allows CDS buyers to transfer credit risk to CDS sellers.[1] More importantly, when creditors buy CDS to hedge against credit losses the dynamics of the debtor-creditor relationship may change and have important ramifications on corporate credit risk. For example, creditors who purchase credit protection may not extend credit to solvent but illiquid firms in distress, which in turn may increase their credit risk (Bolton and Oehmke (2011)). Black and Hu (2008) refer to this situation as the "empty creditor" problem.[2]

There is empirical evidence consistent with the notion that active CDS markets can adversely affect corporate credit risk measured by higher bankruptcy rates and downgrade probabilities (Subrahmanyam, Wang, and Tang (2014)), and that firms find it more difficult to renegotiate with creditors outside of bankruptcy (Danis (2016)). However, the identification strategy in these papers as well as almost every other study examining how CDS trading affects the debtor–creditor relationship is typically based on whether or not a CDS market simply exists for firms. Moreover, the traded volume in the CDS market for each firm is used to proxy for the hedging activity done by the firms' lenders or debt holders.[3] However, the existence of a CDS trade (or quote) provides no information about who is buying or selling the derivative contract, much less whether or not the CDS buyer or seller has an insurable interest in the CDS reference entity. The lack of detailed transaction-level information on CDS use renders tests of how CDS affect the debtor-creditor relationship indirect. In fact, many empirical studies on CDSs explicitly state this limitation (see Subrahmanyam et al. (2014), Bedendo et al. (2016), and Streitz (2017), to cite a

[1] A CDS is a contract between two counterparties for the transfer of a reference entity's credit risk. Typical reference entities in the corporate CDS market are either single firms, a basket of firms, or a large group of firms that comprise an index. The credit protection buyer pays monthly or quarterly premiums for the life of the contract to the credit protection seller in exchange for insurance against a pre-specified credit event. If a pre-specified credit event occurs, the protection buyer is entitled to receive payment equal to the notional value of the CDS contract purchased. If a credit event does not occur, the protection seller owes nothing to the protection buyer and the contract is closed. JP Morgan is credited with creating the first CDS contract referencing Exxon Valdez in 1997.

[2] In particular, Bolton and Oehmke (2011) show that purchasing CDS against default increases a creditor's outside option relative to renegotiating with solvent but illiquid borrowers. CDS protections destroys creditors' incentive to share in any renegotiation surplus. The incentive to renegotiate is destroyed because the derivative makes the contract owner whole while any surplus from renegotiation is split between the borrower and lender. In this sense, firms find it harder to renegotiate debts and are too frequently pushed into default and liquidation.

[3] See Ashcraft and Santos (2009), Saretto and Tookes (2013), Bedendo et al.(2016), Streitz (2017) for more examples.

few).

In this paper, we provide the first attempt to overcome the data limitation and more directly assess how CDS use affects the debtor-creditor relationship using a new U.S. supervisory data set to match bank holding company (BHC) credit derivative transactions to their detailed securities and loan portfolios. As such, we are able to shed new light on how banks use CDS and what the effects are on the debtor-creditor relationship. Using the bank-firm data match, we isolate observations in which banks are both net buyers of credit protection and creditors to the same firm to test how corporate credit risk is affected when banks transfer credit risk via CDS purchases. The data used in our analysis come from two sources. We obtain BHCs' loan and security data from the Capital Assessments and Stress Testing Report (FR Y-14Q Report) collected from BHCs during the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) process. The report contains detailed information on corporate loans that are held for investment or for sale and on individual securities that are available-for-sale or held-to-maturity for each BHC. Data on transactions on corporate single-name and index CDS are obtained from the Depository Trust & Clearing Corporation (DTCC). The DTCC data contains details on notional amount of CDSs bought and sold by each counterparty for all the reference entities. Our analysis assesses how the different measures of credit protection purchased are associated with various measures of credit risk. The credit risk measures include the probability of default, the probability of credit rating downgrades, and the probability of becoming a fallen angel (being downgraded from investment grade to high yield).

Our study makes two contributions. First, we provide novel evidence that the CDS positions of the largest U.S. banks do not adversely affect various measures of corporate credit risk at any level of statistical significance. This result, or more accurately lack thereof, holds for tests that have been previously explored in the literature (Subrahmanyam et al. (2014)), as well as across new sets of tests that our data allow us to compute. We examine both the extensive and intensive margin of CDS use based purely on banks being net buyers of CDS. Furthermore, we are able to condition tests based on observations where banks actively begin, on net, buying credit protection. The results suggest that actively purchasing CDS does not lead to a deterioration in firm credit quality. For the intensive margin analysis, we create hedge ratios isolating bank-firm observations in which banks purchase more credit protection than they have in underlying credit exposure (*i.e.* over insurance). A specific prediction of the empty creditor theory is that borrowers over insure against credit losses in a competitive equilibrium, and too frequently push borrowers into default. Our results indicate that borrower credit quality is not worse when banks are overinsured against losses compared to otherwise similar borrowers for whom banks are either not over insured or do not purchase CDS protection against default losses. The results are robust to including CDS index positions in addition to the standard single name positions, which addresses concerns that banks may hedge their portfolio more efficiently with index CDS rather than single name CDS. The results are also robust to using different snap shots of when we measure the amount of credit protection banks purchase, addressing concerns that banks may window dress credit risk hedging around the supervisory reporting window.

Second, we find new evidence suggesting that corporate credit risk is on average *better* when BHCs purchase credit protection. In particular, compared to otherwise similar firms with no CDS positions on BHC balance sheets, we find that firms are less likely to be downgraded one notch when banks begin purchasing CDSs. In terms of economic significance, the estimates suggest that CDS firms are 22% less likely to be downgraded after banks actively begin purchasing CDS. We also find that firms have lower default probabilities when banks over insure against default risk. Specifically, over insuring against default is associated with a 2.5bps lower default probability compared to otherwise similar firms for whom banks either under insure or do not purchase CDS against default. The economic significance of this result is smaller; a 2.5bps lower default probability represents a 1.3% difference relative to the average firm in our sample.

The main takeaway from the analysis is that we rule out U.S. banks as empty creditors. This is an important finding because the banks in our sample are particularly prominent agents in both CDS markets and credit markets. Specifically, they represent approximately 70% of all CDS trading and originate approximately 73% of all U.S. commercial and industrial loans. From an aggregate perspective, CDS markets do not appear to have widespread negative consequences for corporate credit quality, and, in fact, tend to be associated with improved credit quality measures on bank balance sheets.

The finding that corporate credit risk measures are positively associated with bank CDS purchases is consistent with efficient credit risk transfer (CRT) without undermining bank monitoring. In particular, Parlour and Winton (2013) show that banks purchase CDS to comply with risk based capital requirements, which frees equity capital for new projects. Their study shows that once repeat lending in the credit market and reputation in the CRT market are considered, banks efficiently use both CDS and secondary loan markets to lay off credit risk. Efficient credit risk transfer (CRT) is only achieved when banks lay off *high quality credit risk that does not require monitoring* through CDS markets and directly sell low quality loans that do require monitoring. In this sense, bank CDS use does not *cause* borrowers to be less risky as the risk mitigation function is tied to a banks monitoring technology, which would be undermined if banks laid off credit risk through CDS while retaining control rights over their borrowers. Rather, banks purchase CDS for certain borrowers *because* those borrowers do not require expensive monitoring and laying off credit risk via CDSs is the least expensive CRT instrument to loosen capital constraints.

We provide further evidence consistent with banks' use of CDS as predicted by Parlour and Winton (2013). Specifically, we interact the CDS buyer measures that are associated with lower downgrade and default probabilities in the baseline regressions with a borrower investment grade dummy. According to the intuition from the Parlour and Winton framework, one should expect to find a positive association between net buy CDS positions and improved credit quality measures. Indeed, we find statistically significant results for the investment grade interaction term, which suggests that downgrade and default probabilities are lower for investment grade firms relative to high yield firms when banks purchase CDS protection on both types of firms. To our knowledge, ours is the first study to find evidence consistent with efficient CRT in the CDS market as suggested by Parlour and Winton. More importantly, our results suggest that credit risk management via CDS purchases does not undermine bank monitoring incentives and does not lead to a deterioration in borrower credit quality.

As further robustness, we conduct instrumental variable analysis to assess whether improved credit risk measures are due to CDS use and not merely a reflection of separation in the CRT market. We use lender leverage and a liquidity based measure of bank funding (ratio of wholesale funding to total assets) as instruments for CDS purchasing. The intuition for bank leverage is that, irrespective of borrower credit risk, highly levered banks have less risk baring capacity and may be more likely to lay off credit risk to free capital for new lending. The intuition for the liquidity based funding measure is that bank who are more liquidity constrained will increase their propensity to use CDS to hedge to hedge trading book flows (Boyarchenko et al. (2016)) and for regulatory capital relief (Shan, Tankg, and Yan (2016)). The IV regressions indicate that the probability of default or downgrades are no longer statistically different from zero at any level of confidence. The lack of statistical significance indicates that there is not CDS effect of credit risk hedging on corporate default probabilities in the baseline regressions. Rather, credit risk hedging through CDS is simply associated with relatively safe firms, consistent with the Parlour and Winton story.[4]

In addition, our data allow us to examine CDS affects conditional on the type of credit exposure banks have to different firms. For example, we explore potential differences between bank-firm observations where banks have combined loan and bond exposure versus only loan exposure.[5] The estimates of CDS use on the various credit risk measures are both quantitative and qualitatively similar for the combined loan and bond observations and the loan only observations, despite the respective sets of bank-firm pairs being mutually exclusive. This suggests that the improved credit quality measures we find appear to be driven by loan exposure rather than bond exposure. Prior findings in the literature have focused on or at least have been interpreted as operating mainly through bond markets. Saretto and Tookes (2013) suggest that borrowers have improved access to credit markets due to sellers being able to hedge their credit risk to bond exposure. Bedendo et al. (2016) and Danis (2016) analyze debt restructuring in bond markets in the presence of CDS markets. Subrahmanyam et al. (2014) do not find any differences in firm bankruptcy filings based on differences in capital structure complexity. Compared to our study, these studies conduct all analysis at an aggregate level and do not match debtors to their creditors.

The granularity of the data allows one to study firm fixed effects, when computationally feasible, in addition to bank and time fixed effects. Most existing studies only use industry and time fixed effects.[6] The results suggest that firm fixed effects matter when assessing how CDS affect borrower credit risk. On the extensive margin, CDS referenced borrowers have lower default probabilities when their lenders, on net, purchase CDS controlling for firm fixed effects rather than industry fixed effects and differences between CDS and non-CDS referenced firms. This suggests

[4]Darst and Refayet (2018) show that CDSs can induce firms to issue small levels of safe debt rather than larger levels of risky debt if CDS increase credit spreads. Higher credit spreads cause firms to scale back risky debt issuance, which reduces the benefit of leverage relative to issuing a small amount of safe debt. In this sense, CDS can reduce the probability of default to zero, but we do not explicitly test for these effects.

[5]Unfortunately we do not have enough observations to confidently assess only bond exposures.

[6]Saretto and Tookes (2013) use firm fixed effects to show robustness. Their estimates are affected both statistically and economically when firm fixed effects are used rather than industry fixed effects, but their conclusions are not qualitatively altered.

that there are unobserved firm differences both within industry and within the subset of CDS traded firms affecting credit risk. Moreover, on the intensive margin, banks being over insured against credit risk does not affect default probabilities when controlling for firm fixed effects. By contrast, over insurance does have a statistically significant association with lower default probabilities controlling for industry fixed effects and differences between CDS and non-CDS referenced firms. Lastly, on both the intensive and extensive margins, using firm fixed effects explains an additional 30% of the variance in firm default probabilities. All told, not controlling for firm specific differences outside of industry similarities and differences between CDS and non-CDS firms may lead to incorrect inference concerning the effects of CDS use on the debtor-creditor relationship. Finally, we issue one note of caution. Our results do not suggest that empty creditor effects are irrelevant or do not appear anywhere in the data. It is possible, and perhaps likely, that empty creditor effects manifest through financial market participants other than banks. We save this discussion for the conclusion section.

The rest of the paper is structured as follows. Section 2 reviews the literature related and discusses hypothesis development. In Section 3, we describe the databases used in our study and our set of stylized facts. In Section 4 we study the effect of CDS trading by banks on firms credit risk. In Section 5 we perform robustness tests to corroborate our results. We discuss the results in the context of existing models in Section 6 and conclude.

2 Literature

The closest paper to ours is Subrahmanyan et al. (2014), who find evidence that firms with a CDS market on their debt tend to default more and are more likely to receive credit-rating downgrades. Relatedly, Colonnello et al. (2016) find that, unconditionally, firms are not more likely to default once CDS begin trading on their debt. However, after controlling for proxies of shareholder strength, they find that firms with strong shareholders are more likely to default because their creditors are more likely to purchase credit protection to avoid renegotiation. Chakraborty et al. (2015) show that CDS firms do not go bankrupt at a higher rate or decrease investment than non-CDS firms when loan covenants are violated, but they do pay higher loan spreads. Danis (2016) suggests that the likelihood creditors participate in out-of-court restructuring is lower for CDS-referenced firms in distress. Bedendo et al. (2016) find that CDS referenced firms are not more likely to file for Chapter 11 bankruptcy rather than an out-of-court distressed debt exchange. Common to all of these studies is the assumption that creditors are hedging credit risk without knowing who the creditors are or what CDS positions creditors have. We advance the literature on bank-firm relationships in particular by matching bank credit exposure to CDS positions, and provide empirical support to notion that banks use CDS to efficiently lay of credit risk suggested by Parlour and Winton (2013).

Several studies consider various aspects of the CDS-credit market nexus. Hirtle (2009) suggests that aggregate bank-level CDS use modestly increases credit supply. Ashcraft and Santos (2009) suggest that CDS markets minimally impact the cost of corporate debt, and only for relatively safe and transparent firms. Our result that CDS use is associated with lower default risk is consistent with their pricing results. Streitz (2017) finds that banks use CDS for risk management in conjunction with loan syndication and credit risk transfer practices. Saretto and Tookes (2013) document that CDS referenced firms have higher leverage ratios and borrow on longer debt maturities. Li and Tang (2016) highlight the leverage externalities to non-CDS reference firms that are closely linked to CDS referenced firms. Subrahmanyam, Tang, and Wang (2017) find that CDS lead firms to increase their cash holdings to avoid funding constraints in times of distress. Shan, Tang, and Winton (2015) suggest that CDS referenced firms have looser net worth and collateral requirements in loan contracts, which they interpret as lenders using CDS to forgo costly monitoring when CDS are available.[7] A complete survey of the effects of CDS on a variety of credit market outcomes can be found in Augustin et al. (2014).

More broadly, our paper relates to a growing empirical literature on risk management by financial institutions. Gunduz, Ongena, Tumer-Alkan, and Yu (2017) using data on German banks, find that banks with hedging CDS positions increase their supply of credit to safe firms and that banks who are properly hedged purchase more CDS and extend loans to risky firms following standardization in the CDS market. Our study is for U.S. banks and firms, which constitute the majority of CDS market participants and focuses on the effect of CDS purchases on underlying corporate

[7]Most of the empirical work on CDS use and loans exposure assumes that banks purchase credit protection against their loan exposure and that CDS sellers will adjust the price of credit risk due to moral hazard in the loan monitoring market making CDS an expensive way to lay off credit risk. However, Caglio, Darst and Parolin (2017) and Campbell and Gallin (2015) provide evidence that banks actually *sell* more credit protection than they buy, especially when they lend to the CDS reference entity. Their evidence further underscores the importance of data limitations for the CDS literature.

credit risk. We also include index CDS positions to provide a broader measure credit derivative use, especially since the single-name CDS market is giving way to the index market. Boyarchenko, Castello, La'O, and Sachar (2016) also incorporate CDS index use and document that banks hedge a relatively small portion of changes in credit risk associated with market making activities. They do not find evidence that banks hedge credit risk on assets held for investment purpose. The focus of their study is the activity in the bond market by the trading desk while our paper looks at the assets and loans held for maturity and held for sale. Rampini, Viswanathan, and Vuillemey (2017) find evidence that tighter financial constraints reduce bank interest rate hedging because financial constraints jointly affect lending and hedging related activities. Our results are broadly consistent with the notion that banks use CDS as risk management devices due to risk based capital constraints (*à* la Parlour and Winton (2013)).

2.1 The link between CDS and credit risk

How can derivative securities affect the credit risk of the firm it references? Bolton and Oehmke (2011) argue that creditors' bargaining power is improved when they purchase default insurance via CDS. In their model, borrowers have limited commitment to pay cash flows in future states. Borrowers may strategically renegotiate debt repayments to divert cash for themselves, even when fully liquid. Insured creditors have less incentive to renegotiated debts, which debtors *ex ante* anticipate. They show that a competitive equilibrium typically involves over insurance and inefficient default because lenders fail to internalize the gains from renegotiating debts initiated by solvent but illiquid borrowers.

Hypothesis 1: Firm credit risk is worsened when lenders purchase CDS protection because lenders' incentives to renegotiate debt are lower.

Parlour and Winton (2013) show that laying off credit risk via CDS alters lenders' monitoring incentives. In their model, banks need to lay-off credit risk in order to make new profitable loans; hence, there is a benign motive to lay off credit risk. There are two information frictions in their model: 1) moral hazard and risk shifting at the borrower level, which generates the need for costly monitoring; and 2) banks have private information about their borrowers. A bank's private information only gets transmitted to other uninformed banks if there is separation among the types of loans sold or separation in the types of instruments used for credit risk; information is never conferred in the credit risk transfer market when all loans are sold or when banks purchase CDS for all borrower types. In a model with repeated lending and reputation concerns – which is the most natural setting for banking, they show that a separating equilibrium with CDS use and loan sales can co-exist. Banks sell risky loans outright to others banks that commit to monitoring the risky borrowers. Banks purchase CDS against relatively safe firms that do not require monitoring. In equilibrium, both monitoring and risk sharing are efficient when CDS are used with loan sales.

Hypothesis 2: Banks purchase CDS for relatively safe firms and corporate credit risk is not adversely affected by CDS markets.

3 Data description and some stylized facts

We use two main data sets for our analysis. We obtain corporate loan and bond holding data for 31 of the largest U.S. bank holding companies (BHCs) from the Capital Assessment and Stress Testing (CCAR) Report.[8] The report (also called FR-Y 14 Report) is collected on a quarterly basis and contains asset class and capital component data for the BHCs with more than $50 billion in assets. For the purpose of our analysis, we use the Wholesale Risk–Corporate Loan Data (Schedule H1) and the Securities Schedules (Schedule B). Our sample covers the period from Q3:2011 to Q1:2016.

Loan level details on corporate loans and leases that are held for investment and for sale by the BHCs at each quarter-end are reported in the Corporate Loan Data Schedule. The population of loans is reported at the credit facility level and is limited to commercial and industrial loans with a committed balance greater than or equal

[8]The bank holding companies included in the sample are: beginning in Q3:2011 Ally Financial, Bank of America Corporation, BB&T Corporation, Bank of New York Mellon Corporation, Citigroup Incorporated, Capital One Financial Corporation, Fifth Third Bancorp, Goldman Sachs Group Incorporated, JPMorgan Chase & Co., Keycorp, Morgan Stanley, PNC Financial Services Group Incorporate, Regions Financial Corporation, Suntrust Banks Incorporated, State Street Corporation, U.S. Bancorp, Wells Fargo & Company. Beginning in Q3:2012 Comerica Incorporated, Huntington Bancshares Incorporated, HSBC North America Holdings Incorporated, M&T Bank Corporation, Northern Trust Corporation, RBC USA Holdco Corporation, Santander Holdings USA Incorporated, UnionBanCal Corporation (renamed to MUFG Americas Holding Corporation in Q3:2014), Zions Bancorporation. Beginning in Q2:2014 Discover Financial Services. Beginning in Q4:2014 BNP Parisbas.

to $1 million.[9] If borrowers have multiple facilities from the same bank, each facility is reported separately. The data provide information on borrower and loan specific characteristics, including bank level assessments of borrower financial health. For the purpose of our analysis, we focus on commercial and industrial loans issued to domestic non-financial firms.

Figure 1 plots the total amount of commercial and industrial loans issued over the sample period by the BHCs filing the FR Y-14 Report. The data are split according to whether the borrowers are CDS or non-CDS firms.[10] The annual growth rate of loans to CDS and non-CDS firms is 7.2% and 2.3%, respectively. Although the sample of banks in our study is small relative to overall population of U.S. banks, the FR-Y14 data collection covers roughly 73% of the total C&I lending done by all banks in the U.S.[11] The jump in total credit during the third quarter of 2012 is the result of additional banks being included in the CCAR supervisory exercise.

Portfolio position data for individual securities that are available-for-sale or held-to-maturity are reported in the Securities Schedule. The BHC positions of each security are reported as amortized cost, market value, current face value, and original face value. From the overall Securities Schedule, we select only corporate bonds issued by domestic non-financial corporations.[12]

Figure 2 reports the market value of the banks' corporate bond portfolios also broken down by CDS and non-CDS firms. Overall, the market value of bank corporate bond portfolios has declined from a peak of around $87 billion in Q2 2012 to around $25 billion by Q1 2016.[13] The market value of corporate bond holdings for CDS firms and non-CDS firms has fallen at an annualized rate of 24% and 3.1%, respectively.

Weekly data on the outstanding CDS contracts traded on U.S. firms are ob-

[9]A credit facility is defined as any legally binding credit extension to a legal entity under a specific credit agreement. A credit facility may be secured or unsecured, term or revolving, drawn or undrawn (excluding informal advised lines).

[10]We use DTCC data to split the sample according to whether or not debtors in the FR Y-14 data have CDS contracts (CDS Firms) or not (non-CDS Firms). We provide more details about the methodology in Section 3.1.

[11]The ratio is obtained from call report data data. It is the fraction of C&I lending done by banks that participates in the CCAR test divided by the sum of all C&I in the banking sector.

[12]There is no materiality threshold for securities reporting at the individual obligor level. BHCs must report their securities holdings if the entire portfolio is greater than either $5 billion or five percent of Tier 1 capital on average for the four quarters preceding the reporting quarter.

[13]Corporate bond holdings represent a small fraction of BHCs' total bond portfolios in our sample period. This evidence could reflect the post-crisis regulations, in particular the restrictions the Volcker Rule imposed on most banks regarding proprietary trading.

tained from the DTCC Trade Information Warehouse (TIW).[14] From the overall data reported through TIW, we can only observe transactions for which at least one counterparty, or the reference entity, is supervised by the Federal Reserve Board (FRB-regulated entity), or a FRB-regulated entity acts as the clearing agent. When compared with the total CDS activity for single name contracts, our data cover on average about 70% of the total gross notional for single-name transaction and about 60% for the index products.[15] The data include information about the name of the reference entity, trade date, effective date, contract maturity date, the names of the counterparties participating in the transaction, including their type (dealer vs. non-dealer entity), the notional amount,[16] and the reference entity's market sector. This database allows us to compute net notional amounts of CDS protection bought at the bank-firm level. We begin by combining the weekly outstanding CDS transactions executed by each of the BHC affiliates' and subsidiaries' accounts operating under the BHC umbrella.[17] Then, we compute the net notional CDS position as the difference between the amount of protection bought and sold for each counterparty across all CDS reference entities.

Figure 3 reports the total credit exposure (the sum of the market value of corporate bond positions and loan exposure) banks in our sample have to firms conditional on the bank being a net buyer of CDS for the firm. The total exposure figure is depicted by the dashed line. On average, total exposure declined between 2012 through the end of 2015, but quickly picked up into 2016. On aggregate, the amount of credit protections that banks purchase, on net, relative to the underlying credit exposure declined steadily from over 33% in 2012 to around 15-16% in 2015 where it has stabilized, as indicated by the red dashed line.

The main limitation of the data lies in the inability to identify CDS trades based

[14]The data includes only trades that constitute *risk transfer activity*, that is new trades, terminations of existing transactions (due to a credit event that triggered the settlement of the contract or to the natural maturity of the contract), and assignments of existing transactions to a third party, but exclude the portfolio compression trades.

[15]See Boyarchenko et al (2016), who computed a similar percentage of CDS activity for the same set of BHCs.

[16]The notional amount represents the par amount of credit protection bought or sold, equivalent to debt or bond amounts, and is used to compute the coupon payment and the recovery amounts in case of a credit event. The notional amount is most commonly denominated in US dollars, Euro, British Pound, Japanese Yen, and Swiss Franc. We use the prevailing foreign exchange rate for each end of the week the positions are computed.

[17]We exclude transactions from asset managers because our focus is on how CDSs affect corporate credit risk, which in theory should be driven by positions at the loan desk and the Asset and Liabilities Committees (ALCO) more generally. We explain below the limitation this imposes.

on the BHCs' line of business. Thus, we cannot be sure if a trade is done by the broker-dealer arm of the BHC for pure market-making activity or whether or not the loan desk passes a CDS transaction through its broker-dealer. However, our concerns are mitigated by three considerations. First, at the BHC level, the banks in our sample are almost never flat on their CDS positions as one would expect from pure market-making activity. The assumption we are therefore making is that the persistent and open CDS positions we observe are not driven by pure market-making activity. There are several reasons why this assumption is reasonable. First, Boryachenko et al. (2016) find that the same BHCs only hedge about 16% of their bond trade flows with offsetting CDS positions. Second, internal discussions with on-site BHC regulators assure us that the trading book is certainly not unilaterally engaging in CDS activity on behalf of other BHC's lines of business without the line of business' consent. Finally, from a risk management perspective, the BHC consolidates the balance sheet data from the entities that comprise the BHC. As argued by Rampini and Vishwanathan (2010, 2013), when financial institutions' financing needs and risk management are subject to the same collateral requirements, scarce resources have be allocated between the different functions. Whether or not a CDS is sold by one entity or the other is immaterial from the top-level BHCs' perspective when contracts require collateral. CDS positions are now highly collateralized, typically with cash. Collateral encumbered for derivative positions in one line of business cannot be used to finance loans or purchase other assets by another.

3.1 CDS use and firm characteristics

We use DTCC data to split the sample according to whether or not debtors in the FR Y-14 data have CDS contracts (CDS Firms) or not (non-CDS Firms). Specifically, a "CDS firm" is defined as a firm that has a CDS contract traded on its debt at least once in our sample period. The final sample includes 658 unique U.S. corporations with CDS contracts traded by at least one of the BHCs during the period from September 2011 to March 2016.

Panel A of Table 2 presents summary statistics for firms that have at least one outstanding loan issued and/or their bond issuances held by at least one of the BHCs in our sample. Our data confirm the well-documented finding that CDS contracts tend to exist for larger and well-established firms. On average, firms with CDS contracts have more assets, more cash and outstanding liabilities, and are more profitable than firms without CDS. Panels B and C present the loan and bond characteristics, respectively, for both CDS and non-CDS firms. In any given quarter, BHC's committed a total of $1.40 trillion in loans to non-CDS firms and $466 billion in loans to CDS firms. However, the average committed amount to non-CDS firms was only $2 million compared $959 million for CDS firms. CDS firms borrow, on average, from eight lenders and the non-CDS firms typically borrow from a single lender. Turning to bond positions, in any given quarter, BHCs hold a total book (market) value of $33 billion ($32 billion) in bonds issued by non-CDS firms compared to $19 billion ($13 billion) in bonds issued by CDS firms. The average book (market) value of the bond issuance held by BHC's is $51 million ($34 million) for a CDS firm compared to $30 million ($30 million) for a non-CDS firm.

We also distinguish the amount of loans that CDS and non-CDS firms obtained from the banks based on their rating. For this purpose, we use the internal ratings that each BHC assigns to its obligors in the Schedule H of the FR Y-14 report. To compare of the ratings across reporting institutions, the internal rating is converted to a standardized rating scale going from AAA (very low risk of default) to D (in default).[18] Finally, if in a given quarter there is more than one rating assigned to one obligor, we take the lowest rating assigned by the reporting BHCs. As shown in Table 3, most of the loans to non-CDS firms are issued to firms with internal rating equivalent to BB (37% of the committed exposure), followed by firms with internal rating equivalent to BBB. For CDS firms, the loans are mostly issued to firms with internal rating equivalent to BBB (40% of the committed exposure) followed by firms with internal rating equivalent to A. Loan exposure to CDS firms is slightly more concentrated at the top end of the ratings distribution and mostly to investment grade firms than loans to non-CDS firms. That CDS firms are an overage better quality than non-CDS firms is consistent with the prediction of Parlour and Winton (2013). Namely, CDS markets are most likely to exist for relatively safe firms that may not require intensive and costly monitoring.

Table 4 repeats the same analysis for the bond positions. For issuer rating, when available, we use the same internal rating that banks assign to firms; otherwise, Standard & Poor's (S&P) long-term issuer ratings are obtained from Compustat.[19] For

[18]See, for example, the Supervisory Stress Test Methodology and Results document for 2015, https://www.federalreserve.gov/bankinforeg/stress-tests/2015-Appendix-B.htm.

[19]The reported level of disaggregation for bond holdings based on rating is slightly different than level for loans to mitigate confidentiality concerns associate with the smaller numbers of firms in some rating buckets.

CDS-firms, most of the CDS positions exist for firms with internal rating equivalent to A or higher (56% based on market value), followed by firms with internal rating equivalent to BBB (37% of total market value). For non-CDS firms, CCAR banks hold bonds mostly issued by firms with internal rating equivalent to BBB (approximately 43% of total market value), followed by firms with internal rating equivalent to A and higher (36% of total market value). The ratings distribution for CDS firms is also slightly more concentrated at the higher end of the rating scale than for non-CDS firms. In sum, the data on CDS versus non-CDS firms, irrespective of loan versus bonds, is consistent with Parlour and Winton (2013) in that CDS firms tend to be larger and relatively safe investment grade firms.

Our data allows for a breakdown of CDS positions based on the type of credit exposure banks have–loans, versus bonds, versus both. In Table 5 we present statistics for net buy CDS positions by type of credit exposure. Each panel contains two sets of statistics. The *Total Exposure* variable is a measure of how much credit exposure banks have that is matched to net buy CDS positions. In other words, it broadly measures the percentage of credit exposure banks purchase credit protection against. The *Protection Bought* measure is a break down of mean and median size of bank net buy CDS positions. Both measures are broken down based on type of credit exposure banks have to a given firm. For example, in the first two panels we show CDS positions for firms that banks only lend to (measured by committed amount) and CDS for bond only holdings. The last panel shows the CDS positions when banks both extend loans to and own bonds issued by the same firm. The average size of net protection bought by the banks in our sample is only 22% of the average credit exposure to a firm, when the exposure is measured as amount of loans extended to the firm. The percentage drops to 19% when the exposure is measured by the sum of extended loans and held bonds. Although it is clear that banks do not purchase CDS to cover all of their credit exposure, banks do use CDS to cover roughly one-fifth when they actively buy CDS, which is economically relevant.

The high percentage for bond only exposure is due to the relatively small corporate bond holding amounts held in the BHC securities portfolios.[20] In the sections we conduct more thorough analysis looking specifically at the relationship between CDS-protected bank credit exposure and the underlying firm's credit risk.

[20]Boyarchenko et al. (2016) find that BHCs typically use CDSs to offset bond positions for only about 15% of their corporate bond trade flows. Their definition of offset includes both buying a bond and a CDS as well as selling a bond and a CDS. Thus, the percentage of hedged position that buying both a bond and a CDS comprise is even smaller.

4 CDS positions and corporate credit risk

4.1 Extensive CDS use and corporate credit risk

In this section, we exploit the granularity of our data to analyze whether banks purchasing credit protection through CDSs affects the credit risk of the CDS referenced firm.

For this purpose, we consider various measures of firm credit risk as dependent variables: the probability of being downgraded at least one notch,[21] the probability of being downgraded to high yield status (fallen angels), and the probability of default. All measures of credit risk are reported by the BHCs for each firm in Schedule H of the FR Y-14 report. One advantage of using the probabilities of default reported by the BHCs rather than market based measures is that self-reported values are available for both public and private firms, creating a more comprehensive sample.[22]

We compute several indicators to study the extensive margin between CDS use and credit risk. Following Ashcraft and Santos (2009), Saretto and Tookes (2013), and Subrahmanyam et al. (2014) among others, we include *CDS*, an indicator equal to one if a firm has any CDS contract traded on its debt at any point in time in our sample period. This indicator captures the unconditional effect of CDS trading on firm i's credit risk irrespective of whether or not firm i's lenders are trading the CDS. Because we are interested specifically in the effect of the CDS trading done by lenders, we include a second indicator, *CDS lender*, that equals one if a bank actually trades CDS on the firms to which it has credit exposure. This indicator provides additional information on whether the impact of CDS on corporate credit risk comes from lenders trading CDS. Third, we compute an indicator variable, *CDS Buyer*, equal to one if a lender j is a net buyer of CDS protection on the firm to which it provides credit. This indicator captures the effect of how *purchasing* credit protection affects corporate credit risk. Lastly, we compute an indicator variable equal to one if a bank changes its net derivative position from selling in quarter *t-1* to buying in quarter t and 0 otherwise, *Sell-to-Buy*. Intuitively, if banks are worried about default and they use their superior monitoring information, they may begin purchasing CDS to protect their investment. Alternatively, a lender may be

[21] The results hold (qualitatively) when we test the effect on two-notch downgrades. The results are not reported but are available upon request.

[22] As a robustness check against market based measures, we compared the average probability of default by credit rating against average market based measures and the results are both qualitatively and quantitatively similar.

concerned about an impending default or renegotiation attempt for which the lender purchases protection to improve her outside option and take a tough stance in the renegotiation (Bolton and Oehmke (2011)). The regime shift variable is a further innovation to the literature aimed at identifying empty creditor effects of bank CDS use on corporate credit risk.

Table 1 provides a description of the independent variables used in our analysis. We follow Bharath and Shumway (2008) and include firm characteristics that may impact its credit risk profile. The controls include *Leverage* computed as the ratio of total book debt to total assets, where total book debt is the sum of debt in current liabilities and 50% of long-term debt, equity volatility (*Volatility*) firm profitability (*Profitability*), firm cash to total assets (*Cash ratio*), and *Size* measured by the log of total assets. We also include a *Tangibility* indicator following Almeida and Campello (2007). The conjecture is that the assets of firms operating in nondurables (durable) industries are perceived as more (less) liquid by lenders, and assign to firms in these industries the value of 1(0).[23] To compute this indicator, we use industry durable/nondurable dichotomy to associate asset illiquidity to operations in the durable sector. We also include the total dollar value of loan and/or bond exposure to a given firm as a fraction of firm's total assets to control for lender specific assessments of credit risk. Lastly, we include the number of lenders a firm has in quarter t (*#Lenders*), as a measure of the degree to which renegotiation hold-up problems may arise (Lummer and McConnel (1989) and Gilson, Kose, and Lang (1990)).

The main specification to study the extensive margin of CDS trading on the probability of downgrade follows Subrahmanyan et al. (2014). We estimate a proportional hazard model of one-notch and high-yield downgrades using a bank-firm quarterly panel. It is assumed that the marginal probability of being downgraded in a given quarter follows a logistic-distribution with parameters (α, β) and time-varying covariates:

X_{it-1}:

$$\Pr\left(Y_{it}=1|X_{it-1}\right)=\frac{1}{1+\exp\left(-\alpha-\beta' X_{it-1}\right)}. \tag{1}$$

Y_{it-1} is an indicator equal to 1 if firm i is downgraded one-notch or to high-yield

[23]We groups industries according to the historical covariance between their sales and the GNP. The set of high covariance industries includes all of the durable goods industries (except SICs 32 and 38) plus SIC 30. We refer to these industries as durables and label the remaining industries nondurables.

status, where the regressions are run separately for the different dependent variables. We also include year, industry and bank fixed effects in the panel data analysis. To control for autocorrelated observations from the same firms, we cluster the standard errors within firms.

A multivariate linear regression model is used for the continuous probability of default variable:

$$Y_{ijt} = \alpha + \beta_1 x_{it-1} + \beta_2 z_{ijt-1} + \gamma_1 c_i + \gamma_2 c_k + \gamma_3 t + \epsilon_{ijt} \tag{2}$$

where x_{it-1} are firm specific controls, z_{it-1} are bank specific controls, and the remainder of the terms are bank, industry, and time fixed effects respectively.[24] Errors are clustered at the firm level. Lastly, to control for the concern that CDS firms are different from non-CDS firms in ways that are related to their credit quality, we perform our analysis of CDS firms on a matched sample of non-CDS firms, using a propensity score methodology. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. Propensity score-firms are selected based on the nearest neighbor (without replacement). We obtain matches for 583 CDS firms. [25]

Table 6 reports the logit regression estimates for the probability of being downgraded at least one notch (Panel A) and from investment grade to high yield status (Panel B). The logit model is linear in the log-odds metric. Therefore, we report the regression coefficients, but interpret them in terms of odds ratios (the exponentiated coefficients). Neither the *CDS Lender* (columns (1) and (2)) nor the *CDS Buyer* (columns (3) and (4)) indicators are statistically significant, suggesting that the lender trading CDS on the borrower's debt or being a net buyer of credit protection does not affect the probability of firm being downgraded one notch or to high yield status. When we add the *Sell-to-Buy* indicator, the results suggest that firms are less likely to be downgraded one notch when their lenders start purchasing CDSs (column (5) and (6) in Panel A. The estimate is statistically significant at 5% and economically significant as well. Specifically, the log odds ratio suggests that firms are about **22%** less likely to be downgraded once banks begin buying CDS relative to all other firms. This result is robust to dropping the *CDS* dummy, which suggests

[24] We replace industry fixed effect with firm fixed effects and discuss the relative importance of the two in the following sections.

[25] A similar methodology is used in Subrahmanyam et al. (2014) and Saretto and Tookes (2013)

that the result is not driven by differences in CDS and non-CDS firms. The results for the high yield specification are reported in Panel B. None of the CDS indicators are statistically different from zero, indicating that there is no discernible effect of bank CDS use on the likelihood that firms become fallen angels.[26]

Table 7, reports the panel regression estimates for the probability of default. We use similar specification as in Table 6. Columns (1), (3) and (5) contain the results for the various CDS indicators. There is no statistically significant effect of CDS trading on the probability of firm's default. Following Saretto and Tookes (2013), in columns (2), (4) and (6) of Panel B, we replace the *CDS* dummy with firm fixed effects to control for time-invariant differences between firms above and beyond industry and CDS differences. The results indicate that purchasing CDS is associated with lower default probabilities. The association is also economically significant. For example, a firm's default probability is 21.5 bps lower when its lender on net buys CDS compared to similar non-CDS firms and CDS firms for whom the bank does not purchase CDS. The average probability of default in our sample is 184 bps, which means that firms for whom banks on net purchase CDS are 12% less likely to default over the next year. The effect is statistically significant at 5% level.

Overall, the regressions contain a new result compared to the current literature. Corporate credit risk is not adversely affected when lenders purchase credit protection. We find that firms if anything, are less likely to be downgraded when banks actively begin, on net, purchasing CDS.[27] To our knowledge, this is the first study to find such an effect. Because we are looking specifically at CDS positions held by banks, the credit risk transfer model developed by Parlour and Winton (2013) offers a interesting framework to explain our findings. The authors show that with repeat lending and reputation concerns, banks will lay off credit risk by purchasing CDS contracts for relatively safe firms that do not require monitoring and directly sell loans of relatively risky firms that require monitoring. Because there is separation in the instruments used to lay off credit risk, loan buyers know that loans are risky and need monitoring. Thus, both credit risk transfer and monitoring can occur at efficient levels when CDS and loan sale markets co-exist. Our findings are consistent with the notion that banks purchase CDS for relatively safe firms with low credit

[26]For robustness, we re-estimate all the baseline logit results using the linear probability model and confirm there are no qualitative changes; CDS use is not associated with higher probabilities of being downgrade at least one notch or to high yield status.

[27]Using a less granular dataset, Subrahmanyam et. al (2014) find the opposite effect. Because they use aggregate CDS data and cannot directly identify CDS positions at the bank-firm level.

risk where monitoring incentives are not adversely impacted.

The remainder of the results for the control variables are generally in line with other studies. Larger and more profitable firms are less likely to be downgraded and have lower probabilities of default. Firms with higher equity volatility are more likely to be downgraded and have higher probabilities of default. Interestingly, firms with more leverage are generally less likely to be downgraded either one notch or to high yield status. However, more levered firms do have higher associated default probabilities. This could indicate that within a rating class, firms that are more levered are more likely to default, but higher leverage is generally indicative of higher quality credits i.e. leverage is endogenous as in the collateral equilibrium models of Fostel and Geanakoplos (2008, 2012, 2016) and Darst and Refayet (2017 and 2018). We also find that the likelihood that firms are downgraded is correlated with the number of lenders they have, which is indicative of a hold up problem in renegotiation (Bolton and Scharfstein (1996)). The evidence for the number of creditors and the probability of default again depends on whether one controls for firm fixed effects. Without firm fixed effects, more lenders are associated with lower default probabilities, most likely capturing a size effect. But with firm fixed effects, the number of lenders does not have a statistically significant association with firm default probability.

4.2 Intensive CDS use, over insurance and corporate credit risk

In the second part of our analysis, we exploit the matched bank-firm dataset to study the *intensive margin* between the amount of credit protection bought by banks and corporate credit risk.

To this end, for each bank-firm pair we compute a hedge ratio defined as the net CDS position that bank j has on firm i divided by a measure of credit exposure:

$$\text{hedge ratio} \equiv \frac{\text{CDS}_i^b - \text{CDS}_i^s}{\text{Exposure}_i} \geq 0. \tag{3}$$

The superscript $b(s)$ indicates buy (sell) positions.

The economic interpretation of an increase in the hedge ratio is an increase in the amount of credit protection bought relative to underlying credit risk. Table 8 reports the summary statistics of the coverage ratio. First, for a given creditor, banks net buy CDS positions represent, on average, 27% of the credit exposure they have to combined loan and bond positions. Second, when banks only extend loans to a firm the net buy CDS positions represent, on average, 66% of the committed loan amounts. The medians of these two measure are substantially smaller indicating that there are large outliers for which banks have substantial CDS protection relative to underlying credit risk *i.e.* over insurance. All told, CDS protection represents an economically large fraction of the credit risk banks retain on their balance sheets. The significant CDS use suggests that the lack of statistical significance from the extensive margin analysis is likely not driven by economically insignificant CDS use.

One particular prediction of Bolton and Oehmke (2011) is that the competitive allocation is characterized by creditors overinsuring their exposure relative to the social optimum. As a result, borrowers will too frequently be pushed into bankruptcy. We directly test this prediction by using hedge ratios > 1 (and call them *overinsurance* ratios, OI), indicating that banks overinsure their credit exposure, i.e. have more credit protection than underlying loan and/or bond exposure.[28] We repeat all of our previous analysis on downgrades, fallen angels, and the probability of default, using a matched and treated sample and the same set of controls. We only report the results for the overinsurance ratio because the results for the basic hedge ratio are virtually identical both quantitatively and qualitatively and are available upon request.

The results for the probability of downgrade (both by 1-notch and to HY status) are reported in Table 9. The overinsurance variable (OI_{total}, if the bank exposure includes both loans and bond holdings, and OI_{loans}, if the bank exposure includes only loans never suggests that over insuring against default risk negatively affects corporate credit risk.

In Table 18 we report the results for the probability of default. The evidence suggests that firms have lower default probabilities when their creditors are overinsured. Column 1 indicates that the average CDS firm's default probability is 2.5 bps lower when their lender increases her CDS protection by 1% above a ratio of one to its credit exposure. The estimate is significant at 5%, although the economic significance is small. The average credit exposure to CDS firms in our sample is $997 million, which means a relative one percent increase in CDS purchase is roughly $10

[28]For robustness, we also consider hedge ratios greater than .75 and 1.25. All the results hold the same across the different ratios.

million. $10 million of additional CDS protection is associated with a 1.3% lower default probability (2.5bps/186bps) relative to all other firms. In column 3 we repeat the same analysis but only include the observations for firms to which banks have loan exposure. The estimate is virtually identical indicating that a higher CDS to credit exposure ratio has roughly the same association with firm default probabilities irrespective of whether the credit exposure is joint through loans and bond or only through loans. This is perhaps not surprising given that the majority of bank credit exposure to firms is through lending relationships. In columns 2 and 4 we repeat the same analysis but we replace industry fixed effects with firm fixed effects.[29] The point estimates in the firm fixed effects regression are roughly 68% (with the same negative sign) of those obtained using industry fixed effects and the CDS firm control dummy. However, the estimates are no longer significant at the 5% cutoff. The firm fixed effects specification also explains roughly half of the variation in default probabilities while the industry fixed effects specification only explains 30%.

Both the extensive and intensive CDS use analysis suggests that, if anything, firms are less likely to default when banks buy CDS protection, are not more likely to be downgraded, and are not more likely to become severely distressed. Also, firms are less likely to be downgraded when their bank creditors actively begin buying CDS. All of these results are clearly not supportive of the notion that banks purchasing CDS may adversely affect firm credit quality.

The theory that better explains our findings is the reputation equilibrium analyzed in Parlour and Winton (2013). The authors show that creditors will choose to efficiently lay off risky credit via loan sales while retaining relatively safe credit risk on the balance sheet and buy CDS protection. The reason is that the market price of CDS protection will be relatively inexpensive for safe firms because only the risky firms are sold outright through loan sales. In an equilibrium with both CDS and loan sale markets (which is what we see in practice), monitoring is efficient as resources are not wasted on monitoring safe borrowers for whom bank purchase CDS protection.[30] In the model, banks purchase CDS to comply with regulatory risk weights in order to free capital to finance new positive net present value projects. In this sense, banks have a benign motive to use CDS for high quality borrowers which

[29] Bank fixed effects are used through our analysis

[30] CDS do not *cause* banks to monitor or not monitor. Thus, in their model, CDS do not improve credit risk, they are simply used to cover risk for high quality borrowers and not result deterioration of credit risk. We note that our results do not establish causality between CDS use and the improved measures of credit risk.

does not impair bank monitoring in equilibrium and leads to efficient risk transfer.

4.3 CDS protection and high quality borrowers

In this section we present additional evidence that the relationship between bank credit exposure and improved measures of corporate credit risk is driven by high quality borrowers rather than low quality borrowers. We interact the net purchase CDS measures that were associated with statistically significant and improved measures of credit risk with an investment grade dummy. The investment grade dummy equals one if the CDS firm has an investment grade rating and 0 otherwise. The investment grade-net CDS purchase interaction term captures the effect of purchasing CDS protection conditional on the borrower being a high quality investment grade firm.

The results across the measures of credit risk are generally consistent with the benign credit risk transfer motive. In particular, the coefficient on the interaction term with the net buyer CDS dummy suggest that investment grade firms have lower default probabilities than high yield firms when banks purchase CDS against both types of firms. Economically, when banks purchase CDS for both investment grade and high yield firms, the investment grade firms default probabilities are on average 81 bps lower than high yield firms. The estimate is statistically significant at 5%. Moreover, on the intensive margin, our interaction term specification suggests that investment grade firms have lower default probabilities than high yield firms even when banks are over-insured against default risk for both types of firms. For investment grade firms, a one percentage point increase in the amount of credit protection BHCs purchase relative underlying credit risk is associated with a 2.6 bps lower default probability compared to purchasing additional credit protection against high yield firms, on average. The coefficient is also statistically significant at 5%. Lastly, the interaction term in the down grade specification is not statistically different from zero.

What about loan sales? Parlour and Winton (2013) show that banks use CDS to comply with regulatory risk-constraints and directly sell off risky loans. Streitz (2017) finds that lenders retain larger shares of loans they syndicate once CDS markets become available. His evidence suggests that large reputable banks are less likely to sell loans and that firms are less likely to violate covenants after CDS inception, which are inconsistent with a moral hazard explanation of loan retention. Our results are consistent with the notion that banks retain larger loan portions for CDS firms that do not require extensive monitoring. Separation of credit risk transfer instruments–CDS and loans sales–implies that loans sold are generally lower quality and loan purchasing banks subsequently monitor firms, which is why there is no evidence of moral hazard when CDSs are available.

5 Robustness

In this section we test the robustness of our results in three ways. First, we conduct an instrumental variable (IV) analysis using instruments that are correlated with bank CDS use but uncorrelated with firm credit quality. A significant result from the IV analysis would suggest that there is a CDS specific effect on firm credit risk that is perhaps not explained by the separation in credit risk transfer theory of Parlour and Winton. Second, we supplement our analysis with data from CDS index trading. CDS users can buy an index CDS covering a broad range of potential credit exposure. We expect banks to use the index CDS contracts, in addition to single–name CDS, to cover the credit risk exposure to their borrowers given the high liquidity of this segment of the market. Third, to alleviate concerns with window dressing for regulatory report purposes, we redo our analysis by using a 4-week window prior to the Y-14 filing date instead of one-week window. All of our results for both the extensive and intensive margin analysis are robust to these alternative tests.

5.1 Instrumental variable analysis

Our data suggest that there is modest evidence that corporate default probabilities are slightly better when banks purchase CDS, especially for high quality borrowers. One potential concern with the propensity score analysis is that unobserved differences between CDS and non-CDS firms could influence banks' decision to trade CDS. In fact, we have argued that our results are consistent with the notion that banks purchase CDS protection against high quality firms precisely because these firms do not require extensive monitoring and CDS protection reduce monitoring incentives. In this vein, CDS purchases by banks are indeed endogenous to firm type and the improved credit quality measures are not due to a CDS effect *per se*.

In this section, we try to discern whether there is an additional CDS effect on firm credit quality. Specifically, a statistically significant result for the interaction term would indicated that firm credit quality is affected by bank CDS trading and perhaps not consistent with the efficient credit risk transfer equilibrium studied proposed by Parlour and Winton (2013). To address the endogeneity concern, we consider two instruments for the CDS hedging measure (CDS buyer indicator) that proxy for bank risk-baring capacity and funding structure that are exogenous to borrower credit quality.: *Lender Leverage*, computed as the ratio of book equity to book assets, and *Lender Funding Ratio*, computed as the ratio of wholesale funding to book assets. The first variable captures the capital constraints that the institution may be subject to: Because banks must have equity capital to issue loans, banks with more equity as a fraction of total assets will have less need to lay off credit risk via CDS. Thus, we expect a higher *Lender Leverage* ratio to be associated with less CDS use since *Lender Leverage* is an inverse measure of leverage. The second instrument is a liquidity constraint measure. Institutions that are more constrained may increase their propensity to hedge in line with Boyarchenko et al (2016) and Shan, Tang, and Yan (2016).[31]

The instrumental variable results are in table 13. The results we are interested in are for one notch downgrades and the probability of default.[32] The results do not suggest that banks' net buy CDS positions *lead* to lower default probabilities or lower likelihoods of being downgraded. The lack of a CDS effect in our setting is consistent with our baseline results. Specifically, Parlour and Winton (2013) show that when CDS and loan sales markets co-exist, banks use loan sales to lay off credit risk for risky firm that require monitoring, not CDS. Banks only purchase CDS on safe firms that do no require monitoring. Thus, CDS use does not cause changes in credit risk, consistent with our results. Although we are not aware of any theory that could explain how purchasing CDS can cause credit quality *improvements*, Darst and Refayet (2018) offer some insights on how CDS markets can alter risk profile

[31] Initially, we follow the literature and use bank foreign exchange derivatives holdings (FX) (see Saretto and Tookes (2013) and Subrahmanyam et al (2014)) as instrument for *CDS Buyer*. Previous studies typically compute the average amount of FX used for hedging (not trading) purposes by the BHCs that are lead syndicate member or bond underwriter for the firm during the past five years relative to total assets of the same group of banks. Minton et al. (2009) suggest that banks that use FX for hedging are also more likely to use CDS for credit risk hedging. Our granular data allow us to compute a FX measure for each bank and that can be matched to each of its borrowers. However, the bank holding company FX usage did not pass the test for weak identification and is not good instrument for *CDS Buyer*. It is a good instrument for for *CDS Lender*, which captures general CDS trading by the banks but not specifically the hedging activity related to credit exposure.

[32] There were no results obtained for the fallen angle regressions. The IV analysis for fallen angel regressions confirm the same thing and are omitted to save space, but are available upon request.

of corporate debt instruments on the extensive margin. In their model, firms may switch between safe and risky debt. However, the probability of default within a risky debt financing regime (*i.e.* intensive margin) is not altered; bank CDS use does not cause firms become less risky conditional on firms issuing risky debt.

5.2 Impact of Index CDS trading

To provide a more complete assessment of the net derivative exposure banks have, and how this exposure may impact corporate credit risk, we supplement the single-name analysis with index CDS positions data. An index CDS is a standardized credit derivative contract on a diversified set of obligors. The contract provides protection against the default on each index constituents. Twice a year (in March and September) a new series of an index is created and obligors are revised based on credit rating and liquidity criteria. For the purpose of our analysis, we use the North America credit indices for investment–grade and high–yield, CDX.IG and CDX.HY, respectively.[33] To assign the CDS positions in the CDS indices to the underlying firms, we first take each BHCs total buy and sell positions for each index as reported in DTCC. For each index, we then equally weight the net CDS position across all constituents. Finally, we add the weighted CDS position for each index constituent to the corresponding single name CDS position for each bank-firm pair. We take existing indexes–on and off-the-run–across all categories for our analysis. To our knowledge, ours is the first study on corporate credit risk to include both single and CDS index positions to give a more complete picture of the effects of hedging on corporate credit risk.

We run the same battery of regressions for both the extensive and intensive margin analysis and for all measures of credit risk as in Tables 6, 7, and 9. The extensive margin results including the index positions for the probability of downgrade are reported in Table 15 and confirm the baseline analysis that firms are less likely to be downgraded one notch when banks actively start, on net, buying CDS (Panel A). The estimate is statistically significant at 5% and the economic magnitude very similar to the baseline. The log odds ratio suggests that firms are about 19% less likely to be downgraded one notch relative to all other firms. The results for the probability of being downgraded to high yield status (Table 15, Panel B) and for the

[33] CDXs are equally weighted by their constituent components. The investment grade index, CDX.IG, typically has 125 single name constituents, while the high yield index, CDX.HY, typically has 75.

probability of default (16) are also consistent with the baseline results.

Including the index CDS positions in the analysis of the intensive margin for CDS use does not alter the conclusions discussed in section 4.2. Firms are not more likely to be downgraded (both 1-notch or to high-yield status) when banks, on net, purchase more CDS protection than underlying credit exposure (Table 17). Table 16 reports the results for probability of default. Firms continue to have slightly lower default probabilities when their creditors purchase CDS protection in excess of underlying credit exposure. Again, this result is sensitive to what fixed effects are specified. In particular, there is a statistically significant relationship between overinsurance and default probabilities once we control for firm fixed effects instead of industry fixed effects and the CDS firm dummy control variable. Summing up, including CDX positions along with single name positions to capture a more comprehensive credit risk hedging strategy does not appear to be associated with adverse corporate credit quality, and in some cases appears to be associated with better measures of credit risk.

5.3 Four-week CDS positions

In this section, we consider the possibility that banks window dress the reporting of their CDS positions. In particular, banks may purchase more CDS around Y-14 reporting quarters to appear as if they are covering more potential losses than they actually do throughout the reporting quarter. To this end, we take a snapshot of the bank CDS positions four weeks prior to the Y-14 reporting data instead of one week as we used in the baseline analysis. We then repeat the extensive and intensive margin analysis as in Tables 6, 7, and 9. The extensive margin analysis using the four-week window in Table 19 supports the baseline findings. Firms are less likely to be downgraded one notch when their lenders actively begin on net purchasing up to four weeks prior to the Y-14 reporting date. The point estimate is -.031 and is significant at 5%. Economically, the magnitude is very similar to the baseline specification. Firms are about 26% less likely to be downgraded when their lenders are actively purchasing CDS on net compared to 22% less likely using the one-week threshold. The results for default probabilities in Table 20 are virtually unchanged as well. The CDS indicator variables are not statistically different from zero in the model with industry fixed effects and CDS control dummy. However, when we control for firm fixed effects, net buy CDS positions are associated with lower default probabilities with similar magnitudes as the baseline analysis. The coefficient on the net buyer indicator is -0.212 using the 4-week prior CDS positions and -0.215 when using the one-week prior positions. Both estimates are significant at 5%.

Turning to the over insurance analysis in Table 21, the results for the downgrade specifications are virtually unchanged from the baseline analysis, and there is no discernable effect on firm downgrade probabilities due to bank CDS purchases. The results for probability of default in Table 22 are virtually the same as the baseline specification, both in terms of economic and statistical significance. The point estimates on the over insurance ratio using the 4-week window are -0.023 for both loan and bond credit exposure and loan only credit exposure (the point estimates in the baseline specification were -.025 for both). Both estimates are significant at 5%. All told, the results that firm credit risk appear if anything better when banks actively purchase CDS are unchanged and do not appear to be driven by window dressing concerns.

6 Discussion and Conclusions

In this paper, we carefully consider when the credit risk of a CDS reference entity can, in fact, be altered due to its creditor purchasing credit protection to provide a more direct assessment of CDS markets' impact on corporate credit risk. Specifically, we use a novel data set for U.S. firms that matches CDS transaction-level data to detailed security and loan portfolio data for the 31 largest banks in the U.S. Using the bank-firm pairs in which banks do purchase credit protection, we do not find evidence that corporate credit risk is adversely affected. In fact, our evidence weakly suggests that corporate credit is lower when banks are protected from default.

The results are more consistent with the notion that banks use CDS markets for efficient risk transfer to comply with risk limits rather than rent extraction or to shirk monitoring duties and push borrowers into default. Specifically, Parlour and Winton consider a model where banks have a costly monitoring technology and make loans to firms. Banks are also subject to portfolio risk requirements in which fresh equity capital is needed to lend additional funds. Risk requirements give a benign motive to lay off credit risk. Credit risk can be laid off either by outright selling the loan to another potential monitoring bank or purchasing CDS and maintaining control rights over the loan. The costly monitoring technology prevents moral hazard and risk shifting behavior from borrowers. In this sense, monitoring can cause a reduction in credit risk. They show that when banks have repeat lending opportunities *e.g.* relationship lending and face reputation concerns in the credit risk transfer market, both loan sale and CDS markets can co-exist, which is what we see in practice. The separating equilibrium is characterized by both efficient risk sharing and monitoring. In particular, banks purchase CDS against high quality firms that do not require monitoring in which no monitoring resources are wasted. Loans to high risk firms are outright sold and monitored by purchasing banks, which implies that credit risk transfer is also efficient.

Because we are only considering bank-firm exposure, the interpretation of our findings can only go so far as suggesting that *banks* are not empty creditors or their monitoring efforts after purchasing CDS do not adversely impact the credit risk of their CDS-referenced borrowers. One cannot rule out that other types of creditors, such as fixed-income mutual funds or hedge funds, may still be empty creditors, which is consistent with the findings in Danis (2016). But, our findings do beg a more fundamental question. Why would the empty creditor problem, which is predicated on inefficient renegotiation outcomes, manifest in public bond markets in which renegotiation is ex ante more difficult and often assumed away in models comparing public with private lending choices? An extensive banking literature suggests that part of the major benefit of monitored bank debt is the efficiency advantage banks have over dispersed creditors to renegotiate in times of distress (Diamond (1984, 1991), Park (2000), Bolton and Freixas (2000), Bolton et. al (2016). Thus, banks should be precisely the agents for whom empty creditor type incentives are strongest because of their monitoring ability and position to renegotiate solvent but illiquid firms. The disconnect likely lies in repeat lending and reputation concerns that banks face as modeled by Parlour and Winton (2013), but are not considered in the static empty creditor theory.

To conclude, our understanding of what effects CDS and credit risk transfer markets have on debtor-creditor relationships is still limited. Theoretical models should carefully consider the heterogeneity between the different agents that participate in corporate credit markets and empirical work should proceed with caution when data limitations prevent us from knowing exactly what positions agents take in both the debt and credit risk transfer market.

References

[1] Hector Almeida and Murillo Campello. Financial constraints, asset tangibility and corporate investment. *The Review of Financial Studies*, 20:1429–60, 2007.

[2] Adam B. Ashcraft and Joao A.C. Santos. Has the cds market lowered the cost of corporate debt? *Journal of Monetary Economics*, 56:514–23, 2009.

[3] Patrick Augustin, Marti Subrahmanyam, Dragon Y. Tang, and Sarah Q. Wang. Credit default swaps: A survey. *Foundations and Trends in Finance*, 9(1-2):1–196, 2014.

[4] Mascia Bedendo, Lara Cathcart, and Lina El-Jahel. Distressed debt restructuring in the presence of credit default swaps. *Journal of Money, Credit and Banking*, 48(1):165–201, February 2016.

[5] Patrick Bolton and Xavier Freixas. Equity, bonds, and bank debt: Capital structure and financial market equilibrium under asymmetric information. *The Journal of Political Economy*, 108(2):324–51, 2000.

[6] Patrick Bolton, Xavier Freixas, and Leonardo Gambacorta. Relationship and transaction lending in a crisis. *The Review of Financial Studies*, 29(10):2643–76, 2016.

[7] Patrick Bolton and Martin Oehmke. Credit default swaps and the empty creditor problem. *The Review of Financial Studies*, 24:2617–55, 2011.

[8] Patrick Bolton and David S. Scharfstein. Optimal debt structure and the number of creditors. *Journal of Political Economy*, 104(1):1–25, 1996.

[9] Nina Boyarchenko, Anna Costello, Jennifer La'O, and Or Shachar. Credit risk hedging. Working Paper, 2016.

[10] Cecilia Caglio, R. Matthew Darst, and Eric Parolin. A look under the hood: How banks use credit default swaps. FEDS Notes 2016-12-22. Washington: Board of Governors of the Federal Reserve System, 2016.

[11] Sean Campbell and Joshua Gallin. Risk transfer across economic sectors using credit default swaps. FEDS Notes 2014-09-03. Washington: Board of Governors of the Federal Reserve System, 2015.

[12] Stephan Colonnello, Matthias Efing, and Francesca Zucchi. Empty creditors and strong shareholders. Research Paper No. 16-17. Swiss Finance Institute, 2017.

[13] Depository Trust Clearing Corporation. Trade information warehouse confidential data. `http://www.dtcc.com/derivatives-services/trade-information-warehouse/`.

[14] Andras Danis. Do empty creditors matter? evidence from distressed exchange offers. *Management Science*, 63:1285–1301, 2016.

[15] R. Matthew Darst and Ehraz Refayet. A model of endogenous debt maturity with heterogeneous beliefs. Finance and Economics Discussion Series 2017-057. Washington: Board of Governors of the Federal Reserve System, 2017.

[16] R. Matthew Darst and Ehraz Refayet. Credit default swaps in general equilibrium: Endogenous default and credit spread spillovers. *Forthcoming: Journal of Money Credit and Banking*, 2018.

[17] Douglas Diamond. Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414, 1984.

[18] Douglas Diamond. Monitoring and reputation: The choice between bank loand and directly placed debt. *The Journal of Political Economy*, 99(4):689–721, 1991.

[19] Stuat Gilson, John Kose, and Larry Lang. Troubled debt restructurings: An empirical study of private reorganization of firms in default. *Journal of Financial Economics*, 27(2):315–53, 1990.

[20] Yalin Gunduz, Steven Ongena, Gunseli Tumer-Alkan, and Yuejuan Yu. Cds and credit: Testing the small bang theory of the financial universe with micro data. Working Paper, 2017.

[21] Beverly Hirtle. Credit derivatives and bank credit supply. *Journal of Financial Intermediation*, 18:125–50, 2009.

[22] Henry T.C. Hu and Bernard Black. Debt, equity, and hybrid decoupling: Governance and systemic risk implications. *European Financial Management*, 14:663–709, 2008.

[23] Henry T.C. Hu and Bernard Black. Equity and debt decoupling and empty voting ii: Importance and extensions. *University of Pennsylvania Law Review*, 156:625–739, 2008.

[24] Gi H. Kim. Credit derivatives as a commitment device: Evidence from the cost of corporate debt. *Journal of Banking and Finance*, 73:67–83, December 2016.

[25] Jay Li and Dragon Youngjun Tang. The leverage externalities of credit default swaps. *The Journal of Financial Economics*, 120(3):491–513, 2016.

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

[27] Martin Oehmke and Adam Zawadowski. The anatomy of the cds market. *The Review of Financial Studies*, 2015.

[28] Cheol Park. Monitoring and structure of debt contracts. *The Journal of Finance*, 55(5):2157–2195, 2000.

[29] Adriano Rampini, Vishy Viswanathan, and Guillaume Vuillemey. Risk management in financial institutions. Working paper, 2017.

[30] Alessio Saretto and Heather Tookes. Corporate leverage, debt maturity, and credit default swaps: The role of credit supply. *The Review of Financial Studies*, 26:1190–247, 2013.

[31] Daniel Streitz. The impact of credit default swap trading on loan syndication. *Review of Finance*, 20(1):265–86, 2017.

[32] René M. Stulz. Credit default swaps and the credit crisis. *Journal of Economic Perspectives*, 24:73–92, 2010.

[33] Marti Subrahmanyam, Dragon Y. Tang, and Sarah Q. Wang. Does the tail wag the dog? the effect of credit default swaps on credit risk. *The Review of Financial Studies*, 27:2927–60, 2014.

[34] Marti Subrahmanyam, Dragon Y. Tang, and Sarah Q. Wang. Credit default swaps, exacting creditors, and corporate liquidity management. *Journal of Financial Economics*, 124:395–414, 2017.

[35] Hong Yan Susan Shan, Dragon Tang. Credit default swaps and bank regulatory capital. Working paper, 2016.

Figure 1: Loan Positions

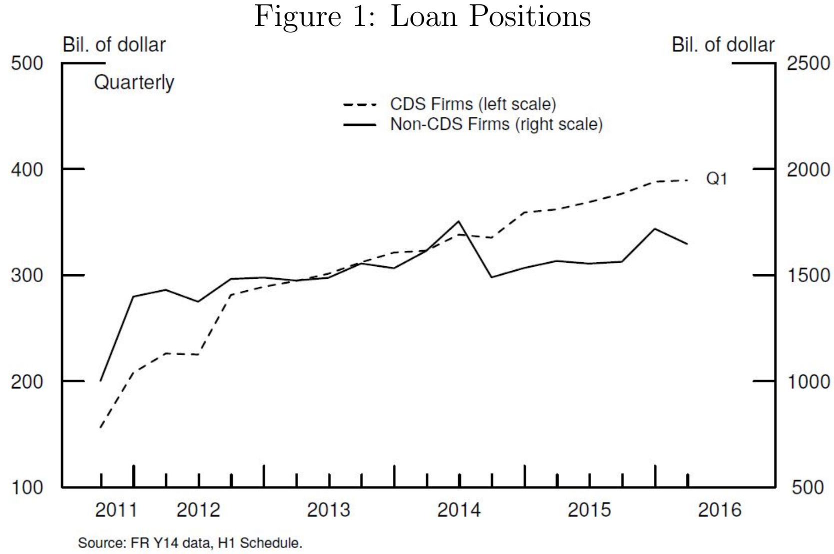

Figure 2: Bond Positions

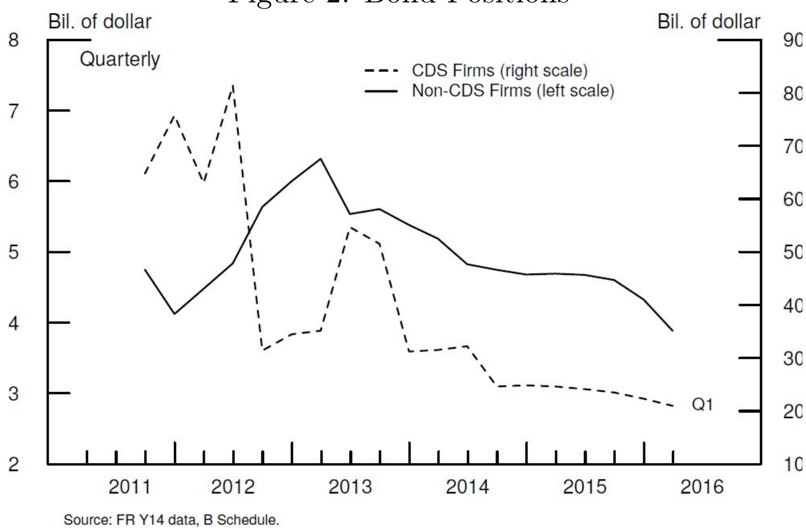

Figure 3: CDS Use and Insured Positions

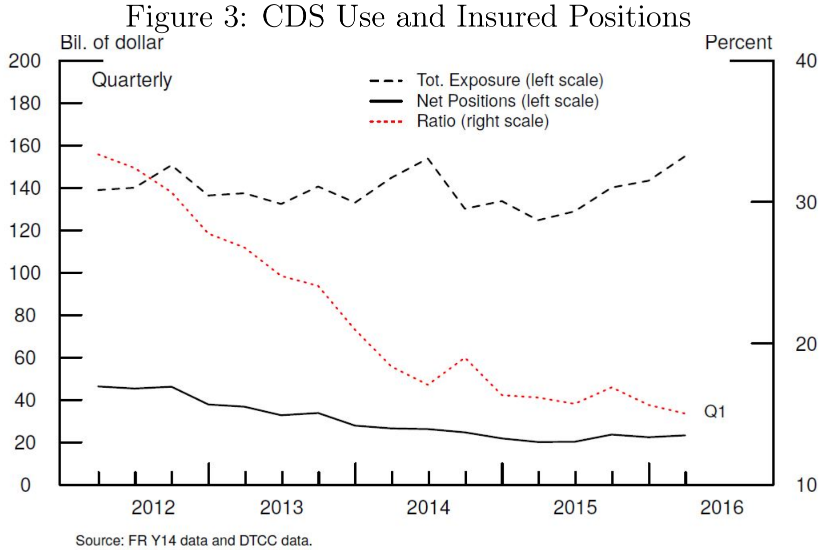

Table 1: Variable Definitions

Variable	**Definition**
CDS	A dummy indicator equals to one if the firm has a CDS traded at any point in our sample period, zero otherwise.
CDS Lender	A dummy indicator equals to one if the firm's lender j trades CDS contracts on the firms$i$ in quarter t.
CDS Buyer	A dummy indicator equals to one if the firm's lender j is a net buyer of CDS contracts on the firm i in quarter t.
Sell-to-Buy	A dummy indicator equals to one if the firm's lender j becames a net buyer of CDS contracts on the firm i in quarter t.
Size	ln(Total assets)
Leverage	$\frac{\text{Book Debt}}{\text{Total Assets}}$, where book debt is the sum of short-term debt and 50% of long-term debt.
Profitability	$\frac{\text{Net Income}}{\text{Average Annual Assets}}$
Cash Ratio	$\frac{\text{Firm's Cash}}{\text{Total Assets}}$
Tangibility	A dummy variable equal to one if the firm operates in a durable goods industries, as identified by the SIC code (except SICs 32 and 38, but plus SIC 30).
# Lenders	Number of lenders that a firm i has in quarter t.
Loan am./Tot. Assets	$\frac{\text{Total dollar value of loan issued to a given firm}}{\text{Firm's total assets}}$
Bonds/Tot. Assets	$\frac{\text{Total dollar value of bond exposure to a given firm}}{\text{Firm's total assets}}$

Table 2: Summary Statistics on Firm, Loan and Bond Characteristics (in millions)

This table provides summary statistics for firms that have at least one outstanding loan issued and/or their bond issuances are held by at least one of the BHC in our sample. The values are computed from Q3:2011-Q4:2015. We define firms that have at least one CDS contract written on them by any bank in any of quarter in our sample as "CDS Firms". In Panel A, *Total Assets*, *Cash*, *Total Liabilities*, *Current Liabilities*, *Net Income*, *Tangible Assets*, *Capital Expenditure* are from Compustat, if available, or from Schedule H in FR Y-14 report. In Panel B, *Avg. Committed Amount* (*Tot. Committed Amount*) is the average (total) dollar amount over the sample period the obligor is legally allowed to borrow according to the credit agreement with the lender, net of any charge-offs. *Average # Lenders* is the average number of lenders that each obligor has over the sample period. In Panel C, *Avg. Book Value* (*Tot. Book Value*) is the average (total) book value of bonds issued by a firm held in the CCAR banks' portfolios. *Avg. Market Value* (*Tot. Market Value*) is the average(total) market value of bonds issued by a firm held in the BHCs' portfolios. *Total # Bond Issuers* is the total number of firms that issued at least a bond in the sample period. The book and market values of bonds are from Schedule B in FR Y-14 report. All dollar amounts in the table are expressed in millions.

	Non-CDS	CDS
Panel A: Firm characteristics		
Total Assets	1,146	26,896
Total Liabilities	709	10,249
Current Liabilities	275	5,643
Net Income	51	517
Tangible Assets	917	20,443
Capital Expenditure	17	757
Cash	117	1,792
Total # Firms	141,787	658
Panel B: Loan Characteristics		
Avg. Market Value	21	959
Tot. Committed Amount	1,408,058	466,079
Average # Lenders	1	8
Panel C: Bond Characteristics		
Avg. Book Value	30	51
Avg. Market Value	30	34
Tot. Book Value	32,952	19,407
Tot. Market Value	32,423	13,081
Total # Bond Issuers	2,938	514

Table 3: Loan Amount by Rating (in millions)

The table reports the amount of committed loans issued to CDS and non-CDS firms based on their rating. We use the internal ratings that each BHC assigns to its obligors in the Schedule H of the FR Y-14 report. To allow comparison of the ratings across reporting institutions, the internal rating is converted to a standardized rating scale going from AAA (very low risk of default) to D (in default). If in a given quarter there is more than one rating assigned to one creditor, we take the lowest rating assigned by the reporting BHCs. *# Loans* is the total number of loans issued to firms in the sample per rating category. *Avg. Committed Amount* is the average dollar amount over the sample period the obligor is legally allowed to borrow according to the credit agreement with the lender, net of any charge-offs. *% Committed Exposure* is the percentage of total committed exposure in each rating category. All dollar amounts in the table are expressed in millions.

	No CDS Firms		
Internal Issuer rating	# Loans	Avg Committed Exposure	% Committed Exposure
(equiv. AA or higher)	1,331	36.30	3.34
(equiv. A)	4,842	31.09	10.68
(equiv. BBB)	28,620	9.51	33.23
(equiv. BB)	49,449	10.50	37.18
(equiv. B)	14,793	10.80	11.47
(equiv. CCC or lower)	5,348	10.68	4.10
	CDS Firms		
(equiv. AA or higher)	434	142.07	12.88
(equiv. A)	1,537	87.62	28.89
(equiv. BBB)	3,138	58.17	39.48
(equiv. BB)	1,356	43.60	12.63
(equiv. B)	404	43.84	3.76
(equiv. CCC or lower)	199	55.18	2.36

Table 4: Value of Bond Holdings by Rating (in millions)

The table reports the average market value of bonds issued by CDS and non-CDS firms based on their rating. For issuer rating, when available, we use the same internal rating banks assign the their obligors in the Schedule H of the FR Y-14 report, otherwise we use Standard & Poor's (S&P) long-term issuer ratings from Compustat. To allow comparison of the ratings across reporting institutions, the internal rating is converted to a standardized rating scale going from AAA (very low risk of default) to D (in default). If in a given quarter there is more than one rating assigned to one creditor, we take the lowest rating assigned by the reporting BHCs. *# Issuers* is the total number of issuing firms in the sample per rating category. *Avg. Market Value* is the average market value of bonds issued by a firm held in the CCAR banks' portfolios. *% Market Value Exposure* is the percentage of total market value of bond issues in each rating category. All dollar amounts in the table are expressed in millions.

	No CDS Firms		
Bond rating	Avg. # Issuers	Avg. Market Value	% Market Exposure
(equiv. A or higher)	50	10.98	36.38
(equiv. BBB)	121	8.51	43.74
(equiv. BB)	71	6.78	14.63
(equiv. B or lower)	29	6.34	5.25
	CDS Firms		
(equiv. A or higher)	93	14.99	56.56
(equiv. BBB)	162	10.40	36.63
(equiv. BB)	39	9.84	5.44
(equiv. B or lower)	16	6.55	1.36

Table 5: Credit Protection Bought by Type of Credit Exposure (in Millions)

The table reports the mean and median net buy CDS positions that banks hold by type of credit exposures. Panels A and B show the CDS positions associated only with bonds or loans for a specific firm. Panel C shows the CDS positions for the firms that have both loans issued and bonds held by the banks in our samples. All dollar amounts in the table are expressed in millions.

obs	CDS Protection Bought		Total Exposure		Loan Exposure		Bond Exposure	
	mean	median	mean	median	mean	median	mean	median
Panel A: Only Loans								
9,796	38.10	18.24	173.62	110.91	173.62	110.91		
Panel B: Only Bonds								
1,465	44.06	16.32	10.30	5.42			10.30	5.42
Panel C: Bonds and Loans								
2,706	62.17	20.23	327.50	208.40	317.55	200.00	9.96	5.77

Table 6: Determinants of the Probability of a Downgrade

This table presents the estimates of the probability of credit downgrades by at least one notch (Panel A) and to high yield status (Panel B), using a logit model in a sample of CDS-firms and propensity score-matched non-CDS firms. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

Panel A	***1-notch Downgrade***					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.012	0.003	0.002	0.013	0.013	0.003
	(0.026)	(0.029)	(0.029)	(0.025)	(0.025)	(0.029)
Leverage	-0.752**	-0.768**	-0.772**	-0.750**	-0.751**	-0.772**
	(0.358)	(0.359)	(0.358)	(0.356)	(0.356)	(0.358)
Profitability	-2.905**	-2.906**	-2.904**	-2.906**	-2.906**	-2.905**
	(1.429)	(1.424)	(1.422)	(1.429)	(1.430)	(1.424)
Cash Ratio	1.006	1.003	1.006	1.005	1.007	1.008
	(0.514)	(0.515)	(0.514)	(0.513)	(0.514)	(0.515)
Tangibility	-0.038	-0.046	-0.048	-0.037	-0.038	-0.048
	(0.273)	(0.273)	(0.273)	(0.273)	(0.273)	(0.274)
Volatility	2.116***	2.112***	2.113***	2.116***	2.115***	2.113***
	(0.229)	(0.229)	(0.229)	(0.229)	(0.229)	(0.230)
# Lenders	0.047***	0.048***	0.048***	0.047***	0.047***	0.048***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan am./Tot. Assets	1.733	1.751	1.761	1.729	1.720	1.752
	(1.057)	(1.056)	(1.056)	(1.057)	(1.055)	(1.055)
Bonds/Tot. Assets	-10.192	-11.931	-11.871	-10.168	-9.082	-10.777
	(37.587)	(37.379)	(37.373)	(37.630)	(37.445)	(37.188)
CDS		0.063	0.055			0.054
		(0.075)	(0.070)			(0.070)
CDS Lender	0.009	-0.031				
	(0.065)	(0.069)				
CDS Buyer			-0.016	0.001	0.122	0.105
			(0.068)	(0.068)	(0.090)	(0.091)
Sell-to-Buy					-0.248**	-0.247**
					(0.119)	(0.119)
Constant	-3.517***	-3.505***	-3.492***	-3.523***	-3.522***	-3.491***
	(0.499)	(0.497)	(0.494)	(0.496)	(0.496)	(0.494)
Lender FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73936	73936	73936	73936	73936	73936
Pseudo R-squared	0.09504	0.09509	0.09509	0.09504	0.09520	0.09525

Panel B	*HY Downgrade*					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	-0.157***	-0.177***	-0.175***	-0.147***	-0.147***	-0.174***
	(0.041)	(0.046)	(0.045)	(0.040)	(0.040)	(0.045)
Leverage	-2.544***	-2.600***	-2.595***	-2.511***	-2.512***	-2.595***
	(0.541)	(0.547)	(0.547)	(0.539)	(0.539)	(0.547)
Profitability	-2.210***	-2.248***	-2.246***	-2.194***	-2.194***	-2.247***
	(0.632)	(0.633)	(0.632)	(0.632)	(0.632)	(0.632)
Cash Ratio	0.107	0.085	0.085	0.106	0.107	0.086
	(0.786)	(0.794)	(0.792)	(0.785)	(0.785)	(0.793)
Tangibility	0.435	0.425	0.424	0.441	0.441	0.424
	(0.393)	(0.394)	(0.394)	(0.393)	(0.394)	(0.394)
Volatility	1.109***	1.098***	1.096***	1.108***	1.106***	1.095***
	(0.253)	(0.254)	(0.254)	(0.252)	(0.252)	(0.254)
# Lenders	0.086***	0.087***	0.087***	0.084***	0.084***	0.087***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Loan am./Tot. Assets	2.247	2.257	2.253	2.217	2.206	2.242
	(1.342)	(1.339)	(1.341)	(1.348)	(1.346)	(1.339)
Bonds/Tot. Assets	42.463	39.020	38.301	42.220	42.658	38.737
	(49.071)	(48.942)	(48.923)	(49.039)	(48.919)	(48.805)
CDS		0.117	0.129			0.128
		(0.099)	(0.095)			(0.095)
CDS Lender	0.089	0.022				
	(0.115)	(0.120)				
CDS Buyer			-0.043	-0.003	0.066	0.025
			(0.113)	(0.112)	(0.147)	(0.148)
Sell-to-Buy					-0.145	-0.142
					(0.186)	(0.186)
Constant	-18.084***	-18.020***	-18.042***	-18.159***	-18.158***	-18.041***
	(2.370)	(3.021)	(3.859)	(3.539)	(1.877)	(3.172)
Lender FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73624	73624	73624	73624	73624	73624
Pseudo R-squared	0.07341	0.07358	0.07359	0.07335	0.07338	0.07362

Table 7: Determinants of the Probability of Default

This table presents the estimates of the probability of default, using an OLS panel model on a sample of CDS-firms and propensity score-matched non-CDS firms. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. The dependent variable in the regressions is the internal probability of default, as reported by BHCs for each firms in the Schedule H of the FR Y-14 report. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Probability of Default					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.067	-1.855***	0.070*	-1.854***	0.070*	-1.853***
	(0.065)	(0.384)	(0.038)	(0.384)	(0.038)	(0.384)
Leverage	8.534***	27.466***	8.535***	27.498***	8.535***	27.502***
	(1.689)	(4.568)	(1.105)	(4.569)	(1.105)	(4.570)
Profitability	-18.212***	-3.852	-18.219***	-3.857	-18.219***	-3.861
	(5.018)	(3.506)	(3.822)	(3.506)	(3.823)	(3.506)
Cash Ratio	2.054**	0.551	2.055***	0.557	2.054***	0.560
	(1.032)	(1.096)	(0.549)	(1.095)	(0.549)	(1.095)
Tangibility	0.383	0.215	0.377	0.213	0.376	0.213
	(0.286)	(0.134)	(0.209)	(0.134)	(0.209)	(0.134)
Volatility	10.543***	5.356***	10.535***	5.352***	10.535***	5.352***
	(1.814)	(0.905)	(1.023)	(0.905)	(1.023)	(0.905)
# Lenders	-0.044	-0.026	-0.045***	-0.025	-0.045***	-0.024
	(0.023)	(0.044)	(0.011)	(0.044)	(0.011)	(0.044)
Loan am./Tot. Assets	-6.324***	-3.763**	-6.331***	-3.829***	-6.339***	-3.808***
	(2.260)	(1.465)	(1.900)	(1.457)	(1.899)	(1.453)
Bonds/Tot. Assets	-169.285***	-40.875	-170.169***	-41.822	-170.300***	-42.057
	(65.445)	(38.811)	(62.629)	(38.939)	(62.588)	(38.977)
CDS	0.186		0.212**		0.212**	
	(0.181)		(0.090)		(0.090)	
CDS Lender	0.015	0.019				
	(0.158)	(0.109)				
CDS Buyer			-0.148	-0.215**	-0.120	-0.284**
			(0.118)	(0.102)	(0.164)	(0.128)
Sell-to-Buy					-0.043	0.105
					(0.195)	(0.151)
Constant	-4.195***	8.112**	-4.171***	8.120**	-4.173***	8.119**
	(1.188)	(3.920)	(0.726)	(3.925)	(0.726)	(3.925)
Lender FE	X	X	X	X	X	X
Industry FE	X		X		X	
Firm FE		X		X		X
Time FE	X	X	X	X	X	X
Number of Observations	27560	27598	27560	27598	27560	27598
R-squared	0.29347	0.48614	0.29354	0.48627	0.29354	0.48628
Adjusted R-squared	0.29150	0.47092	0.29156	0.47105	0.29154	0.47104

Table 8: CDS Hedge Ratios

This tables presents summary statistics for various CDS hedge ratios. We define a coverage ration for a BHC on a given firm as the net CDS position over different measures of credit exposure. We compute two different measures hedge ratios: *Net CDS position/Total Exposure*, where Total Exposure is defined as the combined total utilized loan exposure and market value of bonds held in the banks' portfolio; *Net CDS position/Loan Amount*, where Utilized Loan Amount is the amount that the obligor is legally allowed to borrow according to the credit agreement with the lender, net of any charge-offs.

	Mean	Median	St Dev
Hedge Ratio$_{total}$: Net CDS position/Total Exposure	0.27	0.10	0.60
Hedge Ratio$_{loans}$: Net CDS position/Loan Exposure	0.66	0.18	2.74

Table 9: Probability of Downgrade and Over Insurance

This table presents the estimates of intensive margins between the CDS trading and the probability of being downgraded one notch (columns 1-4) and to high yield status (columns 5-8) using a logit model on a sample of CDS-firms and propensity score-matched non-CDS firms. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	1-notch Downgrade				**Downgrade to HY**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.012	-0.001	-0.024	-0.012	-0.196***	-0.168***	-0.171***	-0.149***
	(0.028)	(0.023)	(0.028)	(0.023)	(0.044)	(0.038)	(0.042)	(0.037)
Leverage	-0.790**	-0.767**	-0.912**	-0.889**	-2.577***	-2.492***	-2.655***	-2.590***
	(0.361)	(0.358)	(0.366)	(0.365)	(0.551)	(0.543)	(0.564)	(0.558)
Profitability	-2.841**	-2.843**	-2.621	-2.622	-2.238***	-2.184***	-2.290***	-2.248***
	(1.437)	(1.444)	(1.436)	(1.446)	(0.638)	(0.637)	(0.648)	(0.646)
Cash Ratio	0.976	0.975	0.681	0.684	0.084	0.106	-0.040	-0.019
	(0.520)	(0.519)	(0.531)	(0.530)	(0.800)	(0.792)	(0.813)	(0.806)
Tangibility	-0.055	-0.046	0.083	0.094	0.405	0.421	0.507	0.520
	(0.273)	(0.273)	(0.277)	(0.277)	(0.395)	(0.394)	(0.382)	(0.382)
Volatility	2.136***	2.137***	2.218***	2.220***	1.108***	1.118***	1.097***	1.105***
	(0.232)	(0.231)	(0.232)	(0.232)	(0.257)	(0.255)	(0.260)	(0.258)
# Lenders	0.049***	0.048***	0.045***	0.044***	0.089***	0.086***	0.082***	0.079***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.015)	(0.015)	(0.016)	(0.016)
CDS	0.051		0.053		0.123		0.094	
	(0.069)		(0.069)		(0.094)		(0.093)	
OI_{total}	0.017	0.017			0.018	0.019		
	(0.009)	(0.009)			(0.012)	(0.012)		
OI_{loans}			-0.035	-0.033			-0.308	-0.296
			(0.033)	(0.032)			(0.204)	(0.201)
Constant	-3.318***	-3.356***	-3.326***	-3.367***	-17.852	-17.978***	-15.702***	-16.924***
	(0.495)	(0.497)	(0.494)	(0.498)	(.)	(4.726)	(0.938)	(0.752)
Bank FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Number of Observations	73,726	73,726	66,818	66,818	73,414	73,414	66,182	66,182
Pseudo R-squared	0.09560	0.09555	0.09559	0.09554	0.07386	0.07363	0.07269	0.07255

Table 10: Probability of Default and Over Insurance

This table presents the estimates of intensive margins between the CDS trading and the probability of default using a OLS model on a sample of CDS-firms and propensity score-matched non-CDS firms. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. The dependent variable in the regressions is the internal probability of default, as reported by BHCs for each firms in the Schedule H of the FR Y-14 report. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Probability of Default			
	(1)	(2)	(3)	(4)
Size	0.113	-1.793**	0.110	-1.863**
	(0.063)	(0.832)	(0.067)	(0.862)
Leverage	8.502***	27.489***	8.606***	27.443***
	(1.691)	(9.241)	(1.704)	(8.764)
Profitability	-18.200***	-3.879	-18.291***	-3.497
	(5.021)	(6.713)	(5.100)	(6.724)
Cash Ratio	2.130**	0.537	2.395**	1.017
	(1.046)	(2.401)	(1.104)	(2.545)
Tangibility	0.435	0.214	0.462	0.298
	(0.289)	(0.184)	(0.321)	(0.194)
Volatility	10.580***	5.346***	10.533***	5.421***
	(1.816)	(1.419)	(1.761)	(1.464)
# Lenders	-0.046	-0.026	-0.048**	-0.035
	(0.023)	(0.080)	(0.024)	(0.086)
CDS	0.198		0.206	
	(0.190)		(0.187)	
OI_{total}	-0.025**	-0.017		
	(0.010)	(0.010)		
OI_{loans}			-0.025**	-0.017
			(0.010)	(0.010)
Constant	-4.639***	7.540	-4.639***	8.011
	(1.174)	(7.221)	(1.163)	(7.427)
Bank FE	X	X	X	X
Industry FE	X		X	
Firm FE		X		X
Time FE	X	X	X	X
Number of Observations	27,462	27,500	25,392	25,418
R-squared	0.29501	0.49043	0.29858	0.49158
Adjusted R-squared	0.29308	0.47532	0.29653	0.47525

Table 11: Probability of downgrade, CDS protection and Investment Grade Firms

This table presents the estimates of the extensive margin between the CDS trading and the probability of one-notch downgrade on a sample of CDS-firms and propensity score-matched non-CDS firms, controlling for the interaction between the *CDS Buyer* indicator and the Investment Grade (*IG*) indicator. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. The dependent variable in the regressions is the internal probability of default, as reported by BHCs for each firms in the Schedule H of the FR Y-14 report. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Extensive Analysis	
	(1)	(2)
Size	0.151***	0.147***
	(0.023)	(0.026)
Leverage	-1.630***	-1.637***
	(0.280)	(0.282)
Profitability	-2.463***	-2.467***
	(0.521)	(0.521)
Cash Ratio	1.477***	1.475***
	(0.348)	(0.348)
Tangibility	-0.280	-0.285
	(0.282)	(0.283)
Volatility	1.259***	1.256***
	(0.141)	(0.142)
# Lenders	0.027***	0.027***
	(0.008)	(0.008)
Loan am./Tot. Assets	0.810***	0.806***
	(0.232)	(0.233)
Bond/Tot. Assets	57.783***	57.198***
	(10.733)	(10.706)
CDS		0.019
		(0.047)
Sell-to-Buy	-0.149	-0.155
	(0.153)	(0.153)
IG	-1.401***	-1.401***
	(0.049)	(0.049)
Sell-to-Buy # IG	0.017	0.019
	(0.189)	(0.189)
Bank FE	X	X
Industry FE	X	X
Time FE	X	X
Constant	-3.689***	-3.676***
	(0.577)	(0.578)
Number of Observations	73936	73936
Pseudo R-squared	0.13354	0.13355

Table 12: Probability of Default, CDS protection and Investment Grade Firms

This table presents the estimates of extensive margins (in Panel A) and intensive margin (in Panel B) between the CDS trading and the probability of default using a OLS model on a sample of CDS-firms and propensity score-matched non-CDS firms, controlling for the interaction between measures of CDS hedging and the Investment Grade (*IG*) indicator. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. The dependent variable in the regressions is the internal probability of default, as reported by BHCs for each firms in the Schedule H of the FR Y-14 report. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

Panel A	**Extensive Analysis**	
	(1)	(2)
Size	0.109*	-1.911**
	(0.065)	(0.863)
Leverage	8.486***	27.589***
	(1.784)	(9.290)
Profitability	-18.109***	-3.649
	(5.030)	(6.727)
Cash Ratio	2.343**	0.706
	(0.996)	(2.379)
Tangibility	0.185	0.214
	(0.289)	(0.180)
Volatility	9.922***	5.250***
	(1.877)	(1.407)
# Lenders	-0.032	-0.019
	(0.023)	(0.077)
Loan am./Tot. Assets	-0.807*	-1.153**
	(0.432)	(0.578)
Bond/Tot. Assets	-144.901***	-149.338***
	(45.892)	(55.562)
CDS	0.286	
	(0.194)	
CDS Buyer	0.507	-0.232
	(0.387)	(0.425)
IG	-0.481***	-0.694***
	(0.184)	(0.101)
CDS Buyer # IG	-0.815**	0.035
	(0.400)	(0.403)
Constant	-4.266***	8.918
	(1.240)	(7.421)
FE quarter	Yes	Yes
FE firm		yes
FE industry	yes	
Number of Observations	27560	27598
R-squared	0.29791	0.48860
Adjusted R-squared	0.29589	0.47341

Panel B	**Intensive Analysis**	
	(1)	(2)
Size	0.161**	0.110
	(0.063)	(0.067)
Leverage	8.202***	8.606***
	(1.764)	(1.704)
Profitability	-18.225***	-18.291***
	(5.043)	(5.100)
Cash Ratio	2.323**	2.395**
	(1.040)	(1.104)
Tangibility	0.327	0.462
	(0.285)	(0.321)
Volatility	10.061***	10.533***
	(1.905)	(1.762)
# Lenders	-0.050**	-0.048**
	(0.024)	(0.024)
CDS	0.201	0.206
	(0.190)	(0.187)
OI	-0.036	
	(0.026)	
IG	-0.625***	
	(0.178)	
OI # IG	0.013	
	(0.026)	
OI_{total}		-0.016
		(0.027)
OI_{loans} # IG		-0.026**
		(0.011)
Constant	-4.360***	-4.639***
	(1.230)	(1.163)
FE quarter	Yes	Yes
Number of Observations	27560	25468
R-squared	0.29542	0.29631
Adjusted R-squared	0.29344	0.29423

Table 13: Instrumental Variable Analysis

This table presents the estimates of extensive margins between the CDS trading and the probability of being downgraded one notch (column 1 and 2) and to high yield status (column 3 and 4), and the probability of default (columns 5 and 6) using instrumental variables to control for the endogeneity of the CDS lender and CDS Buyer indicators. The instruments are *Lender Leverage*, computed as the ratio of book equity to book asset, and *Lender Funding Ratio*, computed as the ratio of wholesale funding to book assets. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	One-notch downgrade	**Downgrade to HY**	**Probability of Default**	**First Stage**
	(1)	(2)	(3)	(4)
Size	-0.028***	-0.009**	-2.324***	0.009
	(0.007)	(0.004)	(0.617)	(0.005)
Leverage	0.010	-0.057***	17.153***	0.046**
	(0.037)	(0.017)	(5.277)	(0.019)
Profitability	-0.440***	-0.131***	-11.865***	0.008
	(0.071)	(0.034)	(3.596)	(0.017)
Cash Ratio	-0.033	-0.020	1.813	-0.008
	(0.026)	(0.018)	(1.754)	(0.020)
Tangibility	-0.002	0.001	0.495	0.004
	(0.004)	(0.003)	(0.573)	(0.010)
Volatility	0.097***	0.022***	4.280***	0.000
	(0.017)	(0.006)	(1.107)	(0.004)
# Lenders	0.002**	0.002***	-0.185	-0.000
	(0.001)	(0.000)	(0.155)	(0.001)
Loan am./Tot. Assets	-0.081*	-0.004	3.642	-0.061
	(0.049)	(0.038)	(8.013)	(0.071)
Bond/Tot. Assets	2.533	2.264	212.739	-2.444
	(1.955)	(1.434)	(331.045)	(4.205)
Lender Leverage				-0.802***
				(0.216)
Lender Funding Ratio				0.156***
				(0.057)
IV CDS Buyer	-0.216	-0.188**	48.123	
	(0.119)	(0.084)	(46.595)	
Number of Observations	111,696	111,696	44,585	111,696

Table 14: CDS Positions including CDS Indexes by Type of Credit Exposure (in millions)

The table matches the type of credit exposures the banks have with the CDS positions (protection bought). Specifically, we consider three types of credit exposures. Panels A and B show the CDS positions for firms that have only bonds held by CCAR banks or have only loans issued by CCAR banks. Panel C shows the CDS positions for the firms that have both loans issued and bonds held by CCAR banks. All dollar amounts in the table are expressed in millions.

Panel A: ***Only Loans***

	obs	Net CDS Position		Total Exposure		Bond Exposure		Loan Exposure	
		mean	median	mean	median	mean	median	mean	median
Protection Bought	4,872	36.55	15.00	46.03	21.30			46.03	21.30

Panel B: ***Only Bonds***

	obs	Net CDS Position		Total Exposure		Bond Exposure		Loan Exposure	
		mean	median	mean	median	mean	median	mean	median
Protection Bought	1,564	41.83	14.24	10.52	5.64	10.52	5.64		

Panel C: ***Bonds and Loans***

	obs	Net CDS Position		Total Exposure		Bond Exposure		Loan Exposure	
		mean	median	mean	median	mean	median	mean	median
Protection Bought	1,519	61.38	16.15	72.66	35.14	10.03	6.21	62.63	23.42

Table 15: Determinants of the Probability of Downgrade - Index Trading

This table presents the estimates of the probability of credit downgrades by at least one notch (Panel A) and to high yield status (Panel B) once we include CDS index positions to CDS single name positions, using a logit model in a sample of CDS-firms and propensity score-matched non-CDS firms. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

Panel A	***1-notch Downgrade***					
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Assets)	0.015	0.004	0.003	0.015	0.021	0.005
	(0.026)	(0.029)	(0.029)	(0.025)	(0.026)	(0.029)
Leverage	-0.761**	-0.781**	-0.041	-0.032	-0.028	-0.040
	(0.361)	(0.362)	(0.274)	(0.274)	(0.274)	(0.274)
Profitability	-2.850**	-2.851**	0.997	0.999	0.998	0.994
	(1.445)	(1.439)	(0.517)	(0.516)	(0.517)	(0.518)
Cash Ratio	1.001*	0.998*	-2.851**	-2.851**	-2.851**	-2.851**
	(0.517)	(0.518)	(1.438)	(1.445)	(1.450)	(1.443)
Tangibility	-0.034	-0.045	2.140***	2.143***	2.143***	2.140***
	(0.273)	(0.274)	(0.232)	(0.231)	(0.231)	(0.232)
Volatility	2.143***	2.142***	-0.784**	-0.760**	-0.747**	-0.777**
	(0.231)	(0.232)	(0.361)	(0.360)	(0.361)	(0.361)
# Lenders	0.047***	0.048***	0.049***	0.047***	0.047***	0.048***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan am./Tot. Assets	1.760	1.778	1.780	1.755	1.722	1.748
	(1.067)	(1.066)	(1.064)	(1.067)	(1.070)	(1.066)
Bonds/Tot. Assets	-10.363	-12.232	-11.796	-10.194	-10.468	-12.800
	(37.528)	(37.346)	(37.359)	(37.580)	(37.651)	(37.479)
CDS		0.081	0.066			0.093
		(0.075)	(0.072)			(0.073)
CDS Lender	-0.016	-0.067				
	(0.069)	(0.072)				
CDS Buyer			0.056	0.030	0.063	0.109
			(0.068)	(0.066)	(0.070)	(0.074)
Sell-to-Buy					-0.155	-0.201**
					(0.100)	(0.099)
Constant	-3.494***	-3.481***	-3.520***	-3.526***	-3.599***	-3.614***
	(0.499)	(0.498)	(0.504)	(0.506)	(0.511)	(0.510)
Bank FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73726	73726	73726	73726	73726	73726
Pseudo R-squared	0.09558	0.09566	0.09565	0.09558	0.09569	0.09582

Panel B			*HY Downgrade*			
	(1)	(2)	(3)	(4)	(5)	(6)
Size	-0.150***	-0.174***	-0.176***	-0.151***	-0.150***	-0.175***
	(0.042)	(0.046)	(0.046)	(0.040)	(0.041)	(0.046)
Leverage	-2.519***	-2.585***	-2.596***	-2.522***	-2.519***	-2.591***
	(0.542)	(0.548)	(0.549)	(0.541)	(0.542)	(0.549)
Profitability	-2.192***	-2.234***	-2.239***	-2.192***	-2.190***	-2.237***
	(0.634)	(0.634)	(0.634)	(0.633)	(0.633)	(0.634)
Cash Ratio	0.153	0.130	0.133	0.156	0.157	0.133
	(0.784)	(0.792)	(0.792)	(0.784)	(0.784)	(0.793)
Tangibility	0.437	0.422	0.422	0.433	0.434	0.422
	(0.394)	(0.395)	(0.395)	(0.394)	(0.395)	(0.395)
Volatility	1.134***	1.128***	1.125***	1.135***	1.135***	1.125***
	(0.255)	(0.256)	(0.256)	(0.254)	(0.254)	(0.256)
# Lenders	0.086***	0.088***	0.088***	0.086***	0.086***	0.088***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)
Loan am./Tot. Assets	2.235	2.239	2.260	2.243	2.238	2.245
	(1.347)	(1.342)	(1.339)	(1.346)	(1.346)	(1.339)
Bonds/Tot. Assets	47.736	44.076	44.457	47.538	47.465	43.999
	(48.783)	(48.598)	(48.643)	(48.743)	(48.755)	(48.663)
CDS		0.144	0.122			0.131
		(0.099)	(0.095)			(0.097)
CDS Lender	0.021	-0.065				
	(0.114)	(0.119)				
CDS Buyer			-0.003	-0.052	-0.047	0.018
			(0.116)	(0.117)	(0.125)	(0.126)
Sell-to-Buy					-0.028	-0.089
					(0.151)	(0.152)
Constant	-18.085***	-18.012	-17.974***	-18.024***	-18.037***	-18.010***
	(3.984)	(.)	(1.468)	(2.615)	(3.386)	(3.636)
Lender FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73414	73414	73414	73414	73414	73414
Pseudo R-squared	0.07381	0.07406	0.07404	0.07383	0.07383	0.07406

Table 16: Determinants of the Probability of Default - Index Trading

This table presents the estimates of the probability of default once we include CDS index positions to CDS single name positions, using an OLS panel model in a sample of CDS-firms and propensity score-matched non-CDS firms. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. The dependent variable in the regressions is the internal probability of default, as reported by BHCs for each firms the the Schedule H of the FR Y-14 report. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

			Probability of Default			
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.073	-1.777**	0.073	-1.790**	0.072	0.093
	(0.065)	(0.831)	(0.064)	(0.832)	(0.064)	(0.066)
Leverage	8.430***	27.196***	8.422***	27.245***	8.420***	8.466***
	(1.698)	(9.242)	(1.698)	(9.252)	(1.697)	(1.721)
Profitability	-18.400***	-3.886	-18.397***	-3.866	-18.401***	-18.379***
	(5.047)	(6.724)	(5.048)	(6.733)	(5.048)	(5.061)
Cash Ratio	2.089**	0.450	2.104**	0.416	2.108**	2.107**
	(1.035)	(2.402)	(1.036)	(2.403)	(1.036)	(1.037)
Tangibility	0.391	0.197	0.381	0.447	0.388	0.403
	(0.287)	(0.182)	(0.286)	(0.240)	(0.285)	(0.286)
Volatility	10.533***	5.754***	10.536***	5.766***	10.537***	10.530***
	(1.834)	(1.382)	(1.835)	(1.388)	(1.835)	(1.832)
# Lenders	-0.043	-0.029	-0.043	-0.027	-0.042	-0.044**
	(0.023)	(0.081)	(0.023)	(0.081)	(0.023)	(0.022)
Loan am./Tot. Assets	-6.319***	-3.464**	-6.299***	-3.360**	-6.299***	-6.398***
	(2.250)	(1.566)	(2.241)	(1.558)	(2.240)	(2.198)
Bonds/Tot. Assets	-151.918**	-35.682	-150.819**	-41.595	-150.654**	-146.155**
	(63.558)	(39.894)	(63.437)	(40.266)	(63.386)	(61.873)
CDS	0.150		0.139		0.122	
	(0.175)		(0.187)		(0.180)	
CDS Lender	0.069	0.116				
	(0.168)	(0.163)				
CDS Buyer			-0.177	-0.311	-0.213	-0.269
			(0.158)	(0.160)	(0.159)	(0.192)
Sell-to-Buy					0.195	0.252
					(0.255)	(0.291)
Constant	-4.259***	7.350	-4.058***	7.963	-4.010***	-4.029***
	(1.200)	(7.178)	(1.216)	(7.267)	(1.216)	(1.225)
Lender FE	X	X	X	X	X	X
Industry FE	X		X		X	
Firm FE		X		X		X
Time FE	X	X	X	X	X	X
Number of Observations	27462	27500	27462	27462	27462	27462
R-squared	0.29560	0.49058	0.29569	0.49205	0.29574	0.29564
Adjusted R-squared	0.29362	0.47543	0.29371	0.47647	0.29373	0.29366

Table 17: Probability of Downgrade and Overinsurance - Index Trading

This table presents the estimates of intensive margins between the CDS trading and the probability of being downgraded two notches (columns 1 to 4) and to high yield status (columns 5 to 8) using a logit model once we include CDS index positions to CDS single name positions, using a sample of CDS-firms and propensity score-matched non-CDS firms. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	1-notch Downgrade				Downgrade to HY			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.012	0.025	0.006	0.036	-0.174***	-0.128***	-0.152***	-0.093***
	(0.022)	(0.017)	(0.023)	(0.019)	(0.037)	(0.029)	(0.038)	(0.030)
Leverage	-0.445	-0.495**	-0.503**	-0.657***	-2.013***	-1.954***	-2.094***	-2.074***
	(0.245)	(0.235)	(0.253)	(0.245)	(0.381)	(0.341)	(0.398)	(0.360)
Profitability	-5.414***	-5.791***	-5.432***	-5.918***	-4.600***	-4.912***	-4.790***	-5.160***
	(0.483)	(0.476)	(0.493)	(0.497)	(0.590)	(0.566)	(0.614)	(0.600)
Cash Ratio	0.988***	0.796**	0.679	0.509	0.051	-0.725	-0.136	-0.367
	(0.366)	(0.350)	(0.385)	(0.376)	(0.609)	(0.617)	(0.639)	(0.642)
Tangibility	-0.095	0.225***	0.008	0.181***	0.299	0.187***	0.391	0.120*
	(0.251)	(0.040)	(0.238)	(0.042)	(0.398)	(0.063)	(0.392)	(0.065)
Volatility	2.133***	2.477***	2.159***	2.504***	0.894***	1.501***	0.863***	1.342***
	(0.144)	(0.131)	(0.146)	(0.134)	(0.193)	(0.168)	(0.204)	(0.178)
# Lenders	0.042***	0.044***	0.036***	0.040***	0.085***	0.077***	0.077***	0.071***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.012)	(0.012)	(0.013)	(0.012)
CDS	0.056		0.059		0.143**		0.113	
	(0.047)		(0.049)		(0.073)		(0.075)	
OI_{total}	0.005	-0.005			-0.177	-0.290**		
	(0.014)	(0.007)			(0.130)	(0.135)		
OI_{loans}			-0.037	-0.040			-0.157	-0.165
			(0.036)	(0.036)			(0.134)	(0.135)
Constant	-2.372***	-5.003***	-2.178***	-2.924***	-14.337***	-5.948***	-15.303***	-15.793***
	(0.566)	(0.309)	(0.564)	(0.408)	(1.027)	(1.038)	(0.943)	(0.521)
Lender FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Number of Observations	66138	74655	59751	59914	65842	74655	59139	59511
Pseudo R-squared	0.10551	0.10046	0.10523	0.10007	0.07918	0.07742	0.07795	0.06886

Table 18: Probability of Default and Over Insurance - Index trading

This table presents the estimates of intensive margins between the CDS trading and the probability of default using a OLS model once we include CDS index positions to CDS single name positions, using a sample of CDS-firms and propensity score-matched non-CDS firms. The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Probability of Default			
	(1)	(2)	(3)	(4)
Size	0.120	-1.717**	0.117*	-1.782**
	(0.063)	(0.820)	(0.066)	(0.848)
Leverage	8.405***	27.221***	8.500***	27.181***
	(1.699)	(9.244)	(1.713)	(8.763)
Profitability	-18.387***	-3.921	-18.490***	-3.546
	(5.051)	(6.727)	(5.131)	(6.738)
Cash Ratio	2.162**	0.440	2.435**	0.892
	(1.049)	(2.406)	(1.108)	(2.549)
Tangibility	0.442	0.197	0.467	0.279
	(0.290)	(0.182)	(0.321)	(0.192)
Volatility	10.569***	5.748***	10.523***	5.837***
	(1.836)	(1.385)	(1.781)	(1.429)
# Lenders	-0.044	-0.028	-0.046**	-0.037
	(0.023)	(0.081)	(0.023)	(0.087)
CDS	0.182		0.188	
	(0.191)		(0.187)	
OI_{total}	-0.023**	-0.017		
	(0.010)	(0.011)		
OI_{loans}			-0.023**	-0.017
			(0.010)	(0.011)
Constant	-4.711***	6.795	-4.707***	7.218
	(1.187)	(7.102)	(1.176)	(7.293)
Bank FE	X	X	X	X
Industry FE	X		X	
Firm FE		X		X
Time FE	X	X	X	X
Number of Observations	27462	27500	25392	25418
R-squared	0.29500	0.49043	0.29857	0.49158
Adjusted R-squared	0.29307	0.47532	0.29652	0.47525

Table 19: Determinants of the Probability of Downgrade - Four-week Window

This table presents the estimates of the probability of credit downgrades to one-notch (Panel A) and to high yield status (Panel B), using a logistic model on a sample of CDS-firms and propensity score-matched non-CDS firms, where we compute the bank CDS positions four weeks prior to the Y-14 reporting data. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

Panel A			***1-notch Downgrade***			
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.003	0.012	0.003	0.014	0.015	0.003
	(0.029)	(0.026)	(0.029)	(0.025)	(0.025)	(0.029)
Leverage	-0.767**	-0.750**	-0.771**	-0.747**	-0.749**	-0.773**
	(0.359)	(0.358)	(0.358)	(0.356)	(0.356)	(0.358)
Profitability	-2.906**	-2.905**	-2.905**	-2.907**	-2.905**	-2.903**
	(1.425)	(1.429)	(1.422)	(1.429)	(1.432)	(1.425)
Cash Ratio	1.002*	1.005*	1.007*	1.006*	1.010**	1.011**
	(0.515)	(0.514)	(0.514)	(0.513)	(0.514)	(0.515)
Tangibility	-0.045	-0.038	-0.049	-0.038	-0.039	-0.050
	(0.273)	(0.273)	(0.273)	(0.273)	(0.274)	(0.274)
Volatility	2.112***	2.116***	2.113***	2.115***	2.116***	2.113***
	(0.229)	(0.229)	(0.229)	(0.229)	(0.229)	(0.230)
# Lenders	0.048***	0.047***	0.048***	0.047***	0.047***	0.048***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan am./Tot. Assets	1.749*	1.730	1.763*	1.729	1.722	1.756*
	(1.057)	(1.057)	(1.058)	(1.059)	(1.059)	(1.058)
Bonds/Tot. Assets	-11.965	-10.186	-12.174	-10.357	-9.067	-10.872
	(37.380)	(37.586)	(37.389)	(37.646)	(37.430)	(37.174)
CDS	0.066		0.058			0.057
	(0.075)		(0.070)			(0.070)
CDS Lender	-0.037	0.004				
	(0.069)	(0.065)				
CDS Buyer			-0.038	-0.020	0.120	0.101
			(0.074)	(0.073)	(0.092)	(0.093)
Sell-to-Buy					-0.310**	-0.310**
					(0.126)	(0.127)
Constant	-3.508***	-3.521***	-3.499***	-3.532***	-3.540***	-3.508***
	(0.497)	(0.499)	(0.495)	(0.497)	(0.498)	(0.495)
Lender FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73936	73936	73936	73936	73936	73936
Pseudo R-squared	0.09510	0.09504	0.09510	0.09504	0.09529	0.09535

Panel B	HY Downgrade					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	-0.180***	-0.157***	-0.178***	-0.147***	-0.178***	-0.147***
	(0.046)	(0.042)	(0.046)	(0.041)	(0.046)	(0.041)
Leverage	-2.658***	-2.591***	-2.654***	-2.557***	-2.654***	-2.558***
	(0.551)	(0.544)	(0.551)	(0.543)	(0.551)	(0.543)
Profitability	-2.274***	-2.229***	-2.273***	-2.212***	-2.274***	-2.213***
	(0.629)	(0.629)	(0.629)	(0.629)	(0.629)	(0.629)
Cash Ratio	0.104	0.125	0.106	0.127	0.108	0.128
	(0.801)	(0.793)	(0.800)	(0.792)	(0.800)	(0.792)
Tangibility	0.429	0.441	0.426	0.446	0.427	0.447
	(0.393)	(0.393)	(0.393)	(0.393)	(0.393)	(0.393)
Volatility	1.078***	1.091***	1.076***	1.090***	1.074***	1.088***
	(0.255)	(0.254)	(0.255)	(0.253)	(0.256)	(0.253)
# Lenders	0.088***	0.086***	0.088***	0.085***	0.088***	0.085***
	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Loan am./Tot. Assets	2.246*	2.230*	2.249*	2.204	2.238*	2.193
	(1.347)	(1.351)	(1.350)	(1.357)	(1.349)	(1.356)
Bonds/Tot. Assets	37.855	41.818	36.924	41.412	37.430	41.919
	(49.189)	(49.307)	(49.192)	(49.288)	(49.057)	(49.149)
CDS	0.136		0.146		0.146	
	(0.100)		(0.095)		(0.095)	
CDS Lender	0.004	0.083				
	(0.120)	(0.115)				
CDS Buyer			-0.075	-0.029	0.001	0.048
			(0.118)	(0.118)	(0.148)	(0.147)
Sell-to-Buy					-0.169	-0.172
					(0.196)	(0.196)
Constant	-16.862***	-16.935***	-16.885***	-17.016***	-16.887***	-17.018***
	(0.854)	(1.396)	(0.992)	(1.021)	(1.192)	(0.746)
Lender FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Number of Observations	73060	73060	73060	73060	73060	73060
Pseudo R-squared	0.07502	0.07478	0.07505	0.07474	0.07510	0.07479

Table 20: Determinants of the Probability of Default - Four-week Window

This table presents the estimates of the probability of default, using an OLS panel model in a sample of CDS-firms and propensity score-matched non-CDS firms. Propensity score-firms are selected based on the nearest neighbor (without replacement), where we compute the bank CDS positions four weeks prior to the Y-14 reporting data. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Probability of Default					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.066	-1.856***	0.070*	-1.855***	0.070*	-1.855***
	(0.065)	(0.385)	(0.038)	(0.384)	(0.038)	(0.385)
Leverage	8.529***	27.463***	8.535***	27.493***	8.535***	27.491***
	(1.688)	(4.568)	(1.105)	(4.569)	(1.105)	(4.569)
Profitability	-18.211***	-3.850	-18.219***	-3.851	-18.220***	-3.849
	(5.019)	(3.506)	(3.822)	(3.506)	(3.823)	(3.507)
Cash Ratio	2.059**	0.551	2.054***	0.564	2.054***	0.564
	(1.032)	(1.096)	(0.549)	(1.095)	(0.549)	(1.095)
Tangibility	0.382	0.215	0.378*	0.216	0.377*	0.216
	(0.286)	(0.134)	(0.209)	(0.134)	(0.209)	(0.134)
Volatility	10.546***	5.356***	10.533***	5.354***	10.533***	5.353***
	(1.814)	(0.905)	(1.022)	(0.905)	(1.022)	(0.905)
# Lenders	-0.044*	-0.026	-0.045***	-0.025	-0.045***	-0.025
	(0.023)	(0.044)	(0.011)	(0.044)	(0.011)	(0.044)
Loans	-6.316***	-3.736**	-6.328***	-3.823***	-6.342***	-3.827***
	(2.259)	(1.458)	(1.900)	(1.457)	(1.900)	(1.459)
Bonds	-168.713***	-40.619	-170.513***	-42.052	-170.782***	-42.022
	(65.253)	(38.739)	(62.609)	(38.851)	(62.605)	(38.843)
CDS	0.171		0.215**		0.215**	
	(0.180)		(0.090)		(0.090)	
CDS Lender	0.059	0.065				
	(0.161)	(0.112)				
CDS Buyer			-0.173	-0.212**	-0.124	-0.197
			(0.120)	(0.107)	(0.155)	(0.129)
Sell-to-Buy					-0.091	-0.028
					(0.180)	(0.150)
Constant	-4.203***	8.110**	-4.181***	8.130**	-4.188***	8.133**
	(1.188)	(3.918)	(0.727)	(3.923)	(0.727)	(3.926)
Lender FE	X	X	X	X	X	X
Industry FE	X		X		X	
Firm FE		X		X		X
Time FE	X	X	X	X	X	X
Number of Observations	27560	27598	27560	27598	27560	27598
R-squared	0.29348	0.48615	0.29357	0.48627	0.29357	0.48627
Adjusted R-squared	0.29151	0.47093	0.29159	0.47105	0.29157	0.47103

Table 21: Probability of Downgrade and Overinsurance - Four-week Window

This table presents the estimates of intensive margins between the CDS trading and the probability of being downgraded two notches (columns 1 to 4) and to high yield status (columns 5 to 8) using a logit model, where we compute the bank CDS positions four weeks prior to the Y-14 reporting data. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	1-notch Downgrade				**Downgrade to HY**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.012	-0.000	-0.024	-0.012	-0.195***	-0.166***	-0.171***	-0.149***
	(0.028)	(0.023)	(0.028)	(0.023)	(0.044)	(0.038)	(0.042)	(0.037)
Leverage	-0.787**	-0.764**	-0.913**	-0.890**	-2.571***	-2.482***	-2.655***	-2.590***
	(0.361)	(0.359)	(0.366)	(0.364)	(0.551)	(0.542)	(0.564)	(0.557)
Profitability	-2.844**	-2.846**	-2.620	-2.621	-2.237***	-2.182***	-2.289***	-2.248***
	(1.438)	(1.444)	(1.436)	(1.446)	(0.638)	(0.637)	(0.648)	(0.646)
Cash Ratio	0.977	0.977	0.680	0.683	0.090	0.112	-0.042	-0.021
	(0.520)	(0.519)	(0.531)	(0.530)	(0.799)	(0.791)	(0.813)	(0.806)
Tangibility	-0.055	-0.045	0.083	0.093	0.405	0.422	0.506	0.519
	(0.273)	(0.273)	(0.277)	(0.277)	(0.395)	(0.395)	(0.382)	(0.382)
Volatility	2.134***	2.136***	2.218***	2.220***	1.107***	1.117***	1.097***	1.105***
	(0.232)	(0.231)	(0.232)	(0.232)	(0.257)	(0.254)	(0.260)	(0.258)
# Lenders	0.049***	0.048***	0.045***	0.044***	0.089***	0.086***	0.082***	0.079***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.015)	(0.015)	(0.016)	(0.016)
CDS	0.052		0.052		0.127		0.093	
	(0.069)		(0.069)		(0.094)		(0.093)	
OI_{total}	0.001	0.002			-0.276	-0.264		
	(0.011)	(0.011)			(0.207)	(0.204)		
OI_{loans}			-0.001	0.000			-0.194	-0.185
			(0.019)	(0.018)			(0.182)	(0.178)
Constant	-3.313***	-3.351***	-3.325***	-3.365***	-17.856***	-16.736***	-15.708***	-16.928***
	(0.495)	(0.497)	(0.494)	(0.498)	(2.509)	(1.051)	(0.983)	(1.205)
Lender FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Number of Observations	73726	73726	66818	66818	73414	73414	66182	66182
Pseudo R-squared	0.09547	0.09543	0.09557	0.09552	0.07391	0.07366	0.07263	0.07249

Table 22: Probability of Default and Over Insurance - Four-week Window

This table presents the estimates of intensive margins between the CDS trading and the probability of default using a OLS model on a sample of CDS-firms and propensity score-matched non-CDS firms, where we compute the bank CDS positions four weeks prior to the Y-14 reporting data. Propensity score-firms are selected based on the nearest neighbor (without replacement). The propensity score is estimated using a logit model where the dependent variable is equal to one if the firm has a traded CDS contract in our sample and the explanatory variables are the firm characteristics, lagged one quarter. A description of the independent variables is reported in Table 1. Standard errors are reported in parentheses and are adjusted for clustering at the firm's level. Statistical significance is denoted by *** and ** at the 1% and 5% respectively.

	Probability of Default			
	(1)	(2)	(3)	(4)
Size	0.120	-1.717**	0.117	-1.782**
	(0.063)	(0.820)	(0.066)	(0.848)
Leverage	8.405***	27.221***	8.500***	27.182***
	(1.699)	(9.244)	(1.713)	(8.763)
Profitability	-18.387***	-3.921	-18.490***	-3.546
	(5.051)	(6.727)	(5.131)	(6.738)
Cash Ratio	2.163**	0.441	2.435**	0.893
	(1.049)	(2.406)	(1.108)	(2.549)
Tangibility	0.442	0.197	0.468	0.279
	(0.290)	(0.182)	(0.321)	(0.192)
Volatility	10.568***	5.748***	10.523***	5.837***
	(1.836)	(1.385)	(1.781)	(1.429)
# Lenders	-0.044	-0.028	-0.046**	-0.037
	(0.023)	(0.081)	(0.023)	(0.087)
CDS	0.182		0.188	
	(0.191)		(0.187)	
OI_{total}	-0.023**	-0.015		
	(0.010)	(0.009)		
OI_{loans}			-0.023**	-0.016
			(0.010)	(0.009)
Constant	-4.712***	6.794	-4.707***	7.218
	(1.187)	(7.102)	(1.176)	(7.293)
Bank FE	X	X	X	X
Industry FE	X		X	
Firm FE		X		X
Time FE	X	X	X	X
Number of Observations	27462	27500	25392	25418
R-squared	0.29500	0.49043	0.29857	0.49158
Adjusted R-squared	0.29307	0.47532	0.29652	0.47525