The Anatomy of the CDS Market *

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Abstract

What is the economic role of the market for credit default swaps (CDSs)? Using novel position data for single-name corporate CDSs, we provide evidence that CDS markets emerge as an "alternative trading venue" for firms with illiquid bond markets. CDS markets are more likely to exist and more heavily used when the bonds of the underlying firm are hard to trade. CDS positions are increasing in insurable interest (hedging demand) and disagreement (speculative demand); these effects are significantly stronger for firms with illiquid bond markets. We also find evidence suggestive of arbitrage activity linking the CDS and the bond market.

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1 Introduction

The market for credit default swaps (CDSs) has grown tremendously over the last decade. According to the Bank for International Settlements (BIS), the size of the CDS market has increased from a total notional amount of $6 trillion in 2004 to a peak of $57 trillion by mid 2008. While it has since then decreased in size to around $29 trillion at the end of 2011, these numbers show that the CDS market has developed from an exotic niche market to an enormous and very active market for credit risk transfer—arguably one of the most significant financial innovations of the last decades. Concurrent with their growth, CDS markets have become the subject of a number of policy debates, including their role in the recent financial crisis (for a summary of the issues, see Stulz, 2010) and, more broadly, their impact on the debtor-creditor relationship, for example through the emergence of empty creditors (see, e.g., Hu and Black, 2007; Bolton and Oehmke, 2011).

Despite the growing importance of CDS markets, very little is known about the actual positions taken in these markets and, more broadly, the economic function that these markets perform. This paper aims to fill this void. Using newly available, disaggregated data on individual single-name CDS positions, we provide evidence that CDS markets function as "alternative trading venues" for both hedging and speculation in the underlying bond. They are alternative trading venues in the sense that investors could often make the same economic trade directly in the underlying bond, but choose to use the CDS market. This interpretation of CDS markets as alternative trading venues is supported by the finding that CDS markets are more likely to emerge when the underlying bonds of the firm are illiquid or fragmented, and thus hard or expensive to trade. Similarly, conditional on a CDS market existing for a reference entity, the CDS market is more likely to be used as vehicle for hedging or speculation when the underlying bond is illiquid.

In a CDS, a protection seller agrees to make a payment to the protection buyer in the case of a credit event on a prespecified reference entity. In exchange for this promised payment, the protection seller receives a periodic premium payment (and potentially an upfront payment) from the protection buyer. What exactly determines a credit event is defined in the initial CDS contract. Generally speaking, credit events include a bankruptcy filing of the reference entity, non-payment of debt, and, in some CDS contracts, debt restructuring or a credit-rating downgrade. When a credit event occurs, the protection seller pays the protection buyer the difference between the face value of a pre-specified reference bond and the recovery value of that bond, which is typically determined in a CDS settlement auction.

The data underlying our analysis are newly available CDS market statistics on gross and net notional CDS amounts that are released by the Depository Trust & Clearing Corporation (DTCC)—the most comprehensive and disaggregated CDS position data available. In our analysis, we focus on the *net notional* amounts of CDSs outstanding on individual reference entities. The net notional amount is calculated as the sum of *net* protection bought by counterparties that are net buyers of protection for a particular reference entity (or equivalently, the sum of net protection sold by all counterparties that are net sellers of protection for a particular reference entity). In other words, the net notional amount corrects for offsetting positions within counterparties. One way to interpret the net notional outstanding is to think of it as the maximum amount of payments that need to be made between counterparties in the case of a credit event on a particular reference entity.[1]

We focus on the net notional amount, because it provides a more accurate picture of the amount of credit risk transferred in the CDS market than the *gross notional* amount, the main alternative measure of CDS market size. The gross notional amount simply sums up all outstanding contracts: It is the sum of all protection bought, or equivalently all protection sold. The gross notional amount is an inaccurate measure of credit risk transfer through the CDS market because it can increase even when counterparties in the CDS market *reduce* their exposure by taking on offsetting positions. From an economic perspective, the net notional is thus a much better measure of the amount of credit risk transferred in the CDS market.

[1]It is the maximum amount of payments, because actual payments will usually be less than the par value of the CDS, reflecting non-zero recovery rates on the defaulted bonds as well as previous marking-to-market by counterparties.

To investigate the economic role of the CDS market, we combine the DTCC data on net notional CDS amounts with a number of other data sources (e.g., Compustat, Mergent FISD, Trace, Bloomberg, Capital IQ). We then run probit regressions to estimate the determinants of CDS market existence, and censored regressions to investigate the determinants of CDS position sizes. We use a censored regression approach because the DTCC reports notional CDS amounts outstanding only for the 1,000 largest traded reference entities. This means that some traded reference entities with small amounts of CDS outstanding do not make it into the DTCC data.

We first provide evidence suggesting that CDSs are being used as instruments for hedging. First, firms with more debt outstanding are more likely to be traded reference entities in the CDS market. In addition, if they are traded reference entities, firms with more debt tend to have larger CDS amounts outstanding. When looking at disaggregated balance sheet data, we find that the effect of debt on CDS positions is mainly driven by bonds outstanding. The positive association of measures of indebtedness and the net notional CDS amounts outstanding suggests that insurable interest is a determinant of CDS positions. Second, we find that firms close to the cutoff between investment grade and non investment grade have more CDS outstanding. In addition, fallen angels (i.e., firms that have lost investment grade status) have more CDS outstanding. This suggests that investors exposed to these firms use the CDS market to hedge their exposure. Third, firms that provide credit guarantees (e.g., monoline insurers) and thus represent counterparty exposure for market participants that rely on that credit insurance tend to have more CDS outstanding. Taken together, these findings suggest that at least some market participants use the CDS market to hedge their debt, bond, or other counterparty exposure.

We then document that proxies for speculative motives for CDS trading are also associated with larger net CDS positions. In particular, for traded reference entities, disagreement about a reference entity's earnings prospects, as measured by earnings forecast dispersion normalized by price, is associated with larger net notional amounts of CDS outstanding. This suggests that, in addition to hedging, investors use the CDS market to speculate by 'taking views' on the default probabilities of traded reference entities.

While taken together these results suggest that both hedging and speculation are determinants of CDS positions, they do not explain why investors prefer to hedge or speculate in the CDS market, as opposed to trading directly in the underlying bond. Here our analysis suggests that CDS markets emerge as "alternative trading venues" for credit risk: CDS markets are used in particular if the underlying bonds are illiquid or fragmented and thus harder to trade. Specifically, controlling for the amount of bonds outstanding, we show that if a firm's bond issues are fragmented, as proxied by the Herfindahl index, CDS markets are more likely to emerge. In addition, for firms that are traded reference entities in the CDS market, a more fragmented bond market is associated with larger CDS positions. Both of these results suggests that one of the economic functions of CDS markets is to create a unified, liquid market for credit risk when a reference entity's bonds are fragmented and split over multiple heterogeneous bond issues.

We find further support for this interpretation of CDS markets as alternative trading venues when we interact proxies for hedging or speculation motives with measures of trading frictions in the market for the underlying bond. In particular, we find that the effect of both disagreement (a proxy for speculation) and loss of investment grade status (a proxy for hedging pressure) on the net notional amounts of CDS outstanding are stronger for bonds that are illiquid. This gives further support for the view that investors use CDS markets to take views or hedge exposures when trading in the underlying bond is difficult or expensive.

Finally, we document that net notional CDS positions are increasing in the CDS-bond basis, a measure of mispricing of the underlying bond relative to the CDS. Specifically, when the CDS-bond basis is negative (as it has been for many reference entities since the financial crisis), the underlying bond is cheap relative to a synthetic bond formed out of a CDS and a risk-free bond. This situation gives rise to the so-called negative basis trade, in which a trader purchases the bond and buys CDS protection to exploit the relative price difference between the bond and CDS markets. Our analysis shows that firms which have a more negative CDS-bond basis have more CDS outstanding. This result suggests that arbitrageurs use CDSs to lean against the negative CDS-bond basis. By allowing arbitrageurs to lean against mispricing in the bond market, CDS markets may help to compress spreads for bond issuers. Hence, the presence of CDSs may improve firms' access to financing. This interpretation echoes the arguments in Saretto and Tookes (2013), who document that the presence of CDSs allows firms to borrow more and at longer maturities. Interestingly, while a negative basis is associated with larger net amounts of CDSs outstanding, the same is not true for a positive basis (which gives rise to a similar arbitrage trade). We argue that this asymmetry could be due to short-selling constraints in the underlying bond.

The remainder of the paper is structured as follows. In Section 2 we discuss the related literature and in Section 3 develop a number of empirical hypotheses. In Section 4 we describe our data sources. Section 5 discusses our empirical strategy and presents the main empirical findings. In Section 6 we discuss a number of robustness checks. Section 7 concludes.

2 Related Literature

Despite the recent growth in the literature on CDS markets, relatively little is known about positioning and the determinants of position sizes in these markets. To our knowledge, this is the first paper that systematically investigates positioning in the CDS market using position data at the reference entity level. In his survey of CDS markets and their role in the recent crisis, Stulz (2010) provides a number of summary statistics based on aggregate position data from the DTCC and survey data from the Bank for International Settlements (BIS), which was the main source of position information before the DTCC data became available. Stulz (2010) also provides an introduction to the basics of CDS markets and the current policy debates about CDS.

A number of other recent empirical studies look at CDS positions or transaction volume. Chen et al. (2011) analyze three months of confidential trading activity data. They document relatively low unconditional trading volume in CDSs, with spikes in trading around credit events. They also show that most trading in CDS markets concentrates in standardized contracts that follow the industry's "big bang protocol." Shachar (2011) uses detailed transaction level data to investigate price effects of traded volume, order imbalances and dealer inventories in the CDS market. Lee (2011) uses data from the DTCC to document a predictive effect of the ratio of net notional CDS amounts to debt on future stock prices and CDS spreads. None of these papers investigate the determinants of the positions taken in the CDS market. In addition, a number of recent papers investigate the CDS-bond basis, which is the difference between the CDS spread and the spread over the risk-free rate of the underlying bond including Blanco et al. (2005), Nashikkar et al. (2010), Bai and Collin-Dufresne (2010), and Fontana (2011).[2] Our paper contributes to this literature by linking the CDS-bond basis to quantities in the CDS market.

More broadly, there is a growing empirical literature that investigates the effects of CDS markets on information transmission, risk transfer, and credit market outcomes. Acharya and Johnson (2007) document informed trading in CDS markets that leads equity markets in response to negative credit news, suggesting that price discovery for those events tends to happen in CDS markets. Qiu and Yu (2012) examine liquidity provision in CDS markets by investigating the number of distinct dealers that provide quotes for certain reference entities. They link their liquidity proxy to obligor size, credit rating and to information flow from the CDS market to the stock market. Minton et al. (2009) investigate the use of CDSs as risk transfer instruments by U.S. bank holding companies. Ashcraft and Santos (2009) find that the introduction of CDSs has lead to an improvement in borrowing terms for safe and transparent firms, where banks' monitoring incentives are not likely to play a major role. Hirtle (2009) argues that greater use of CDSs leads to an increase in bank credit supply and an improvement in credit terms, such as maturity and required spreads, for large loans that are likely to be issued by companies that are 'named credits' in the CDS market. Saretto and Tookes (2013)

[2]For details on the CDS-bond basis and conditions under which it should be zero by no arbitrage, see Duffie (1999).

document that firms with traded CDS contracts can sustain higher leverage and borrow at longer debt maturities.

Finally, our paper relates to a growing theory literature on the use of CDSs. Much of that literature has focused on why investors may have an incentive to trade in the CDS markets. One strand of literature links trading in CDSs to hedging demands by banks or investors. For example, in Duffee and Zhou (2001), CDS contracts allow for the decomposition of credit risk into components that are more or less information sensitive, thus potentially helping banks overcome a lemons problem when hedging credit risk. Parlour and Plantin (2008) analyze under which conditions liquid markets for credit risk transfer (loan sales or CDSs) can emerge when there is asymmetric information about credit quality. In their model, markets for credit risk transfer are more likely to be active for high-quality issuers. Thompson (2009) and Parlour and Winton (2012) analyze how banks lay off credit risk when they have a choice between loan sales and purchasing CDS protection. In Bolton and Oehmke (2011) CDS contracts strengthen the ex-post bargaining position of creditors and thus allow the firm to raise more financing ex-ante. At the same time, CDSs may also lead to inefficient liquidation of the firm at an interim date. In Zawadowski (2011) investors can use CDS to insure counterparty risk. Atkeson et al. (2012) develop a model in which banks insure loan exposures via an OTC CDS market.

A number of recent papers use heterogeneous beliefs models to analyze trading in CDSs. For example, Che and Sethi (2011) use a model with heterogeneous beliefs to analyze the impact of credit derivatives on firms' cost of capital. In their model, the presence of the CDS market can lead some investors to take CDS positions rather than buying the bond, which can raise a firm's cost of capital. Geanakoplos and Fostel (2011) argue, within a heterogeneous beliefs model, that tranching and CDS may have contributed to the recent boom-bust cycle. One general implication of models with heterogeneous beliefs is that an increase in disagreement among investors usually leads to more CDS outstanding.

3 Hypothesis development

Taken together, the theory literature suggests several economic motives for taking positions in the CDS market. We distill these motives into four hypotheses. In our empirical investigation in Section 5 we show that the data support these four hypotheses.

H1: *Higher hedging demand increases the amount of CDSs outstanding.*

To the extent that CDSs are used for hedging, insurable interest should play a role in determining the net notional amounts of CDSs outstanding. Consider, for example, a setting in which investors insure a constant fraction of their bonds. When more bonds are outstanding (i.e., insurable interest rises) we should expect to see a larger net notional amount of CDSs outstanding. In contrast, speculative activity in the CDS market should not be directly related to insurable interest since it is a pure bet on future changes in credit quality and thus does not directly depend on the amounts of bonds outstanding or the size of the reference entity.

H2: *Higher speculative demand increases the amount of CDSs outstanding.*

Investors may use CDS contracts as speculative vehicles in order to express views about a reference entity's default prospects, even if they do not own the bond or have any other exposure to the reference entity. To the extent that CDSs are used as speculative instruments, all else equal reference entities on which investors' beliefs differ more should have larger CDS positions outstanding than reference entities with less disagreement, as in the heterogeneous beliefs models of Che and Sethi (2011) and Geanakoplos and Fostel (2011).

H3: *Illiquidity of the bond market increases the amount of CDSs outstanding. Furthermore, H1 and H2 should be more pronounced if the bond market is illiquid.*

Since investors can choose between trading in the CDS market or directly in the underlying bond, CDS markets should be more likely to emerge and more heavily used when the underlying bond is illiquid and thus hard or expensive to trade. We also expect the effects of speculation or hedging motives on the amount of net notional CDS protection outstanding (H1 and H2) to be more pronounced for firms with less liquid bonds. The rationale is that, while in principle investors can hedge or take a speculative position either using the bond or the CDS market, they should have a preference for using the CDS market when the underlying bond is illiquid or if the firm's bonds are fragmented into many separate bond issues. As pointed out by Stulz (2009), "firms have all sort of different bonds whose prices are affected by call provisions, covenants, coupon, maturity, liquidity, and so on; in contrast, CDS are like standardized bonds." Hence, the more fragmented and diverse a company's bonds, the more attractive the CDS market becomes as a venue for hedging or speculation.

H4: *Higher demand from arbitrageurs increases the amount of CDSs outstanding.*

No arbitrage implies that a long position in a bond hedged with the appropriate CDS should earn (approximately) the risk-free rate (for the exact conditions under which this arbitrage relation holds, see Duffie (1999)). Deviations from this no-arbitrage relationship should thus generate demand for trading in the bond and the CDS as arbitrageurs attempt to exploit relative mispricing between the bond and CDS markets. For example, if insuring the bond in the CDS market is cheap relative to the default premium offered by the bond (a negative basis), arbitrageurs have an incentive to buy the bond and go long CDS protection, thus increasing the amount of CDS outstanding.

4 Data

4.1 DTCC data

Our data on CDS positions comes from the Depository Trust & Clearing Corporation (DTCC). The DTCC provides clearing, settlement and trade confirmation in a number of markets, such as equities, corporate and municipal bonds, and over-the-counter derivatives. In the CDS market, the DTCC provides trade processing and trade registration services. All major dealers register their standard CDS trades with the DTCC. The DTCC then enters these trades into a Trade Information Warehouse (TIW). Since October 31, 2008, the DTCC has published weekly reports on CDS positions based on the trades recorded in the TIW.[3] The positions recorded in the TIW capture almost the entire market for standard single-name CDSs.[4] According to the DTCC (2009), the TIW captures around 95% of globally traded CDSs. The data is thus the most accurate and comprehensive dataset that is available on CDS positions. In this study we use 39 months of DTCC data, from October 2008 to December 2011.[5] This period, while relatively short, allows us to focus on the time period during which the CDS market is relatively mature and well established.

Prior to the release of position data by the DTCC, the main source of information about position sizes in the CDS market was the survey data from the BIS.[6] Relative to the DTCC data, the BIS data has a number of disadvantages. First, the BIS data only provides aggregate market statistics, while the DTCC data provides positioning at the reference entity level. Second, the BIS data is based on surveys as opposed to actual registered positions in the market. Third, because of its survey-based nature, the BIS data is prone to double counting: The same CDS transaction may be reported both by the buyer and the seller to the transaction, resulting in a double count.

In its weekly reports, the DTCC discloses both the aggregate gross notional as well as the aggregate net notional amounts outstanding on a particular reference entity, where "notional" refers to the par amount of credit protection that is bought or sold. The *gross notional* amount outstanding is the sum of all notional CDS contracts on a given reference entity. The gross notional amount thus reflects the total par amount of credit protection bought (or equivalently sold). It is defined as either the sum of all long or, equivalently, the sum of all short CDS contracts outstanding. With the exception of occasional compression trades, in which offsetting CDS positions are eliminated, the gross notional amount outstanding increases with every trade. In particular, the gross notional position increases even if a trade offsets an existing trade and thus reduces the overall amount of credit risk transfer in

[3]The data is made public online at http://www.dtcc.com/products/derivserv/data/index.php

[4]The DTCC also registers CDS positions on sovereigns, indices, and structured financial instruments. In this study we focus on single-name CDS on companies. According to Stulz (2010), in June 2008 single-name CDS made up about 58% of the overall CDS market.

[5]The monthly DTCC CDS amounts are the last weekly release in a given month.

[6]This data is available from 2004 onward and can be found at http://www.bis.org/statistics/derstats.htm.

the CDS market. This makes the gross notional amount outstanding a very imprecise proxy for the amount of credit risk that is transferred in the CDS market.

The *net notional* amount outstanding adjusts the gross notional amount for offsetting positions in order to better reflect the actual economic protection purchased. The DTCC calculates the net notional amount outstanding as the sum of net protection bought by counterparties that are net buyers of protection for a particular reference entity (or equivalently, as the sum of net protection sold by all counterparties that are net sellers of protection for a particular reference entity). A counterparty's net position is less than its gross position whenever it has entered partially offsetting trades. This is usually the case because entering offsetting trades is a more common way to reduce exposure in the CDS market than canceling an existing CDS contract. One intuitive way to interpret the net notional amount outstanding is to think of it as the maximum amount of payments that need to be made between counterparties in the case of a credit event on a particular reference entity. It is the maximum amount of payments, because actual payments will usually be less than the par value of the CDS, reflecting non-zero recovery rates on the defaulted bonds as well as previous marking-to-market by counterparties.

The difference between gross notional amounts and net notional amounts is best illustrated via a simple example. For a graphical illustration of this example, see Figure 1. Consider three banks, A, B and C, that are trading CDSs on a given reference entity. Assume that initially B has purchased \$10m in credit protection from A. The gross notional amount outstanding, calculated as either the sum of all gross protection bought or sold, is given by \$10m: Bank A has sold a gross amount of \$10m to bank B, and bank B has bought a gross amount of \$10m from bank A. By similar reasoning, the net notional amount, calculated as the sum of all net protection bought or sold, is also given by \$10m. This is illustrated in Panel (a) of Figure 1. Now assume that B offsets the initial trade by selling \$10m in protection to C. This raises the gross notional amount to \$20m: Bank B has bought a gross amount of \$10m in protection from bank A, and bank C has bought a gross amount of \$10m in protection from bank B. The net notional amount, however, remains at \$10m. The reason for this is that B is now fully hedged, such that the only net payment to be made in the case of default is a payment of \$10m from A to C. This is illustrated in Panel (b) of Figure 1. Finally, in Panel (c), C sells \$10m in protection to A, such that all three parties have a net zero position. This means that the net notional outstanding, the sum of all long or short net positions, is also \$0. The gross notional, on the other hand, is now \$30m.

4.2 Sample construction

We combine the DTCC position data with a number of other data sources. We take balance sheet data, credit ratings, and industry codes from Compustat. For more detailed capital structure information, we hand collect information from Capital IQ. We use CRSP for equity market data, IBES for earnings forecasts. We gather data on outstanding bonds from Mergent FISD, and obtain bond trading data from TRACE.

In terms of dataset construction, we start with the universe of US and international firms contained in Compustat. We use consolidated balance sheet data; *debt* is defined as the sum of current and long-term debt. We then merge this data to all 1208 single-name reference entities (excluding states and sovereigns) in the DTCC data using firm name as an identifier. If the DTCC reference entity is not in Compustat but the parent is, we match to the parent. We hand check these merges to make sure that the reference entities in DTCC are correctly assigned to companies in Compustat: 1047 names in the DTCC data can be assigned to a Compustat company. We drop the 161 DTCC reference entities that we could not find in either the domestic or the international Compustat dataset.

We then exclude companies that are not uniquely merged, i.e., cases where several reference entities from DTCC are matched to a single Compustat firm. The rationale for dropping these companies is the following: If there are several different CDSs that refer, directly or indirectly, to the same Compustat company, the netting procedure of DTCC might not yield the true net exposure. The Compustat company AT&T Inc. for example can be matched to four entities in DTCC: the parent company "AT&T INC." and three subsidiaries: "AT&T CORP.", "AT&T MOBILITY LLC" , and "NEW

CINGULAR WIRELESS SERVICES, INC.". For the same reason, we also drop all companies for which both the parent and subsidiary (or two subsidiaries) have a CDS market. We define existence of the CDS market at a given date as having a Bloomberg CDS quote sometime before the given date (but after Jan 2007) or having appeared in the DTCC data before. Companies that could only indirectly be matched to a CDS market (e.g. through a subsidiary) are also dropped. We also exclude companies which are in bankruptcy and ones for which there was a CDS settlement auction after 2007. Finally, we check whether a certain reference entity is part of a major CDS index (CDX.NA.IG, CDX.NA.HY, Itraxx) based on the Markit manual.

We then add data on bonds outstanding of US companies using Mergent FISD. We exclude all short-term bonds; only bonds with at least 366 days of original maturity are considered. We also exclude bonds in the month of their issuance and the month of their redemption. Pass-through notes are also dropped. In Mergent FISD, we drop bonds that have been effectively recalled or decrease the amount outstanding by the recall amount. We also drop bonds with zero or unrecorded offering amount. We calculate bond trading for the bonds in Mergent FISD using Trace and match the two using the CUSIP of the bond issues. In Trace "1MM+" is replaced by 1 million and "5MM+" by 5 million.

Given the complicated legal structure of companies, we construct two different measures of bonds outstanding. The first measure, *bonds outstanding*, includes all bonds of a given limited liability entity, including all bonds issued by companies that have been acquired and fully dissolved. This is important because in case of mergers and acquisitions, the new parent inherits the bonds of the old company. The second measure, *consolidated bonds outstanding*, includes all bonds issued by all companies with the same ultimate parent. This distinction is important but imperfect. For example, ExxonMobil in its 2010 annual report (which is consolidated), reports bonds issued by the acquired companies Mobil, SeaRiver Maritime Financial Holdings, and XTO Energy as liabilities. However while ExxonMobil is legally liable for Mobil bonds since it is a not a separate legal entity, this is not necessarily the case for the bonds of XTO Energy since it is a limited liability subsidiary. SeaRiver

Maritime Financial Holdings is also a limited liability entity and as such ExxonMobil is not necessarily liable in case of a default on these bonds. However, in its 2010 annual report ExxonMobil explicitly states that it guarantees bonds issued by SeaRiver Maritime Financial Holdings, while no explicit guarantees are stated in case of XTO Energy (which of course does not rule out implicit guarantees). In the DTCC database we do find CDS outstanding on both ExxonMobil and XTO Energy but not on the other subsidiaries of ExxonMobil (Note that in this case since CDSs are traded both on the parent and subsidiary, these companies are dropped from our final sample). Thus parent companies may or may not be liable for the bonds of their subsidiaries leading to potential joint defaults. While it is extremely cumbersome to verify all such guarantees, in our regression analysis we analyze whether they matter. Note that Compustat and Capital IQ both look at consolidated balance sheets thus they treat the bond issuances of all subsidiaries as that of the parent or acquirer.

Matching between bond issues and Compustat companies is done along two dimensions. First, since most of the companies issuing debt also have traded equity, we use the CRSP files to match old cusips (e.g., acquired company) to new cusips (e.g., acquirer). In case of a merger or acquisition, we use the same file to find the new parent company. We then hand-check all the matches and verify whether the acquired companies (or subsidiaries) are limited liability entities or not (i.e., whether the parent is liable for the obligations). Second, we use the Mergent FISD parent identifier to consolidate companies with the same parent. To exclude potential erroneous matches between Compustat and FISD Mergent we exclude companies that have more than twice as many bonds than debt.[7] We then use the first six digits of CUSIP (which identifies the issuer) to match our data to bond data from Mergent FISD. In a second round of matching all unmatched issues in Mergent FISD are, if possible, hand matched to Compustat.

We compute three different measures of bond liquidity. First, *number of trades* is the number of all trades in all bonds of a given issuer over the previous 12 months. Second, we compute annual *bond turnover* the following way: we firs compute the monthly trading volume from Trace for all

[7]Note that a company might have somewhat more bonds because Compustat and Mergent FISD data are not perfectly synchronized in time.

bonds outstanding over all bonds of a given reference entity and then take the sum over the previous 12 months. When using the above two measures as a liquidity proxy, we use the rolling average of the preceding 12 months in order to minimize the confounding effect of current trading demand. Our third liquidity measure is *adj. log(bond Herfindahl)* which measures bond market fragmentation at the issuer level adjusted for the dollar amount of bonds an issuer has outstanding. This measure is constructed in the following way: *bond Herfindahl* measures the sum of the squared shares that each bond issue contributes to the overall amount of bonds a limited liability entity (issuer) has issued. It is thus analogous to the Herfindahl index used in industrial organization. In our context, we use the Herfindahl index to measure the fragmentation of a firms total outstanding bonds into separate bond issues. In a similar spirit, Choi et al. (2012) use the Herfindahl index to measure how spread out over time the maturity dates of a firm's bonds are. To adjust for the fact that companies with more bonds outstanding have more issuances, we then run a regression of *log(bond Herfindahl)* on the log of the $ amount of bonds outstanding for the particular issuer. The *adj. log(bond Herfindahl)* is given by the residual of this regression. In calculating the Herfindahl, we exclude companies with only a single bond issue from the adjustment regression, since having one bond issues might reflect a corner solution (lower bound on the number of bond issuances).

For all companies with at least one bond issue identified in the FISD Mergent database, we hand search Bloomberg for *5 year CDS spreads*. We use 5 year CDS spreads because they are the most liquid. For all companies with a CDS spread we then search for fixed-coupon bonds without any embedded options[8] and a remaining maturity of 1 to 10 years. For every issuer we rank these bonds by dollar volume of trade. This enables us to concentrate on the 5 most liquid bond issues of a given company. We then hand-search Bloomberg for the *CDS-bond basis* of these bonds (up to 5), and for every trading day take the average CDS-bond basis of these bonds. Bloomberg calculates this as the difference of the CDS spread (interpolated to the exact remaining time to maturity) and the Z-spread (the yield above the treasury yield of the underlying corporate bond). The monthly *CDS-bond basis*

[8]Thus we exclude all bonds with floating coupon, all bonds that are puttable, redeemable (callable), exchangeable or convertible.

is calculated as an average of all monthly observations (which themselves are averages using up to 5 bonds) in order to reduce noise.

We use IBES earnings analyst forecasts to calculate measures of disagreement. We take monthly data on the two-year earnings per share forecast (since it has the most forecasts). For the *analyst disagreement: std./mean* measure we calculate the standard deviation divided by the mean estimate of 2 year earnings if the mean estimate is above 5 cents per share and there are at least 3 forecasts; *analyst disagreement: std./price* is calculated by dividing the standard deviation of forecasts by the CRSP stock price if the stock price is above one dollar.

After the matching to our CDS data, we also exclude all companies that are subsidiaries. We drop companies with SIC industry code 9995 (non-operating establishments) and companies with no assets. We also drop companies for which we have no SIC codes. To avoid possibly erroneous matches with Capital IQ and Mergent FISD that result in outliers, we filter our matches. We exclude Capital IQ observations for which the total amount of borrowing measured by Capital IQ exceeds the total amount of debt measured by Compustat by more than 50% of assets (measured by Compustat). Similarly we exclude all Mergent FISD observations for which the total amount bonds outstanding measured by Mergent FISD exceeds the total amount of debt measured by Compustat by more than 50% of assets. The results are not sensitive to the exact specification of such data filtering. Companies with SIC code 9997 are hand-assigned to industries.We winsorize all variables computed as ratios at the 99% level. We winsorize the CDS-bond basis at the 5% and 95% level because of outliers but the winsorization does not effect the results. Finally, we drop (quasi) state-owned companies (Fannie Mae, Federal Home Loan Mortgage Corporation, United States Postal Service). These companies have large asset bases but no CDS in DTCC, and thus behave very differently from the regular sample.

In the end, our baseline sample comprises 1798 rated firms in Compustat, out of which 481 are in DTCC. We restrict our baseline sample to companies rated by S&P since we control for credit quality in all regressions. When looking at liquidity measures, we further restrict our sample to rated US companies which have at least one bond issue in Mergent FISD. This restricted sample consists of

1051 firms of which 301 are in DTCC. Our third sample is when we hand-match our data to balance sheet data from Capital IQ. This restricted sample with detailed balance sheet information includes 484 rated Compustat firms, 296 of which have a DTCC entry. Our sample of firms with a CDS-bond basis consists of 56 companies.

5 Empirical Analysis and Results

5.1 Summary Statistics

Table 1 provides summary statistics for our data. The table is split into three parts. First we provide summary statistics for our rated Compustat sample. We then present summary statistics for the subsample of U.S. firms that have at least one bond outstanding in Mergent FISD. We restrict our attention to U.S. firms in Mergent FISD because non-U.S. firms are likely to issue a substantial fraction of their bonds in other jurisdictions and would thus are not be captured in the dataset. Finally, we provide summary statistics for the subset of firms for which we have detailed (annual) balance sheet data from Capital IQ.

Overall, we have data on gross and net notional CDS positions for about 16,520 firm-month observations. The mean gross notional amount of CDS outstanding on a reference entity in our sample is \$14.36bn. The mean net notional amount outstanding is given by \$1.096bn. Hence, on average netting within counterparties reduces the amount of CDS outstanding by a factor of more than ten. The average number of CDS contracts outstanding on firms in our sample is 2,178.

Normalizing the amount of CDS protection bought or sold by either total assets or total debt of the reference entity, we find that the net notional amount of CDS outstanding for the average firm in our DTCC sample is equal to 8.41% of total assets. The 90th percentile of net CDS as a fraction of assets is 20.8%, the 10th percentile 0.7%. When looking at net notional as a fraction of the reference entity's outstanding debt, we find that for the average firm in our sample the amount of net notional outstanding is CDS is equal to 30.0% of the company's debt. Even at the 90th percentile, net notional

CDS outstanding are equal to “only” 69.8% of debt. For companies where we have FISD data on bonds outstanding, the mean ratio of CDS to bonds is 57.1% when only looking at bonds issued directly by that firm, and 48.3% when we consolidate bonds to also include bonds issued by all firms with the same parent. The 90th percentiles given by 125.0% and 110.6%, respectively.

One interesting observation is that while these numbers suggest that significant amounts of credit risk are transferred through the CDS market, the data does not confirm the conventional wisdom that the amounts outstanding in CDS markets usually vastly exceed insurable interest (at least not when looking at the economically more meaningful quantity of net protection bought or sold). For most firms, net notional CDS amounts outstanding are significantly less than their outstanding debt.[9]

Turning to the time series of outstanding CDS amounts, Figure 2 plots the total outstanding gross notional and net notional amounts in single-name CDS over our sample period. Both quantities are relatively stable over our sample period; the gross notional hovers around $15 trillion, while the total net notional amount outstanding is relatively constant (although somewhat decreasing) around $1.5 trillion. Figure 3 digs deeper into the evolution of the total net notional amounts outstanding. The top solid line depicts the total amount of net CDS outstanding on all single-name reference entities, as reported by the DTCC. It thus captures the net notional outstanding in the entire single-name CDS market. The dashed line below the solid line is the total net notional in CDS protection written on the top 1,000 single name entities. Comparing this line to the total single-name CDS market demonstrates that the top 1,000 reference entities make up a large fraction of the overall single-name CDS market, at least when measured in terms of net notional CDS amounts outstanding. The dotted line plots the top 1,000 single name reference entities excluding states and sovereigns. Finally, the dash-dotted line plots the total net notional amounts of outstanding CDSs for rated reference entities that are in our

[9]Nonetheless, there are a few companies for which the amount of net notional of CDS outstanding exceeds debt or the amount of bonds outstanding, sometimes by significant amounts. However, these companies are exceptions. Some of the companies that have high CDS as a fraction of their debt outstanding are potential buyout targets (with low current debt, but potentially large future debt if a leveraged buyout is to take place). Examples from this group are the clothing retailer Gap, or the electronics distributer Arrow Electronics. Other types of companies with high CDS as a fraction of debt are homebuilders, mortgage insurers and suppliers for the automobile industry.

final sample. While we lose some reference entities in the matching process, our matched reference entities still constitute around 40% of the total single-name corporate CDS market.

Finally, Figure 4 plots the ratio of gross notional to net notional CDS amounts outstanding at the reference entity level. The figure illustrates that over our sample period the ratio of gross notional amounts to net notional amounts outstanding increases. This is true for the median ratio of gross to net, but also for the 10th and 90th percentile. This reflects that over our sample period, net positions have been decreasing, while gross positions have remained roughly constant.

5.2 Censoring in the DTCC Data

For single-name CDSs, the DTCC provides weekly position data (gross and net notional) for the top 1,000 traded reference entities in terms of aggregate gross notional amounts outstanding. This implies that there is a censoring issue in the data: We do not observe CDS positions for firms that have gross notional amounts outstanding that are too small to make it into the top 1,000 reference entities.

The censoring issue is illustrated in Figure 6. The figure plots the logarithm of net notional amounts in CDS outstanding as a function of *log assets*. The figure displays the reference entities for which we have CDS position data from the DTCC and the censored observations, for which we do not have CDS position data. In the figure, we set the censored observations to the log of the minimum contract size of $10m. There are two potential reasons why these observations are censored. A censored firm either has CDS traded but does not make it into the top 1,000 reference entities, or the firm is not a traded entity in the CDS market. For some of the censored reference entities we know that a CDS market exists because CDS quotes are available in the same month on Bloomberg. We can thus infer that these firms have gross notional amounts outstanding that lie below the cutoff to the 1,000 largest reference entities.

Not taking into account this censoring problem would result in censoring bias (see, e.g., Wooldridge, 2010). For example, the slope coefficient in on OLS regression of log net CDS on log assets, illustrated in Figure 6, would be biased downward. In our empirical analysis we thus use a censored regression approach that takes into account that firms for which we do not observe CDS position data either are not traded reference entities, or are traded but do not make it into the top 1,000 reference entities.

One complication that arises in adjusting for the censoring problem is that, while our analysis focuses on the net notional outstanding, the DTCC determines the cutoff as to which reference entity makes the top 1,000 list in terms of the gross notional outstanding. Of course, the resulting censoring problem carries over to net notional values: Reference entities that have low gross notional amounts of CDSs outstanding, are also likely to have low net notional amounts outstanding. Hence, because of the cutoff in terms of gross notional outstanding, our data is also likely to leave out reference entities with small amounts of net notional CDS outstanding. However, because the DTCC cutoff is in gross notional, in adjusting for this bias we have to make an assumption on the relation between gross notional and net notional amounts of CDS outstanding.

We make this adjustment by exploiting the empirical relation between gross notional and net notional amounts. This relation is illustrated in Figure 5. The Figure plots a sample histogram of the net notional divided by the gross notional outstanding in a given observation month (December 2009). From Figure 5, we see that on average net notional amounts outstanding that are roughly 9-10% of the gross notional amount outstanding. However, the figure also shows that there is significant variation in this relation across reference entities. To make the adjustment from gross notional to net notional we assume that for companies that are left out of our data because their gross notional amount outstanding are too small, the relation between gross notional and net notional amounts has the same mean and standard deviation as the empirical gross-net relation of firms for which we observe CDS positions (i.e., for December 2009 we would assume that the gross-net relation has the same mean and standard deviation as the distribution depicted in Figure 5).

5.3 Regression Specification

In our regression specification, we focus on the log of the net notional amount of CDS outstanding as our main left-hand side variable. Our regression specification is thus given by

$$y_{i,t} = \log\left(Net\_CDS_{i,t}\right) = \beta \cdot X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where the vector X contains our explanatory variables and a constant, and ϵ is an error term. The reason we chose a log specification instead of normalizing by assets is that Net_CDS does not scale with the size of the company: Large companies typically have very small $\frac{Net\_CDS_{i,t}}{Assets_{i,t}}$ ratios, while this can be high for mid-size companies.

Because of the censoring in the DTCC data, we cannot estimate equation 1 via OLS, since this would bias our results. We thus run a maximum likelihood estimation that corrects for the cutoff in the reference entities that we observe in the data. The likelihood function is constructed as follows. We observe $y_i = \log\left(Net\_CDS_{i,t}\right)$ for all firms for which $y_{i,t}$ exceeds the threshold $\tilde{y}_{i,t}$, where

$$\tilde{y}_{i,t} = \log\left(NetCutoff_t\right) = log(GrossCutoff_t) + \mu_{n2g,t}, \tag{2}$$

where μ_{n2g} is the average observed log(net/gross) in a given month. Given this observation specific censoring cutoff, we can write the likelihood function as:

$$L_t = \prod_{i=1}^{n} \left[\frac{1}{\sigma} \cdot \phi\left(\frac{y_{i,t} - \beta \cdot X_{i,t}}{\sigma}\right)\right]^{d_{i,t}} \cdot \left[\Phi\left(\frac{\tilde{y}_{i,t} - \beta \cdot X_{i,t}}{\sqrt{\sigma^2 + \sigma^2_{n2g,t}}}\right)\right]^{1-d_{i,t}}, \tag{3}$$

where $d_{i,t}$ is an indicator for observing net notional CDS outstanding,

$$d_{i,t} = \begin{cases} 1 & \text{if} \quad y_{i,t} \geq \tilde{y}_{i,t} \\ 0 & \text{if} \quad y_{i,t} < \tilde{y}_{i,t}. \end{cases} \tag{4}$$

X is a vector that contains our explanatory variables and a constant. $\phi(\cdot)$ is the pdf of the standard normal distribution, and $\Phi(\cdot)$ the cdf of the standard normal distribution. This specification assumes that *NetCutoff* is given by the average ratio of net to gross for a given date t plus an error term with the standard deviation equal to the standard deviation of net to gross ratios on that date. In the specification, this additional error term is captured by σ_{n2g}, the standard deviation of the observed log(net/gross) ratio in a given month. Thus in our estimation we assume that log(net/gross) is independent of the explanatory variables. However, adjusting the cutoff for observables characteristic that may influence log(net/gross), for example size and rating, the results are virtually unchanged.

A reference entity may be left out of our data for two reasons. Either the firm is a traded reference entity in the CDS market but the gross notional amount of CDS outstanding is too small to make it into the top 1,000 traded reference entities. Alternatively, the company may not be a traded reference entity at all (i.e., no CDS market exists for this reference entity). This means that the coefficients resulting from the specification (1) are driven both by the existence of a CDS market for a given firm, and its size conditional on existence.

To disentangle these effects, we then run two separate regressions, one investigating the existence of a CDS market, the other investigating the determinants of the size of net CDS positions conditional on existence of a CDS market. We run a probit regression to investigate which firm characteristics are determinants of the emergence of a CDS market for a firm, i.e., whether a firm is a traded reference entity. Existence of a CDS market is defined as being in the DTCC dataset of the largest 1,000 reference entities and/or having a Bloomberg quote. If we see a company in DTCC or Bloomberg at least once in or after 2007, we assume the CDS market exists from then on.[10] Coefficients from this probit regression should isolate, as much as possible, the determinants of CDS market existence.

We then run a censored regression conditional on existence of a CDS market to investigate the determinants of the size of net CDS positions conditional on existence. Here we again run a censored regression, but only using companies for which we know that a CDS market exists. In other words,

[10]The results are similar if we define existence of the CDS market on a monthly basis as having a Bloomberg quote or a DTCC entry in that given month.

companies for which we know that a market exists because they are traded reference entities on Bloomberg but for which we do not observe net notionals outstanding because they are not among the largest 1,000 traded reference entities, are treated as censored observations. The coefficients from this specification should capture the determinants of the amount of net notional outstanding for a reference entity, conditional on a CDS market existing.

In all of our regressions we control for time fixed effects and industry fixed effects using first-digit SIC codes. Because our time series is relatively short and because of the limited time series variation in our data, we do not control for firm fixed effects. Since most of the variation in our data is cross-sectional, firm fixed effects would soak up most of the variation in the data. Thus our results are predominantly driven by the cross-sectional variation between firms.

5.4 Regression Analysis

5.4.1 Baseline Regression

Table 2 reports our baseline specification, based on the DTCC data and Compustat. In this baseline regression we focus on four potential determinants of CDS market existence and position sizes in the CDS market: (i) insurable interest (as measured by size and by the amount of loans, bonds and other obligations outstanding), (ii) speculative trading demand (as measured by disagreement on the firm's earnings prospects), (iii) bond market turnover and bond market fragmentation (the ease with which the firm's bonds can be traded), and (iv) credit quality (as measured by credit ratings).

Table 2 is structured as follows. Column (1) presents the results of a censored regression using all rated firms. As discussed above, coefficients from this regression indicate both whether a certain right hand side variable is associated with existence of a CDS market on a given reference entity, and whether conditional on existence that right hand side variable is associated with larger net notional CDS positions. Columns (2) and (3) disentangle this effect. Column (2) presents the results of a censored regression conditional on a CDS market existing. In other words, we only use reference entities for which we know that a CDS market exists, either because the reference entity is part of the DTCC sample or because CDS quotes are available on Bloomberg. Column (3) presents the results of a probit regression that investigates the existence of CDS markets.[11] Coefficients from this regression show which right hand side variables are associated with a CDS market existing for a given reference entity. Columns (4)-(9) repeat the analysis in columns (1)-(3) for U.S. firms with at least one bond issue in Mergent FISD. Here we also include a number of additional regressors that proxy for the liquidity of the reference entity's bonds and disagreement about the reference entity's earnings prospects to capture speculative motives for CDS trading.

Size and Insurable Interest. We start by investigating the censored regression that uses all the data, shown in column (1). The regression output shows that firms with more assets tend to have more net notional CDS outstanding: The coefficient on *log(assets)* is positive and statistically significant when looking at the entire sample. Second, we see that firms with more debt outstanding (even controlling for size) have more net notional CDS outstanding, as illustrated by the positive and significant coefficient on *log(debt)*.

However, from column (1) we cannot tell whether these effects arise because *log(assets)* and *log(debt)* are associated with more CDS outstanding, or whether they make it more likely that a CDS market on a given reference entity exists. Columns (2) and (3) decompose these two effects. This decomposition reveals that *log(assets)* and *log(debt)* are significant determinants both for the existence of CDS markets and for the size of outstanding net notional CDS positions conditional on CDS market existence.

In columns (4)-(9) we restrict our sample to US firms with at least one bond in FISD Mergent, i.e., firms for which we have detailed data on their bond market. Controlling for the amount of debt, we see that the amount of bonds outstanding on a reference entity, *log(bonds outstanding)*, is associated with larger net notional CDS positions. Comparing columns (8) and (9), we see that the effect is driven both by the fact that CDS markets are more likely to exist for companies that have

[11] Throughout the paper, in the probit regressions we exclude variables that perfectly predict the existence of the CDS market.

more bonds outstanding and by larger CDS positions conditional on existence. Note also that once we include bonds outstanding, *log debt* generally ceases to be a significant predictor of CDS market existence or size.

The positive coefficients on *log(debt)* and on *log(bonds outstanding)* across the different specifications suggest that insurable interest is a significant determinant both of whether a CDS market emerges on a given reference entity, and of the net notional amount of credit risk traded in the CDS market if a CDS market exists. This finding is consistent with Hypothesis H1 and supports the view that (at least some) traders in the CDS market use CDS to hedge existing debt (or bond) exposure.

Speculative Trading Demand. To investigate the role of speculative trading demand, we investigate the role of analyst earnings disagreement. The rationale is that the more traders disagree on a firm's earnings prospects, the more they may want to use the CDS market to take views on credit risk. While disagreement about earnings may not directly translate into disagreement about credit risk, it should still be a reasonable measure, in particular given that no direct measure of disagreement about credit risk is available: Our disagreement measure, which divides earnings-per-share forecast dispersion by the share price, can be interpreted as measuring the size of the firm's equity cushion relative to disagreement on earnings. Note that by dividing through the equity cushion, this measure automatically adjusts for the firm's leverage.

Columns (4), (7), and (8) in Table 2 show that *analyst disagreement: std/price* is associated with more net CDS outstanding for traded reference entities. This implies that given the existence of a CDS market, net positions in the CDS market tend to be larger when there is more disagreement about the reference entity's earnings prospects, lending support to H2, which predicts a positive relation between speculative trading demand and net CDS amounts. However, as we can see from column (9), disagreement is not significant in the probit regression.

Bond Market Liquidity and Fragmentation. Specifications (4)-(9) in Table 2 include a number of additional control variables that proxy for bond market liquidity and bond market fragmentation. The main result here is that, consistent with H3, the fragmentation of a firm's outstanding bonds, *adjusted log(bond Herfindahl)*, is a highly significant determinant of CDS market existence and outstanding CDS amounts given existence.

Recall that the *adjusted log(bond Herfindahl)* measures the fragmentation of a company's outstanding bonds, controlling for the overall dollar amount of bonds issued. It is thus a proxy for how easy it is to trade a firm's bonds controlling for the overall amount of bonds a firm has issued and is not affected by the mechanical relationship between bond liquidity and the overall size of a firm's bond market.[12] The *adjusted log(bond Herfindahl)* is significant in the overall regression, as well as the regression conditional on existence of a CDS market and the probit regression for existence. The strongly negative coefficient in the existence regression suggests that, controlling for the amount of bonds that a firm has outstanding, CDS markets are more likely to emerge when a firm's bond issues are very fragmented (lower *adjusted log(bond Herfindahl)*) and thus hard to trade. The regression conditional on existence of a CDS market suggests that firms that are traded reference entities in the CDS market tend to have more CDSs outstanding if their bonds are very fragmented.

From an economic perspective, this finding supports the argument in Stulz (2009), who points out that "firms have all sort of different bonds whose prices are affected by call provisions, covenants, coupon, maturity, liquidity, and so on; in contrast, CDS are like standardized bonds." Hence, the more fragmented and diverse a company's bonds (which corresponds to a lower value for the firm's *adjusted log(bond Herfindahl)*), the more attractive the CDS market becomes as a venue for hedging or speculation, consistent with our interpretation of CDS markets as alternative trading venues.

Beyond adjusting for the mechanical relationship between the overall amount of bonds issued and liquidity, another advantage of the Herfindahl index relative to other liquidity measures, such as bond turnover or the number of trades, is that it is more likely to be exogenous to trading and hedging demand: Measures of liquidity that rely on turnover or the number of trades confound the effects of

[12]This measure is consistent with empirical evidence in Longstaff et al. (2005) and Mahanti et al. (2008), who document that bond issues of smaller size tend to have lower secondary market liquidity. Hence, keeping the overall amount of bonds issued fixed, firms that split their bonds over multiple smaller issues tend to have less liquid bonds than firms that issue the same amount of bonds as part of one issue. In Table 3 we confirm that the *adjusted log(bond Herfindahl)* is a significant determinant of bond turnover after controlling for a number of other issuer characteristics (including the amount of bonds issued). Hence, less fragmented bond markets (higher Herfindahl) are associated with higher turnover.

the ease of trading and the demand for trading. In fact, this confounding factor may explain why we do not find a significant effect of *bond turnover (last 12 months)* on net CDS amounts outstanding. The confounding effect of trading demand in bond turnover may also explain why turnover is associated with a marginally significantly higher likelihood that a company is a traded entity in the CDS market (i.e., trading demand is associated with the establishment of a CDS market).

Credit Risk. The next set of explanatory variables explores the effect of credit risk, as proxied by credit ratings, on the net notional CDS amount outstanding. To investigate credit quality, we include dummies for ratings classes, such as AA, A, BBB, etc. We use dummies for ratings buckets rather than a numerical rating scale to allow for non-linear and non-monotonic effects of credit quality. The regression does not include a dummy for BB, which is the benchmark case. The dummy coefficients should thus be interpreted as level effects relative to a BB rated firm. We also include a regressor to capture changes in credit quality. Specifically, *lost inv. grade in last 5 years* is a dummy variable that takes value one for reference entities that are not currently investment grade, but were investment grade at some point over the preceding five years.

The analysis of credit quality reveals two main effects. First, we see that firms tend to have more CDSs outstanding when they are closer to the investment grade/non investment grade cutoff. Across the different specifications in Table 2, the coefficients on the ratings dummies are generally increasing when we move from AA or higher towards the investment grade cutoff BBB. The positive coefficient on BBB indicates that reference entities that are just above the investment grade cutoff tend to have more CDSs outstanding than reference entities that are BB, which is the highest credit quality that is not investment grade. Reference entities that are rated B, on the other hand, have similar amounts of CDS outstanding as the benchmark BB firm (the dummy coefficient on ratings class B is not significant). Finally, firms rated CCC or lower have more net CDSs outstanding than the BB benchmark: The coefficients on CCC or lower are generally positive and significant. This may reflect additional hedging demands or speculative trading for firms that are distressed or close to bankruptcy.

In addition to the level of a reference entity's rating, the change in the rating also matters. In particular, the positive and significant coefficient on *lost inv. grade in last 5 years* across all specifications indicates that reference entities that were investment grade at some point, but have lost their investment grade rating, tend to have more CDSs outstanding. This could be driven by the fact that, after loss of investment grade, many investors may decide (or even be required) to hedge their exposure, consistent with H1. We return to this point in Section 5.4.2 below.

Industry Dummies. Finally, Table 2 investigates a number of industry dummies, two of which warrant discussion. First, there is a large amount of net notional CDS protection written on companies that provide credit enhancement. These include monoline insurers and other insurance companies.[13] Most likely, there are more CDS outstanding on companies that provide credit enhancement because investors who rely on insurance from monoline insurance companies and other providers of credit enhancement purchase CDS in order to eliminate their counterparty risk (for a model where CDS are used to insure counterparty risk, see Zawadowski (2011)). In these cases, the protection provided by credit enhancement firms represents an insurable interest that purchasers of this insurance may want to hedge in the CDS market. Anecdotal evidence for such behavior is given by the report of the Financial Crisis Inquiry Commission:[14] In 2007-2008 Goldman Sachs purchased CDS protection on AIG after buying substantial amounts of under-collateralized OTC derivatives on subprime housing from AIG. Once we move to the US sample of FISD firms, the *credit enhancement* dummy is dropped because only a few firms providing credit enhancement have traded stock, which means that we cannot calculate the earnings disagreement or equity turnover variables.

Second, the negative coefficient on the financial industry dummy indicates that, on average, there are less net CDSs outstanding on financial companies than on non-financial companies. Mostly, this effect seems to be driven by smaller, non-systemic financial institutions. This can be seen by the

[13]The list of companies we categorized as providing credit enhancement are: AMBAC, MBIA, Primus Guaranty, Triad Guaranty, Assured Guaranty, XL Group, Radian Group, ACE, Berkshire Hathaway, PMI Group, AIG.

[14]See the supporting document of "The Financial Crisis Inquiry Report" compiled by the FCIC describing the timeline of Goldman's hedges with AIG downloadable from http://fcic-static.law.stanford.edu/cdn_media/fcic-testimony/2010-0701-Goldman-AIG-Collateral-Call-timeline.pdf

positive coefficient on the systemic financial institution dummy which, conditional on existence of a CDS market, roughly cancels out the negative effect of the finance dummy. The systemic dummy takes value one if a certain reference entity belongs to the top 30 systemic financial institutions as ranked by NYU-Stern's mean expected shortfall measure.[15] Finally, looking at the entire sample we find that service companies are less likely to be traded reference entities in the CDS market, as indicated by the negative coefficient on the service dummy in the probit regression.

Economic Magnitudes. The documented effects in our baseline regression are economically meaningful. For example, a coefficient of 0.301 on *log(bonds outstanding)* in column (8) of Table 2 implies that a 10% increase in bonds outstanding (keeping assets fixed) roughly translates into a 3.01% increase in net CDS outstanding. Looking again at column (8) in Table 2, a one-standard deviation increase in disagreement, which proxies for speculative trading demand, increases the amount of net CDS outstanding by $e^{3.352*0.0291} - 1 = 10.2\%$. Looking at the results on credit quality in the same specification (column (8)), we see for a firm with traded CDS loss of investment grade rating within the last 5 years is associated with an increase in the net notional CDS amount of $e^{0.991} - 1 = 169.4\%$. Finally, from the industry dummies we see that financial institutions, on average, have 45.8% less in net notional CDS outstanding (since $-[e^{-0.614} - 1] = -45.8\%$)

.

5.4.2 Hedging, Speculation, and Liquidity

In this section we further investigate the uses of CDSs by linking the effects of hedging and speculation motives in the CDS market to the liquidity of the underlying reference bond. As pointed out in Section 3, investors who hold a reference entity's bonds or are otherwise exposed to the reference entity's credit risk may use CDSs to partially or fully hedge this exposure (H1). Alternatively, investors may use CDSs to take bets: They may purchase naked CDS protection on a reference entity to profit from future deterioration in the reference entity's credit quality, or they may sell CDS protection to other

[15]We use the list as of September 2008, the month before our DTCC sample starts. For details, see http://vlab.stern.nyu.edu/analysis/RISK.WORLDFIN-MR.GMES.

investors such that they profit from future improvements in the reference entity's credit quality. We expect these types of speculative trades to be particularly pronounced when there is more disagreement about the reference entities credit prospects (H2).

Recall that the analysis in the previous section suggested that both hedging needs and speculation are significant determinants of CDS positions. However, both hedging and speculation need not necessarily involve trading in CDSs. A trader who wants to rid himself of the exposure to the credit risk inherent in a particular bond can also simply sell the bond. A speculator who wants to bet that a reference entity's credit is going to deteriorate can simply take a short position in the bond. The effects of hedging and speculation on CDS markets should thus be related to liquidity in the reference entity's bond(s): Because it is possible to take views directly in the underlying or, alternatively, through the CDS market, we expect that the choice of the instrument that is used for speculation depends on how expensive it is to trade directly in the bond market relative to trading the CDS market (H3). Tables 4 and 5 investigate this hypothesis by examining the effect of the liquidity of the underlying bond on the incentives to use the CDS market in order to hedge or speculate.

Liquidity Measures. In order to investigate the impact of bond market illiquidity, we use three measures for bond market liquidity to group companies into three liquidity buckets. Our first liquidity measure is the number of trades in a company's bond in a given year. Given that the number of trades is relatively low for many companies, this measure is similar to that of the number of zero return days measure used in other studies, such as Chen et al. (2007). Our second liquidity measure is the annual turnover in the firm's bonds, which is constructed using the TRACE bond market data. Our third liquidity measure is the *adjusted log(bond Herfindahl)* discussed in the previous section. This proxy is based on the hypothesis that, controlling for the amount of bonds outstanding, a more fragmented bond market is less liquid and makes trading directly in the bond harder. We calculate these three bond liquidity measures using the methodology described in Section 4.2 for each U.S. firm with at least one bond issue in the Mergent FISD dataset. We then sort firms into terciles based these three liquidity measures.

Speculation and Liquidity. Table 4 investigates speculation and liquidity. The results indicate that disagreement, our proxy for speculation, is a stronger determinant of the net notional amount of outstanding CDS for firms whose bonds are not particularly liquid. Specifically, column (2) shows that conditional on existence of a CDS market, increased analyst forecast dispersion is associated with larger net notional amounts of CDS when the underlying bond has low or medium liquidity than when it has high liquidity. This is indicated by the statistically significant and positive coefficients on *low liquidity * disagree* and *medium liquidity * disagree* relative to the benchmark case of high liquidity. The same broad pattern emerges for all three liquidity measures (although when using the Herfindahl index, the effect is strongest for the medium liquidity bucket).[16]

This finding confirms the intuition that more disagreement should go hand in hand with more bets being taken in the CDS market when trading in the underlying bond is costly. This is consistent with the interpretation that when a firm's bond market is liquid, investors are more likely to express their views directly through the bond market, while when the bonds are illiquid and trade infrequently, increased disagreement among investors manifests itself as bets in the CDS market. This corroborates our interpretation of CDS markets as alternative trading venues: CDS markets are more likely to emerge and have larger positions when the bonds of the underlying reference entity are hard to trade, consistent with H3.

Hedging and Liquidity. Table 5 investigates how the CDS market's role as a hedging tool correlates with the liquidity of the reference entity's bonds. In order to proxy for hedging pressure, we look at reference entities that lose investment grade status. This link between loss of investment grade and selling or hedging pressure has been documented, for example, by Acharya et al. (2008) and Feldhütter (2012) in relation to the Ford/GM downgrade of 2005. The reason for selling and hedging pressure in response to a downgrade from investment grade to non-investment grade is that as a company's debt becomes speculative grade, investors may want to, or, in the case of institutional investors with portfolio restrictions, even be required to hedge or offload their exposure.

[16] Note that in contrast to the interaction terms, the dummy coefficients on *medium liquidity* and *low liquidity* cannot be easily interpreted in this regression since the three liquidity samples are different in their basic characteristics (e.g., size).

Recall that in the previous section we found that firms that have lost investment grade status have more CDSs outstanding. This is indicative of investors reducing their exposure to those firms by purchasing CDS protection, either in anticipation or in response to the downgrade. We now use our liquidity proxies to investigate how this effect depends on how easy it is for investors to trade the underlying bond. As with the effects of disagreement on CDS outstanding, we find that this effect is concentrated in firms with less liquid bonds.

In particular, while losing investment grade status is generally associated with higher net notional amounts of CDSs outstanding (the coefficient on *lost inv. grade in last 5 years* is positive and significant across all specifications), the effect of losing investment grade is stronger for firms with less liquid bonds. This is illustrated by the positive and significant coefficient on the interaction term *low liquidity * 5yr lost IG* conditional on CDS market existence in columns (2) and (5). The coefficient is positive but not statistically significant when using the Herfindahl index in column (8). The reason could be that the Herfindahl measure is orthogonal to size and is likely to pick up only a small variation in bond liquidity; thus with only about 20 firms in the sample that have lost IG, we do not obtain statistical significance. Note, however, that even in this case the coefficient of the interaction term is economically significant. Overall, the evidence is thus consistent with the view that investors who wish to reduce their exposure after a downgrade tend to sell their bonds when the market for the bond is liquid, while they tend to use CDSs to hedge their exposure when the market for the downgraded firm's bond is illiquid.

This finding also sharpens our results on credit quality from the previous section. Consider Figure 7, which shows the dummy coefficients for different rating categories and the additional effect of having lost investment grade status. The net notional amount of CDSs outstanding increases as the credit rating deteriorates up to the investment grade cutoff. Once below the investment grade cutoff, on the other hand, the net notional CDS amount for B rated firms is lower than right above the investment grade cutoff, before it increases again for firms rated CCC or lower. This echoes the results on credit quality in Table 2.

However, if a firm used to have investment grade status but has been downgraded to non-investment grade (a so-called fallen angel), it tends to have more CDSs outstanding than firms that have been non-investment grade for all of the 5 preceding years. Figure 7 illustrates this additional effect for each non-investment grade ratings category by adding the interaction term between the underlying bond's liquidity and lost investment grade status to the unconditional ratings dummy. This shows that conditional on having lost investment grade status, firms with more liquid bond markets continue to have a higher level of CDS, comparable to that of investment grade BBB firms. Hence, firms with liquid bonds that used to be investment grade continue to have more CDS outstanding even after losing investment grade status, but there is no clear increase in CDS because of having lost investment grade status. On the other hand, for firms with illiquid bonds, losing investment grade is associated with an *increase* in the amount of CDS outstanding relative to comparable firms right above the investment grade cutoff. This may be the case as for firms with illiquid bonds investors choose to hedge their positions in the CDS market when a firm loses investment grade status, resulting in an increase in the net notional amount of CDS outstanding.

Economic Magnitudes. We again consider a few examples to illustrate the economic size of the effects. Using the number of bond trades as a liquidity measure, we see from Table 4 column (2) that a one standard deviation increase in disagreement increases net CDS by $e^{1.956*0.0291} - 1 = 5.86\%$ for high liquidity companies, which is our benchmark category. For medium liquidity companies, the same increase in disagreement raises net CDS by $e^{(1.956+4.095)*0.0291} - 1 = 19.25\%$. For companies with bonds of low liquidity, a one-standard deviation increase in disagreement raises the net amount of CDS outstanding by $e^{(1.956+14.45)*0.0291} - 1 = 61.2\%$.

Turning to the effect of losing investment grade statues, using the number of bond trades as a liquidity measure, from Table 5 column (2) we see that having been downgraded from investment grade in the last 5 years is associated with an increase in net CDS of $e^{0.801} - 1 = 122.7\%$ for high liquidity companies. For companies with bonds of medium liquidity, losing investment grade status raises net CDS by $e^{0.801+0.228} - 1 = 179.8\%$. and $e^{0.801+1.116} - 1 = 580.0\%$ for companies with low liquidity bonds, illustrating the larger effect of downgrades on net CDSs when the underlying bond market is illiquid.

5.4.3 Which Type of Debt Matters?

Table 6 investigates whether the mix of debt outstanding affects the net notional amount of CDS outstanding, using detailed balance sheet data from Capital IQ. This data allows us to split a firm's debt obligations into finer categorizations such as bonds, commercial paper, capital leases, revolving credit, term loans, trust preferred borrowing, etc. Additionally, we use accounts payable data from Compustat. Because balance sheet information from Capital IQ is only available for a fraction of the companies in our dataset, we can only run this analysis using a smaller sample. Also, the Capital IQ data is annual, which means that we only have four time series observations: 2008-2011.

Table 6 uses a log-log setup, meaning that we regress the log of the net notional amount of CDS outstanding on the log of the different balance sheet items. Before taking logs of each of the debt items, we add 0.1 to each observation. This is necessary, because for this detailed data many observations are zero and we want to avoid taking logs of zero. However, we verified that the exact number added to each observation does not influence our results. As we can see from the summary statistics in Table 1, the three main sources of borrowing for firms are term loans, accounts payable, and bonds.

Across the different specifications (U.S. and International, U.S. firms in FISD, and U.S. firms in FISD with additional controls), the analysis points to two main effects. First, more bonds outstanding are associated with larger net CDS amounts. This confirms the positive effect of *log(bonds outstanding)* in Table 2. This effect is present in all specifications and is driven both by larger CDS positions conditional on existence of a CDS market (see columns (2), (5), and (8)), and a higher likelihood that the issuing firm is a traded reference entity in the CDS market (see columns (3), (6), and (9)). In a similar manner, firms' other borrowing is also a significant determinant both of CDS market existence and net CDS amounts conditional on existence.

Second, we find that firms with more term loans relative to assets on average have smaller net CDS amounts outstanding. In all specifications, this effect arises because more term loans are associated with a smaller probability that a CDS market exists in the first place. However, conditional on existence of a CDS market, term loans are not a significant determinant of CDS positions. This is somewhat counterintuitive as one would expect term loans, such as bank lending, to behave in exactly the same way as other types of insurable interest, as argued in Stulz (2010). However, there are a number of possible explanations for this somewhat surprising finding. First, Minton et al. (2009) also find that few banks use CDS to insure loans and even if they do so, they insure only a small fraction: 2 cents for each dollar of lending. Second, the negative coefficient might be due to firms with term loans being safer, for example, because they face less rollover risk and thus there is less demand for CDS. In a similar manner, trust preferred securities are associated with a smaller likelihood that a company is a traded entity in the CDS market. Third, our data on net amounts of outstanding CDSs only includes CDSs on bonds but not on loans. Hence, it might be the case that lenders use loan CDSs (LCDSs) to offload their credit risk from term loans. However, as of December 2011, the amount of LCDSs registered with the DTCC is small ($7.2bn for American and $1.1bn for European companies).[17]

Hence, overall the effect of insurable interest on the existence and size of CDS markets is driven mainly by bonds and other borrowings. CDS markets are less likely to exist for companies that use term loans or trust preferred securities.

5.4.4 The CDS-Bond Basis

One quantity that has received considerable attention over the last few years (and especially during the financial turmoil of 2008-2009) is the CDS-bond basis. The CDS-bond basis is defined as the CDS spread minus the yield of the underlying bond minus the Treasury rate[18] (or other risk-free rate). No arbitrage implies that the CDS-bond basis should be approximately zero. The reason is that a

[17]The DTCC does not provide an estimate of what fraction of LCDSs are registered in its TIW.
[18]This quantity is also known as the Z-spread.

portfolio consisting of a long bond position and a CDS that insures the default risk of the bond should yield the risk-free rate. While the CDS-bond basis should be exactly equal to zero only if certain assumptions hold (see Duffie, 1999), absent limits-to-arbitrage frictions it should be approximately zero in practice.[19]

During the recent financial crisis, the CDS-bond basis became significantly negative for many reference entities as documented, for example, by Bai and Collin-Dufresne (2010) and Fontana (2011). A negative CDS-bond basis means that the CDS spread is lower than the spread over the risk-free rate on the underlying bond. Intuitively speaking, this implies that one can earn a higher spread on the bond than it costs to insure the default risk of the bond in the CDS market. This gives rise to the so-called negative basis trade, in which a trader buys the underlying bond and purchases credit protection on the bond in the CDS market to profit from the relative mispricing between the two markets. Because the arbitrage trade involves a long position in the CDS, if arbitrageurs seek to profit from a negative CDS-bond basis, such a negative basis should be associated with larger net notional CDS positions outstanding. Similarly, in a positive basis trade a trader would short the reference bond and sell credit protection on the bond to profit from the relative mispricing, thus also increasing net outstanding CDS amounts.

We investigate the role of the CDS-bond basis on net notional amounts outstanding in the CDS market in Table 7. We run a similar regression as before, but include the CDS-bond basis as a right hand side variable. We use the CDS-bond basis as calculated by Bloomberg. To be conservative, we eliminate bonds with embedded options (puttable, callable, redeemable) and end up with data on the CDS-bond basis data for 56 companies. Note that because of the significantly smaller sample, the regressions in Table 7 include fewer control variables than our baseline regressions above.

Column (1) in Table 7 shows that deviations of the CDS-bond basis from zero (i.e., the absolute value of the CDS-bond basis) are associated with more net notional in CDS outstanding, as predicted by the arbitrage trade required to profit from a negative or positive basis. The significant positive

[19]In practice, the CDS-bond basis has historically been slightly positive for technical reasons, such as imperfections in the repo market and the cheapest-to-deliver option (see JPMorgan, 2006).

coefficient on the absolute value of the CDS-bond basis implies that, unconditionally, a deviation of the basis from zero is associated with larger net notional CDS amounts outstanding.

Column (2) decomposes the effect of the CDS-bond basis by examining negative and positive CDS-bond bases separately. The results in Column (2) indicate that the effect of the CDS-bond basis is asymmetric. While a negative CDS-bond basis is associated with a statistically significant increase in net notional CDS outstanding, the coefficient on the positive CDS-bond basis is smaller (even negative) and not statistically significant. While this could partially be driven by lack of data (during our sample period, significant positive CDS-bond bases are rare), the result suggests that there is an asymmetry in the effect of negative and positive CDS-bond bases on net notional amounts of CDS outstanding. One interpretation of this asymmetry is that profiting from a positive CDS-bond basis requires short-selling the bond, which is often difficult and costly. Trading against a negative CDS-bond basis, on the other hand, does not require short-selling the bond. This may explain why arbitrageurs trade less aggressively against a positive CDS-bond basis. Consistent with this interpretation, Blanco et al. (2005) argue that the difficulty of shorting bonds may be one of the reasons why during normal times (i.e., prior to the financial crisis) the CDS-bond basis has usually been slightly positive.

In terms of economic magnitudes, column (2) in Table 7 indicates that for bonds with a negative basis, a one standard deviation decrease in the basis (i.e., a more negative basis of 118 basis points) is associated with an increase in net notional CDS outstanding of $e^{0.239*1.189} - 1 = 32.9\%$.

To the extent that the significant coefficient on the negative CDS-bond basis reflects arbitrage activity, this result points to another potential economic function of CDS markets. By allowing arbitrageurs to lean against mispricing in the bond market, CDS markets may help to compress spreads for bond issuers. Hence, the presence of CDSs may improve firms' access to financing. This interpretation echoes the arguments in Saretto and Tookes (2013), who document that the presence of CDSs allows firms to borrow more and at longer maturities. Interestingly, while a negative basis is associated with larger net amounts of CDSs outstanding, the same is not true for a positive basis (which gives rise to a similar arbitrage trade). This asymmetry could be driven by short-selling constraints in the underlying bond.

6 Robustness

We have performed a battery of robustness checks to corroborate our main results. First, we reran our analysis explicitly controlling for membership of reference entities in the major CDS indices, specifically the CDX.NA.IG (the investment grade CDX index), the CDX.NA.HY (the high yield CDX index), and the iTraxx Europe index. Our results remain significant and economically similar when controlling for CDS index membership. One additional finding from the specification that controls for index membership is reference entities that are in the CDX or iTraxx have more net notional amounts in CDS outstanding than reference entities that are not part of these indices. This result is intuitive for two reasons. First, reference entities with larger outstanding CDS amounts are more likely to be selected for index membership. Second, once part of the CDX or iTraxx, these individual reference entities may become more heavily traded in their single-name CDS, for examples as market participants hedge exposure to or replicate those indices using single-name CDS.

Second, we replicated our results using alternative measures for disagreement. Specifically, we replace our main proxy for disagreement (the dispersion of analyst forecasts scaled by price) with two alternative measures (the dispersion of analyst forecasts scaled by their mean, equity turnover). Also in this case, our main results remain qualitatively unchanged and statistically significant.

Finally, we also check that our main results also carry through when we look directly at the net notional amount of CDS as our left-hand side variable, as opposed to *log(net CDS)*, which we used in our main specification.

These robustness tables can be found in the online appendix. Specifically, Tables A.1 and A.2 replicate our baseline regression controlling for CDS index membership and using net CDS as the dependent variable. Tables A.3, A.4, A.5, and A.6 regenerate our results on disagreement and bond market liquidity using alternative disagreement measures, controlling for CDS index membership, and using net CDS as the dependent variable. Tables A.7 and A.8 repeats the analysis of losing investment grade and bond liquidity using net CDS as the dependent variable and controlling for CDS index membership. Tables A.9 and A.10 repeat the detailed debt structure analysis using net CDS as the dependent variable and controlling for CDS index membership. Finally, Table A.11 and repeats the analysis of the effect of the CDS-bond basis on the log of net CDS outstanding controlling for CDX membership and using net CDS as the dependent variable.

7 Conclusion

This paper investigates the economic role of the CDS market by analyzing the determinants of the amount credit protection bought (or equivalently sold) in the market for credit default swaps (CDSs). Combining novel data on net notional CDS positions outstanding from the Depository Trust & Clearing Corporation (DTCC) with a number of other data sources, our results suggest that CDS markets function as alternative trading venues for both hedging and speculation on the underlying bond. They are alternative trading venues in the sense that investor could often make the same economic trade directly in the underlying bond, but choose to use the CDS market. This interpretation of CDS markets as alternative trading venues is supported by the finding that CDS markets more likely to emerge when the underlying bonds of the firm are illiquid and thus hard or expensive to trade. Similarly, conditional on a CDS market existing for a reference entity, the positions taken in the CDS market are larger when the underlying bond is illiquid. Finally, firms which have a more negative CDS-bond basis (i.e., the bond is undervalued relative to the CDS) have larger amounts of CDSs outstanding, suggesting that arbitrageurs use the CDS market to lean against potential misplacing in the bond market. By allowing arbitrageurs to lean against mispricing in the bond market, CDS markets may thus help to compress spreads for bond issuers. Through this channel, the presence of CDSs may improve firms' access to financing.

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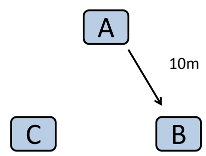
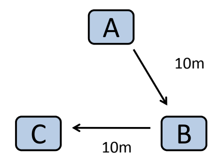
Example (a): Gross and net notional positions



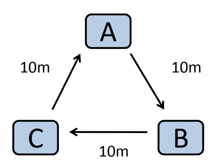
	Gross CDS bought	Gross CDS sold	Net CDS
A	0	10	(10)
B	10	0	10
C	0	0	0
Total	**Gross Notional Bought =10**	**Gross Notional Sold =10**	**Net Notional Bought/Sold=10**

Example (b): Gross and net notional positions



	Gross CDS bought	Gross CDS sold	Net CDS
A	0	10	(10)
B	10	10	0
C	10	0	10
Total	**Gross Notional Bought =20**	**Gross Notional Sold =20**	**Net Notional Bought/Sold=10**

Example (c): Gross and net notional positions



	Gross CDS bought	Gross CDS sold	Net CDS
A	10	10	0
B	10	10	0
C	10	10	0
Total	**Gross Notional Bought =30**	**Gross Notional Sold =30**	**Net Notional Bought/Sold=0**

Figure 1: **Gross Notional vs. Net Notional Amounts**

The figure illustrates the difference between gross notional and net notional amounts in the DTCC data. In Example (a), B has purchased \$10m in protection from A. Both the gross notional and the net notional amount outstanding are \$10m. In Example (b), B offsets the initial trade by selling \$10m in protection to C. This raises the gross notional amount to \$20m. The net notional amount remains at \$10m. In Example (c), C sells \$10m in protection to A, such that all three parties have a net zero position. The gross notional is now \$30m, but because all net positions are zero, the net notional is \$0.

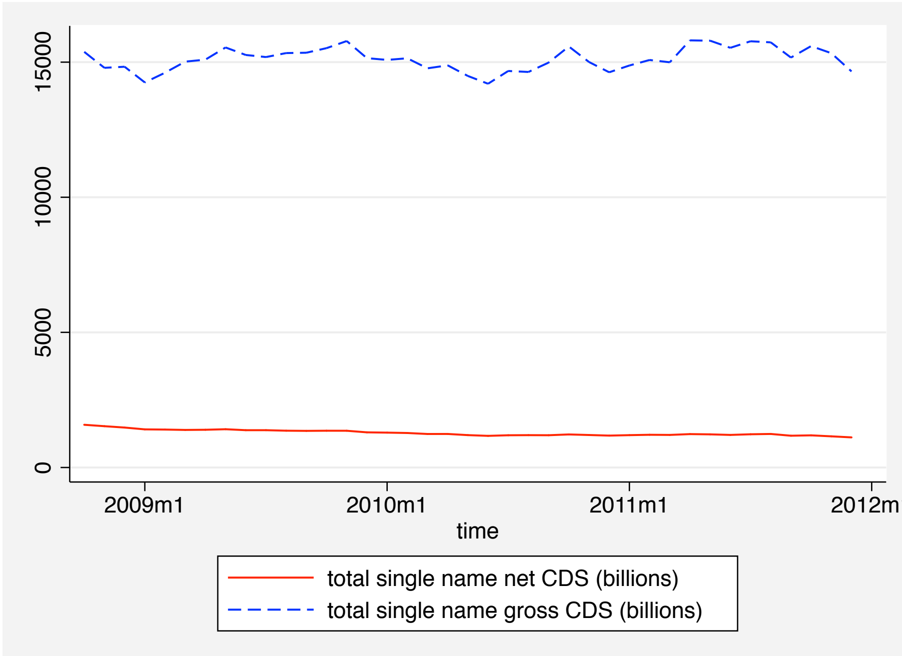


Figure 2: **Single-name CDS gross and net notional outstanding over time**

The figure plots the total gross notional and net notional CDS amounts outstanding on all single-name reference entities, as reported by the DTCC.

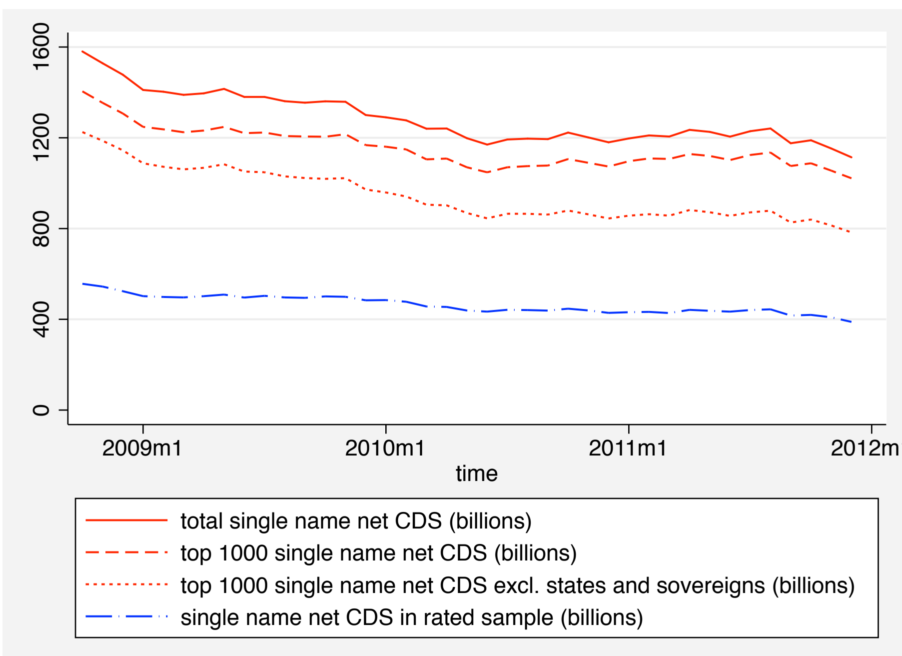


Figure 3: **Single-name CDS net notional outstanding over time**

The top solid line plots the total amount of net CDS outstanding on all single-name reference entities, as reported by DTCC. It thus captures the net notional outstanding in the entire single-name CDS market. The dashed line below the solid line is the net total net notional in CDS protection written on the top 1,000 single name entities. Comparing this line to the total single-name CDS market demonstrates that the top 1,000 reference entities make up almost the entire single-name CDS market when measured in terms of net notional outstanding. The dash-dotted blue line plots the total net notional amounts of outstanding CDSs for the reference entities that we managed to match uniquely with a rated Compustat firm.

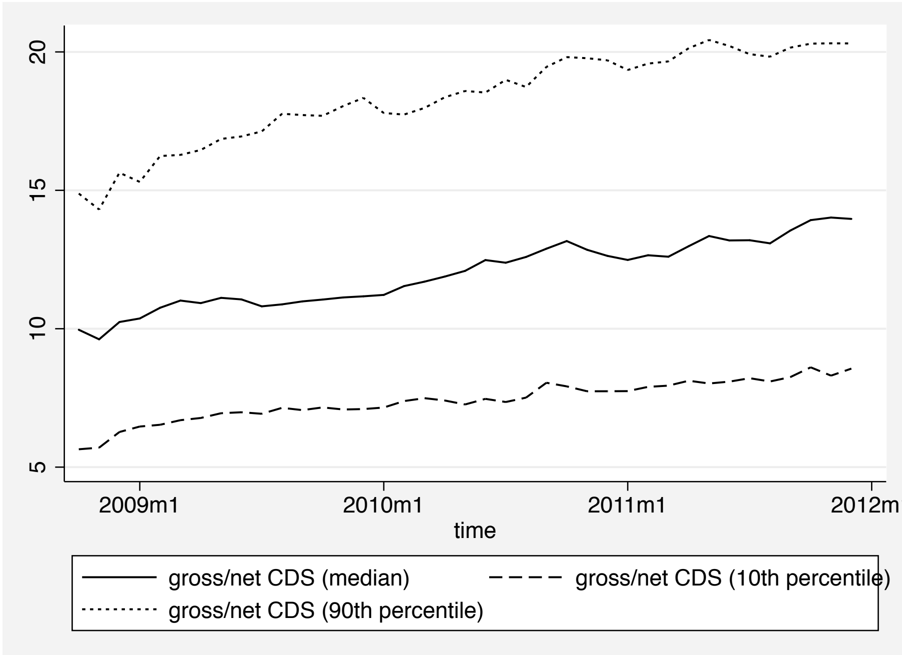


Figure 4: **Gross to net CDS over time**

The figure plots the ratio of gross to net amounts in CDS outstanding over time. While overall positions in CDS markets decline over our sample, the ratio of gross to net increases. This is true for the median ratio of gross to net, but also for the 10th and 90th percentile. Hence, net positions have been decreasing faster than gross positions.

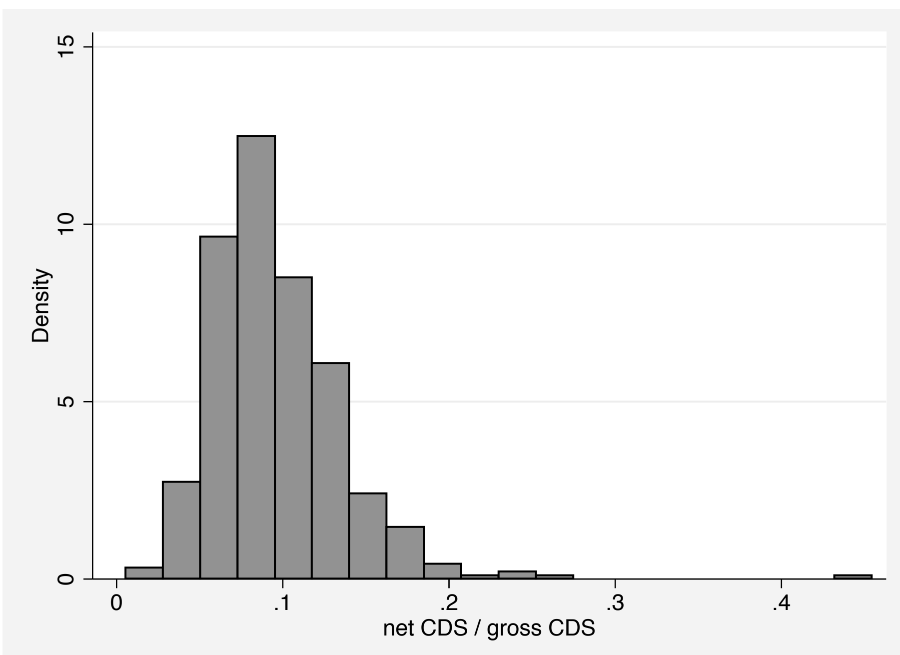


Figure 5: **Gross Notional vs. Net Notional Amounts**

This figure plots the empirical density of the ratio of the net notional amount outstanding to the gross notional amounts outstanding for single-name CDS contracts in the DTCC data for December 2009.

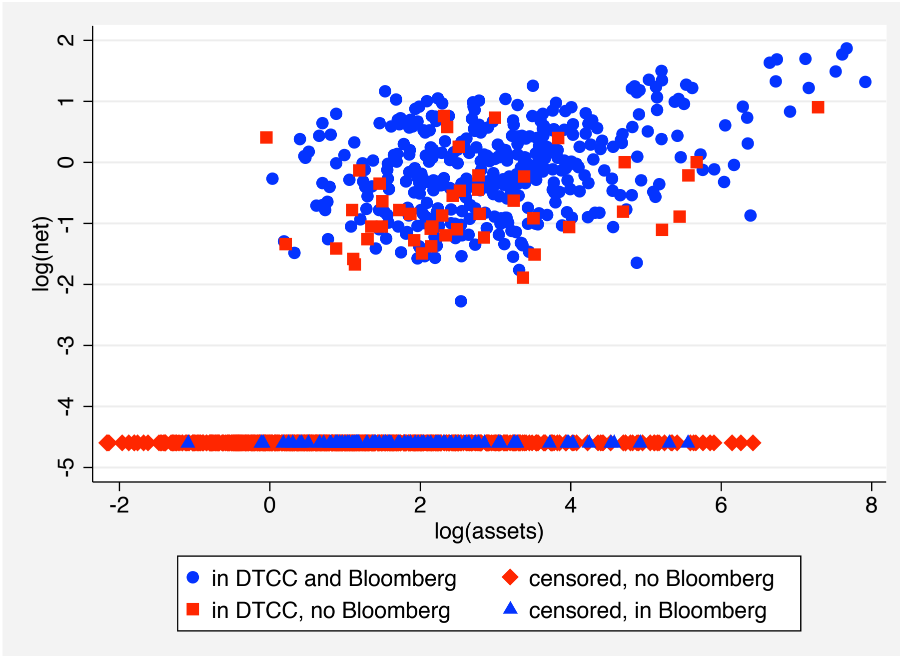


Figure 6: **Net CDS and firm size**

This figure illustrates the censoring and market existence issues in our data for Compustat firms rated by S&P for December 2009. The shape of the marker indicates whether we can locate a certain reference entity (i) as one of the 1,000 largest reference entities as provided by the DTCC and (ii) as a reference entity for which we can find at least one price quote in Bloomberg. For reference entities that we observe in the DTCC data set and/or for which we can find Bloomberg quotes we know that a CDS market exists. If a reference entity is in Bloomberg but not in DTCC we know that it is censored, i.e., a CDS market exists but we do not observe the net notional outstanding. Reference entities that we cannot locate in Bloomberg or DTCC are censored and we do not know whether a CDS market exists for those reference entities. Censored reference entities have been set to the log of the minimum contract size of \$10m, i.e., $log(0.01) \approx -4.61$

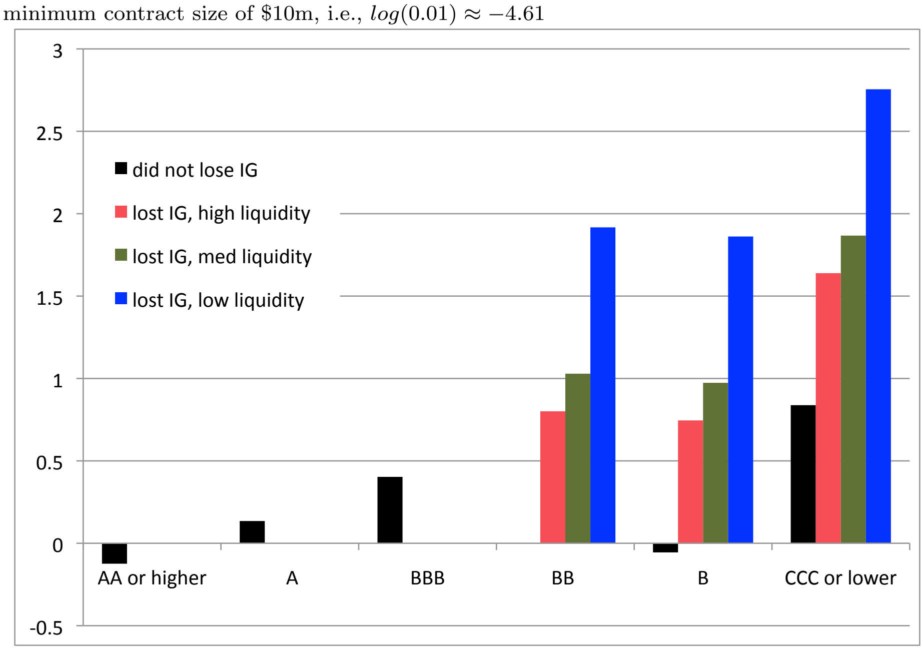


Figure 7: **Effect of ratings and losing investment grade status**

The figure depicts the dummy variables on ratings for the regression in column (5) of Table 5. The black bars are the unconditional dummy coefficients. The other three bars are the coefficients conditionally on having lost investment grade split by the liquidity of the bond market based on the bond turnover measure.

Table 1: **Summary Statistics**

This table presents summary statistics for monthly data from October 2008 to December 2011 for all Compustat companies above 100 million of assets and rated by S&P. *assets* is total assets and *debt* is total long and short-term debt from Compustat. Quarterly data from Compustat is converted into monthly. *net CDS*, *gross CDS*, and *number of CDS* are the net and gross notional amount, and number of CDS outstanding respectively as reported by the DTCC. The last weekly DTCC observation each month is used. *accounts payable* is from Compustat and set to zero for financials. *S&P rating (notch)* captures a firm's S&P rating; it takes value 1 for AAA, 2 for AA+ etc. The maximum value, 22, indicates that the bond has defaulted. *S&P rating change* is defined as the number of notches by which a bond was upgraded (negative values) or downgraded (positive values) over the last 12 months. When S&P rating takes a value between 1 and 10, the corresponding bond is investment grade. *lost investment grade last 5 years* is an indicator variable that takes value one if a company lost its investment grade rating in the last 5 year. *number of trades (last 12 months)* is total number of trades registered in Trace for all bonds in Mergent FISD of a specific company over the preceding 12 months. *annual bond turnover (last 12 months)* is total bond trading volume from Trace for all bonds of a company in Mergent FISD divided by total bonds outstanding over the preceding 12 months. *analyst disagreement: std/price* is defined as the standard deviation of analyst earnings forecast from IBES normalized by stock price. *analyst disagreement: std/abs(mean)* is defined as the standard deviation of analysts earnings forecasts normalized by the mean analyst forecast. *commercial paper*, *other borrowing*, *capital lease*, *revolving credit*, *term loans* and *trust preferred borrowing* are annual data from the detailed balance sheet data from Capital IQ and normalized by total assets from Compustat. *issuer bonds outstanding* is the total amount of bonds outstanding of the issuing entity in from Mergent FISD, while *consolidated bonds outstanding* is the total amount of bonds issued by all entities belonging to the same ultimate parent. All dollar amounts in billions, ratios winsorized at the 1% level.

All Compustat firms rated by S&P:

VARIABLES	N	mean	std	p10	p50	p90
assets (USD billions)	58,035	33.33	151.2	0.806	4.847	48.35
net CDS (USD billions)	16,523	1.096	0.897	0.320	0.851	2.080
gross CDS (USD billions)	16,525	14.36	13.56	2.847	10.08	29.47
number of CDS	16,525	2,178	1,518	573	1,843	4,184
net CDS / assets	16,523	0.0841	0.125	0.00701	0.0382	0.208
net CDS / debt	16,394	0.300	0.461	0.0340	0.150	0.698
book leverage	58,035	0.336	0.232	0.0702	0.306	0.617
accounts payable / assets	58,035	0.0623	0.0697	0	0.0425	0.152
S&P rating (notch)	58,035	10.62	3.632	6	10	15
S&P rating change last year	58,035	0.109	1.026	-1	0	1
investment grade	58,035	0.525	0.499	0	1	1
lost inv. grade in last 5 years	58,035	0.0629	0.243	0	0	0
disagree: analyst std/price	40,404	0.0154	0.0291	0.00181	0.00686	0.0332
disagree: analyst std/abs(mean)	38,895	0.167	0.271	0.0253	0.0828	0.356

US firms conditional on having at least one bond in Mergent FISD:

VARIABLES	N	mean	std	p10	p50	p90
net CDS (USD billions)	10,192	1.018	0.840	0.327	0.785	1.908
net CDS / assets	10,192	0.103	0.130	0.0114	0.0523	0.259
net CDS / issuer bonds (FISD)	9,961	0.570	0.832	0.0916	0.303	1.245
net CDS / consol'd bonds (FISD)	10,043	0.482	0.714	0.0678	0.242	1.104
5y CDS spread (bps)	11,792	268.5	490.3	49.65	132.8	571.4
CDS-bond basis (mly avg, %)	1,773	-.8344	1.189	-2.141	-.6379	.2354
assets (USD billions)	34,536	22.57	111.7	0.872	4.367	34.05
issuer bonds outstanding / assets	32,756	0.216	0.178	0.0272	0.184	0.434
cons'd bonds out. / assets	32,756	0.264	0.312	0.0525	0.214	0.488
S&P rating (notch)	34,536	10.91	3.475	6	11	15
S&P rating change last year	34,536	0.114	1.021	-1	0	1
investment grade	34,536	0.495	0.500	0	0	1
lost inv. grade in last 5 years	34,536	0.0709	0.257	0	0	0
bond turnover (monthly)	32,756	0.0361	0.0388	0	0.0265	0.0825
bond turnover (last 12 months)	30,206	0.442	0.357	0.0455	0.374	0.894
number of trades (last 12 months)	30,206	4,381	16,656	30	764	8,111
issuer bond Herfindahl	32,756	0.517	0.347	0.115	0.455	1
equity turnover (monthly)	32,574	2.706	2.154	0.896	2.106	5.136
disagree: analyst std/price	30,103	0.0154	0.0302	0.00174	0.00658	0.0327

Firms in Capital IQ (annual observations):

VARIABLES	N	mean	std	p10	p50	p90
assets (USD billions)	1,742	99.04	263.4	11.79	28.77	190.8
net CDS (USD billions)	1,042	1.222	1.000	0.347	0.940	2.320
net CDS / bonds	1,038	0.256	0.424	0.0389	0.147	0.518
bonds / assets	1,742	0.160	0.142	0.0146	0.128	0.344
accounts payable / assets	1,742	0.0576	0.0755	0	0.0353	0.155
term loans / assets	1,742	0.0413	0.0781	0	0.00298	0.138
commercial paper / assets	1,742	0.00805	0.0201	0	0	0.0274
other borrowing / assets	1,742	0.0206	0.0458	0	0.00212	0.0598
capital lease / assets	1,742	0.00331	0.00833	0	2.01e-05	0.0102
revolving credit / assets	1,742	0.00951	0.0234	0	0	0.0299
trust preferred / assets	1,742	0.00154	0.00443	0	0	0.00614

Table 2: **Baseline Results**

This table presents the determinants of the size and existence of the CDS market using Compustat companies with S&P ratings. Columns (1)-(3) use all rated companies; columns (3)-(9) only US companies with at least one bond issue in Mergent FISD. Within every sample the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the middle column(s) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the last column runs a probit regression on a dummy variable indicating the existence of a CDS market. *credit enhancement* is an indicator dummy that is one for firms that provide credit enhancement. *systemic* is a dummy for the top 30 most systemic financial institutions. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	Baseline: US and international			US firms in FISD					
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) if exist	(7) if exist	(8) if exist	(9) probit
log(assets)	0.443***	0.172***	0.339***	0.391***	0.206***	0.276***	0.190**	0.244***	0.250**
	(5.32)	(2.87)	(5.61)	(3.81)	(2.67)	(3.54)	(2.47)	(3.08)	(2.33)
log(debt)	0.513***	0.333***	0.217***	-0.147	0.0524	0.0373	0.0967	0.0718	-0.192
	(7.22)	(6.37)	(4.22)	(-1.23)	(0.60)	(0.42)	(1.13)	(0.74)	(-1.60)
log(bonds outstanding)				0.559***	0.392***	0.302***	0.385***	0.301***	0.501***
				(3.56)	(6.09)	(3.74)	(5.86)	(2.62)	(3.13)
log(consol'd bonds outstanding)				0.227				0.0119	0.215
				(1.24)				(0.09)	(1.15)
bond turnover (last 12 months)				0.264	0.00340			0.0303	0.328*
				(1.52)	(0.02)			(0.19)	(1.94)
adj. log(bond Herfindahl)				-0.645***		-0.347***		-0.313***	-0.559***
				(-4.50)		(-2.88)		(-2.58)	(-3.59)
disagree: analyst std/price				4.046***			3.746***	3.352***	1.224
				(3.67)			(4.36)	(3.94)	(1.07)
AA or higher rating	0.108	-0.280	0.289	-0.0123	-0.303	-0.341	-0.259	-0.249	0.283
	(0.40)	(-1.46)	(1.31)	(-0.04)	(-1.44)	(-1.61)	(-1.23)	(-1.12)	(0.72)
A rating	0.907***	0.116	0.764***	0.457*	-0.0813	-0.0843	-0.00278	0.0270	0.651***
	(4.66)	(0.80)	(5.53)	(1.76)	(-0.45)	(-0.47)	(-0.02)	(0.14)	(2.91)
BBB rating	1.149***	0.358***	0.854***	0.866***	0.184	0.163	0.259*	0.262*	1.002***
	(6.92)	(2.65)	(7.76)	(4.24)	(1.26)	(1.10)	(1.74)	(1.66)	(5.71)
B rating	0.0324	-0.156	0.0743	0.0961	-0.0580	-0.0495	-0.0884	-0.0562	0.172
	(0.20)	(-1.15)	(0.70)	(0.53)	(-0.39)	(-0.35)	(-0.58)	(-0.37)	(1.06)
CCC or lower rating	0.359	0.152	0.237	1.335***	0.627**	0.723**	0.803***	0.851***	0.786***
	(1.10)	(0.52)	(1.28)	(4.87)	(2.02)	(2.46)	(4.26)	(4.73)	(2.91)
lost inv. grade in last 5 years	1.926***	0.862***	1.268***	1.919***	0.924***	0.951***	0.963***	0.991***	1.570***
	(9.42)	(5.81)	(8.50)	(8.75)	(5.55)	(6.04)	(5.82)	(5.65)	(6.86)
credit enhancement (dummy)	3.276***	1.789***	perfect +						
	(6.05)	(6.16)	(omitted)						
systemic	0.578*	0.560***	perfect +						
	(1.71)	(2.58)	(omitted)						
industry: finance	-1.920***	-0.606***	-1.300***	-1.404***	-0.495***	-0.583***	-0.533***	-0.614***	-1.129***
	(-10.96)	(-5.08)	(-10.00)	(-6.57)	(-3.40)	(-3.80)	(-3.64)	(-3.97)	(-5.63)
industry: agricultural	0.253	-0.225	0.215	0.535	0.0295	-0.0208	0.263*	0.184	0.253
	(0.47)	(-0.64)	(0.47)	(0.63)	(0.22)	(-0.16)	(1.76)	(1.12)	(0.27)
industry: service	-0.369***	-0.0864	-0.384***	-0.214	-0.0541	-0.0355	-0.0403	-0.0523	-0.259*
	(-3.11)	(-0.95)	(-4.35)	(-1.43)	(-0.47)	(-0.31)	(-0.34)	(-0.43)	(-1.75)
industry: cons. & mining	0.0742	-0.0176	-0.0287	-0.165	-0.0373	-0.0459	-0.0976	-0.118	-0.163
	(0.43)	(-0.14)	(-0.22)	(-0.89)	(-0.28)	(-0.34)	(-0.72)	(-0.85)	(-0.77)
Constant	-3.894***	-1.473***	-1.284***	-2.889***	-1.232***	-1.307***	-1.365***	-1.402***	-0.802***
	(-20.87)	(-9.52)	(-10.96)	(-11.22)	(-6.57)	(-7.33)	(-7.45)	(-6.76)	(-3.62)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	1784	609	1784	685	378	355	360	335	685
Number of Observations	57220	21095	57220	19966	12767	11967	12152	11101	19966

Table 3: **Determinants of Bond and Equity Turnover**

This table presents the results of a tobit regression of bond turnover (left column in each pair) and equity turnover (right column in pair) using S&P rated US companies in Compustat for which we have at least one bond issue in Mergent FISD. A tobit approach is used to account for the fact that turnover is bounded from below by zero. Columns (1)-(2) use *disagreement: std/price* as a measure of disagreement; (3)-(4) use *disagreement: std/abs(mean)* as a measure of disagreement; (5)-(6) use *disagreement: std* (unscaled) as a measure of disagreement; while (7) uses *equity turnover* as a measure of disagreement. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	disagree: analyst std/price		disagree: analyst std/abs(mean)		disagree: equity turnover
	(1) bonds	(2) equity	(3) bonds	(4) equity	(5) bonds
log(bonds outstanding)	0.00779***	0.163	0.00791***	0.177*	0.00687***
	(5.19)	(1.60)	(5.75)	(1.94)	(4.82)
adj. log(bond Herfindahl)	0.0162***	-0.0447	0.0159***	-0.0134	0.0161***
	(6.63)	(-0.37)	(6.60)	(-0.12)	(6.82)
disagree: analyst std/price	0.0455*	14.54***			
	(1.84)	(5.52)			
disagree: analyst std/abs(mean)			0.00478*	1.487***	
			(1.84)	(6.51)	
equity turnover (monthly)					0.00336***
					(8.36)
log(assets)	0.00482***	0.254**	0.00482***	0.261***	0.00397**
	(2.85)	(2.56)	(2.75)	(2.65)	(2.51)
log(debt)	-0.00204	-0.112	-0.00188	-0.128	-0.00163
	(-1.07)	(-0.98)	(-0.95)	(-1.21)	(-0.90)
AA or higher rating	-0.0115***	-2.394***	-0.0126***	-2.315***	-0.00232
	(-2.64)	(-9.11)	(-2.84)	(-8.75)	(-0.57)
A rating	-0.0118***	-1.678***	-0.0127***	-1.592***	-0.00549**
	(-4.05)	(-8.17)	(-4.19)	(-7.79)	(-2.02)
BBB rating	-0.00154	-0.943***	-0.00252	-0.919***	0.00223
	(-0.61)	(-5.76)	(-0.98)	(-5.61)	(0.95)
B rating	0.00701***	0.163	0.00735***	0.210	0.00534**
	(2.71)	(0.73)	(2.77)	(0.90)	(2.12)
CCC or lower rating	0.0151**	2.195***	0.0203*	1.365**	0.00985
	(2.03)	(3.86)	(1.89)	(2.18)	(1.44)
Constant	0.0252***	4.889***	0.0266***	4.827***	0.00797**
	(7.20)	(20.83)	(7.57)	(22.08)	(2.21)
time fixed effects	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes
Number of Firms	710	710	697	696	752
Number of Observations	20664	20664	19466	19423	21921

Table 4: **Disagreement and Bond Market Liquidity**

This table presents the effect of the interaction of disagreement and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure, the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * disagree* and *low liquidity * disagree* measure the additional effect of disagreement on medium and low liquidity companies beyond the unconditional effect measured by *analyst disagreement: std/price*. In the interaction terms *disagree* refers to *analyst disagreement: std/price*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
disagree: analyst std/price	2.785**	1.956***	0.997	4.224***	2.712***	2.092*	0.0545	0.809	-0.329
	(2.55)	(2.60)	(0.72)	(3.83)	(3.13)	(1.88)	(0.02)	(0.43)	(-0.14)
medium liquidity * disagree	3.033	4.095***	0.448	0.268	2.413**	-2.156	5.998**	5.052**	1.141
	(1.52)	(2.65)	(0.25)	(0.18)	(2.38)	(-1.47)	(2.12)	(2.37)	(0.42)
low liquidity * disagree	5.124*	14.45***	-0.941	3.812	5.664**	0.420	3.505	1.226	2.886
	(1.65)	(4.03)	(-0.39)	(1.42)	(2.36)	(0.18)	(1.33)	(0.60)	(0.94)
lost inv. grade in last 5 years	2.084***	1.004***	1.676***	2.039***	0.941***	1.577***	1.889***	0.968***	1.507***
	(9.35)	(5.87)	(7.98)	(8.94)	(5.38)	(7.71)	(8.77)	(5.74)	(6.66)
medium liquidity (dummy)	-0.549***	-0.210*	-0.483***	0.262***	0.0507	0.304***	0.330**	0.0304	0.441***
	(-3.95)	(-1.83)	(-4.00)	(2.58)	(0.64)	(3.17)	(2.40)	(0.28)	(3.58)
low liquidity (dummy)	-1.325***	-0.811***	-0.839***	-0.236	-0.204	-0.0557	0.544***	0.216*	0.579***
	(-6.58)	(-4.02)	(-5.03)	(-1.50)	(-1.58)	(-0.44)	(3.53)	(1.77)	(3.82)
log(assets)	0.275***	0.174**	0.190**	0.344***	0.188**	0.254***	0.399***	0.222***	0.265***
	(2.88)	(2.35)	(2.03)	(3.46)	(2.49)	(2.77)	(3.96)	(2.92)	(2.60)
log(debt)	0.0331	0.129	-0.0149	0.0122	0.109	-0.0140	-0.0407	0.0950	-0.0871
	(0.31)	(1.50)	(-0.16)	(0.11)	(1.28)	(-0.15)	(-0.36)	(1.06)	(-0.78)
log(bonds outstanding)	0.537***	0.267***	0.349***	0.778***	0.359***	0.514***	0.712***	0.314***	0.637***
	(5.42)	(3.81)	(3.79)	(8.37)	(5.45)	(6.11)	(6.37)	(3.81)	(6.24)
AA or higher rating	0.272	-0.172	0.567	0.000976	-0.265	0.285	-0.0542	-0.252	0.238
	(0.90)	(-0.83)	(1.60)	(0.00)	(-1.26)	(0.80)	(-0.17)	(-1.16)	(0.61)
A rating	0.700***	0.0865	0.893***	0.524**	-0.00164	0.706***	0.430*	0.0127	0.604***
	(2.90)	(0.48)	(4.41)	(2.05)	(-0.01)	(3.55)	(1.70)	(0.07)	(2.79)
BBB rating	1.107***	0.347**	1.164***	1.003***	0.266*	1.024***	0.883***	0.263*	0.974***
	(5.60)	(2.29)	(7.16)	(4.96)	(1.75)	(6.63)	(4.38)	(1.67)	(5.78)
B rating	0.0404	-0.0868	0.118	0.0905	-0.0973	0.160	0.124	-0.0478	0.196
	(0.22)	(-0.57)	(0.80)	(0.50)	(-0.63)	(1.16)	(0.68)	(-0.31)	(1.23)
CCC or lower rating	1.070***	0.800***	0.526*	1.141***	0.754***	0.624**	1.265***	0.727***	0.743***
	(3.47)	(4.57)	(1.92)	(3.58)	(4.08)	(2.30)	(4.71)	(3.95)	(2.72)
Constant	-2.459***	-1.198***	-0.461**	-3.058***	-1.339***	-0.954***	-3.132***	-1.436***	-1.056***
	(-10.68)	(-6.50)	(-2.35)	(-13.00)	(-7.20)	(-5.01)	(-11.86)	(-6.89)	(-4.76)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table 5: **Losing Investment Grade and Bond Market Liquidity**

This table presents the effect of the interaction of losing investment grade status and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * lost IG* and *low liquidity * lost IG* measure the additional effect of losing investment grade on medium and low liquidity companies beyond the unconditional effect measured by *lost inv. grade in last 5 years*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
lost inv. grade in last 5 years	1.582***	0.801***	1.310***	1.517***	0.535**	1.329***	1.775***	0.743***	1.540***
	(6.47)	(4.08)	(4.96)	(5.24)	(2.33)	(4.98)	(5.58)	(2.89)	(4.82)
medium liquidity * 5yr lost IG	0.620**	0.228	0.515*	0.341	0.298	0.301	-0.0966	0.234	-0.384
	(1.99)	(0.87)	(1.73)	(1.21)	(1.29)	(0.98)	(-0.26)	(0.83)	(-1.07)
low liquidity * 5yr lost IG	1.289***	1.116***	0.441	1.154***	0.968***	0.392	0.450	0.394	0.677
	(2.77)	(2.77)	(1.16)	(3.07)	(3.22)	(1.10)	(1.21)	(1.29)	(1.53)
disagree: analyst std/price	4.336***	3.719***	1.106	4.823***	3.862***	1.553	4.110***	3.320***	1.259
	(4.09)	(4.49)	(1.08)	(4.51)	(4.53)	(1.52)	(3.69)	(3.94)	(1.12)
medium liquidity (dummy)	-0.568***	-0.179	-0.514***	0.254***	0.0758	0.252***	0.431***	0.0761	0.490***
	(-4.11)	(-1.58)	(-4.26)	(2.61)	(1.01)	(2.79)	(3.31)	(0.72)	(4.33)
low liquidity (dummy)	-1.459***	-0.869***	-0.887***	-0.330**	-0.276**	-0.0853	0.547***	0.186	0.588***
	(-7.33)	(-4.44)	(-5.49)	(-2.11)	(-2.13)	(-0.71)	(3.64)	(1.57)	(4.01)
log(assets)	0.267***	0.177**	0.186**	0.342***	0.189**	0.254***	0.407***	0.231***	0.269***
	(2.79)	(2.39)	(1.99)	(3.46)	(2.52)	(2.77)	(4.05)	(3.04)	(2.64)
log(debt)	0.0524	0.141	-0.0121	0.0318	0.128	-0.00990	-0.0581	0.0844	-0.0956
	(0.49)	(1.64)	(-0.13)	(0.30)	(1.49)	(-0.11)	(-0.51)	(0.93)	(-0.85)
log(bonds outstanding)	0.510***	0.241***	0.343***	0.749***	0.333***	0.509***	0.715***	0.312***	0.644***
	(5.15)	(3.46)	(3.74)	(8.02)	(4.93)	(6.07)	(6.38)	(3.76)	(6.26)
AA or higher rating	0.290	-0.124	0.564	0.0101	-0.249	0.285	-0.0467	-0.255	0.237
	(0.95)	(-0.59)	(1.58)	(0.03)	(-1.19)	(0.80)	(-0.14)	(-1.18)	(0.60)
A rating	0.719***	0.135	0.893***	0.540**	0.0164	0.712***	0.441*	0.0150	0.605***
	(2.96)	(0.74)	(4.41)	(2.11)	(0.09)	(3.60)	(1.74)	(0.08)	(2.80)
BBB rating	1.131***	0.403***	1.165***	1.019***	0.290*	1.025***	0.888***	0.263*	0.977***
	(5.68)	(2.64)	(7.18)	(5.04)	(1.92)	(6.67)	(4.42)	(1.68)	(5.79)
B rating	0.0429	-0.0554	0.105	0.0807	-0.0968	0.156	0.110	-0.0559	0.182
	(0.23)	(-0.36)	(0.70)	(0.45)	(-0.67)	(1.12)	(0.60)	(-0.37)	(1.14)
CCC or lower rating	1.105***	0.838***	0.508*	1.203***	0.873***	0.638**	1.358***	0.864***	0.812***
	(3.56)	(4.27)	(1.87)	(3.71)	(4.33)	(2.37)	(4.58)	(4.86)	(2.86)
Constant	-2.453***	-1.250***	-0.434**	-3.061***	-1.359***	-0.937***	-3.186***	-1.452***	-1.087***
	(-10.55)	(-6.85)	(-2.20)	(-13.10)	(-7.49)	(-4.94)	(-12.26)	(-7.07)	(-5.01)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table 6: **Detailed Debt Structure**

This table presents how different types of debt affects the size and existence of the CDS market using Compustat companies with S&P ratings for which we have detailed balance sheet information from Capital IQ using annual data 2008-2011. In columns (1)-(9) we take logs of all components of debt (after adding 10 million USD). Column (1) uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the column (2) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the column (3) runs a probit regression on a dummy variable indicating the existence of a CDS market. In columns (4)-(6) we restrict the sample to US bonds with at least one bond issue in FISD-Mergent, while in columns (7)-(9) we add further controls to the regressions in columns (4)-(6). The number of observations refer to firm-year observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	US and international			US firms in FISD			US firms in FISD w/ controls		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
log(bonds+0.01)	0.474***	0.244***	0.300***	0.612***	0.378***	0.313***	0.482***	0.303***	0.262**
	(7.13)	(5.26)	(5.65)	(4.98)	(4.43)	(3.43)	(3.83)	(3.66)	(2.47)
log(accounts payable+0.01)	0.0296	0.0469	0.0495	0.0854	0.0647	0.103	0.0448	0.0443	0.137
	(0.49)	(1.11)	(0.61)	(1.08)	(1.22)	(0.83)	(0.55)	(0.74)	(0.91)
log(term loans+0.01)	-0.0548**	-0.00123	-0.0777***	-0.0660*	0.00559	-0.113***	-0.0529	0.0136	-0.0994**
	(-2.40)	(-0.08)	(-2.96)	(-1.90)	(0.28)	(-2.72)	(-1.56)	(0.66)	(-2.18)
log(comm. paper+0.01)	0.0204	-0.0359**	0.0892**	-0.0294	-0.0731***	0.0428	-0.0232	-0.0498**	0.0167
	(0.81)	(-2.11)	(2.34)	(-0.91)	(-3.35)	(0.80)	(-0.74)	(-2.26)	(0.27)
log(other borrowing+0.01)	0.00525	0.0739***	-0.109***	0.00753	0.0731***	-0.0900**	-0.0206	0.0567**	-0.152***
	(0.20)	(4.06)	(-3.39)	(0.19)	(2.80)	(-2.07)	(-0.55)	(2.34)	(-2.97)
log(capital lease+0.01)	0.0187	0.00561	0.0550	-0.00810	0.00703	0.0488	0.00485	0.0164	0.0902
	(0.45)	(0.19)	(0.96)	(-0.14)	(0.17)	(0.49)	(0.09)	(0.42)	(0.80)
log(revolving credit+0.01)	-0.0147	0.0328**	-0.0541	0.0251	0.0156	0.0306	0.0240	0.0164	0.0373
	(-0.52)	(1.99)	(-1.58)	(0.63)	(0.66)	(0.64)	(0.62)	(0.67)	(0.68)
log(trust preferred+0.01)	-0.103*	0.0326	-0.115***	-0.142**	0.0227	-0.153**	-0.138**	0.0307	-0.222***
	(-1.91)	(0.89)	(-2.61)	(-2.24)	(0.56)	(-2.53)	(-2.21)	(0.72)	(-3.08)
log(assets)	0.346***	0.162**	0.343***	0.337**	0.0928	0.382**	0.397**	0.0817	0.639***
	(3.03)	(2.09)	(3.16)	(2.01)	(0.82)	(2.38)	(2.48)	(0.72)	(3.01)
lost inv. grade in last 5 years	0.909***	0.861***	0.468	0.680*	1.044***	-0.0203	0.563	1.142***	-0.590
	(2.83)	(4.50)	(1.32)	(1.93)	(6.11)	(-0.04)	(1.48)	(6.24)	(-1.06)
bond turnover (last 12 months)							0.0780	0.202	-0.0482
							(0.37)	(1.01)	(-0.18)
adj. log(bond Herfindahl)							-0.793***	-0.359***	-1.130***
							(-4.67)	(-2.59)	(-4.21)
disagree: analyst std/price							3.663**	1.625	3.082
							(2.12)	(1.61)	(0.75)
Constant	-3.477***	-1.315***	-1.159**	-3.446***	-1.405***	-0.685	-3.426***	-1.293***	-1.377
	(-6.46)	(-3.50)	(-2.04)	(-5.34)	(-2.95)	(-0.80)	(-5.50)	(-2.72)	(-1.46)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rating fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	478	325	477	255	181	255	215	160	215
Number of Observations	1734	1168	1730	918	643	918	739	562	739

Table 7: **The CDS-bond basis**

This table presents the results of a regression with the dependent variable of log net notional CDS using US companies for which we have S&P ratings and there is at least one bond issue in FISD-Mergent. Column (1) constrains the coefficient on positive and negative basis to be equal, while columns (3) allows them to differ. The *CDS-bond basis (mly avg, bps)* from Bloomberg is the difference between the CDS spread and the Z-spread of the (up to 5) most liquid fixed-coupon uncollateralized senior bonds of the given company that does not have any embedded options. All other variables are defined in Table 1. The number of observations refers to firm-month observations. The CDS basis is winsorized at the 5% and the 95% level to avoid outliers driving the result. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) pooled	(2) split
abs. value of CDS-bond basis (mly avg, %)	0.242***	
	(3.46)	
abs. value of neg. CDS-bond basis (mly avg, %)		0.239***
		(3.42)
abs. value of pos. CDS-bond basis (mly avg, %)		-0.103
		(-1.04)
log(assets)	0.101	0.107
	(0.89)	(1.00)
log(debt)	0.335***	0.328***
	(4.02)	(4.12)
investment grade	0.419*	0.387
	(1.67)	(1.56)
industry: finance	-0.243	-0.232
	(-1.42)	(-1.44)
Constant	-1.628***	-1.523***
	(-6.41)	(-6.17)
time fixed effects	Yes	Yes
Number of Firms	56	56
Number of Observations	1773	1773

A Online Appendix (not for publication)

Table A.1: **Baseline Results: Including CDS index dummies**

This table presents the determinants of the size and existence of the CDS market using Compustat companies with S&P ratings. Columns (1)-(3) use all rated companies; columns (3)-(9) only US companies with at least one bond issue in Mergent FISD. Within every sample the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the middle column(s) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the last column runs a probit regression on a dummy variable indicating the existence of a CDS market. *credit enhancement* is an indicator dummy that is one for firms that provide credit enhancement. *systemic* is a dummy for the top 30 most systemic financial institutions. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	Baseline: US and international			US firms in FISD					
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) if exist	(7) if exist	(8) if exist	(9) probit
log(assets)	0.270***	0.0984*	0.262***	0.268***	0.144**	0.202***	0.123*	0.178**	0.250**
	(3.84)	(1.85)	(4.17)	(2.86)	(2.05)	(2.79)	(1.79)	(2.41)	(2.33)
log(debt)	0.375***	0.288***	0.171***	-0.0240	0.123	0.125	0.154**	0.172*	-0.192
	(6.58)	(6.54)	(3.32)	(-0.23)	(1.53)	(1.50)	(2.00)	(1.88)	(-1.60)
log(bonds outstanding)				0.327***	0.237***	0.135**	0.234***	0.164*	0.501***
				(2.72)	(4.35)	(1.99)	(4.33)	(1.74)	(3.13)
log(consol'd bonds outstanding)				0.141				-0.0302	0.215
				(0.93)				(-0.24)	(1.15)
bond turnover (last 12 months)				0.0530	-0.109			-0.111	0.328*
				(0.37)	(-0.93)			(-0.83)	(1.94)
adj. log(bond Herfindahl)				-0.477***		-0.317***		-0.262**	-0.559***
				(-3.88)		(-2.99)		(-2.47)	(-3.59)
disagree: analyst std/price				2.650**			3.065***	2.916***	1.224
				(2.33)			(3.72)	(3.54)	(1.07)
AA or higher rating	0.696***	0.0926	0.697***	0.695**	0.155	0.0921	0.251	0.179	0.283
	(3.11)	(0.49)	(3.04)	(2.40)	(0.63)	(0.39)	(1.04)	(0.73)	(0.72)
A rating	1.022***	0.243	0.960***	0.750***	0.131	0.105	0.239	0.200	0.651***
	(6.24)	(1.55)	(6.31)	(3.32)	(0.63)	(0.52)	(1.16)	(0.94)	(2.91)
BBB rating	1.132***	0.420***	0.978***	0.995***	0.322*	0.272	0.420**	0.369*	1.002***
	(7.78)	(2.75)	(7.82)	(5.41)	(1.74)	(1.50)	(2.27)	(1.96)	(5.71)
B rating	-0.254*	-0.293**	-0.0803	-0.153	-0.171	-0.192	-0.214*	-0.199	0.172
	(-1.84)	(-2.54)	(-0.63)	(-0.98)	(-1.35)	(-1.57)	(-1.67)	(-1.59)	(1.06)
CCC or lower rating	0.0783	0.0167	-0.00786	0.923***	0.405	0.465	0.625***	0.678***	0.786***
	(0.26)	(0.06)	(-0.04)	(3.04)	(1.20)	(1.43)	(3.04)	(3.29)	(2.91)
lost inv. grade in last 5 years	1.702***	0.981***	1.348***	1.668***	1.005***	1.014***	1.065***	1.031***	1.570***
	(10.61)	(7.38)	(8.29)	(9.28)	(6.64)	(7.18)	(7.35)	(6.85)	(6.86)
credit enhancement (dummy)	2.125***	1.372***	perfect +						
	(3.00)	(3.20)	(omitted)						
systemic	0.787**	0.625***	perfect +						
	(2.50)	(2.72)	(omitted)						
CDX NA IG index (dummy)	1.809***	1.025***	2.249***	1.292***	0.905***	0.878***	0.901***	0.893***	perfect +
	(17.69)	(14.25)	(5.61)	(9.85)	(9.28)	(9.08)	(9.05)	(9.05)	(omitted)
CDX NA HY index (dummy)	2.215***	0.774***	3.571***	1.732***	0.695***	0.664***	0.760***	0.729***	perfect +
	(18.37)	(6.51)	(8.92)	(11.42)	(4.46)	(4.38)	(4.99)	(4.88)	(omitted)
iTraxx Europe index (dummy)	1.383***	0.897***	2.335***						
	(12.59)	(11.89)	(7.91)						
industry: finance	-1.288***	-0.414***	-1.136***	-0.955***	-0.330**	-0.412***	-0.346***	-0.437***	-1.129***
	(-9.40)	(-3.97)	(-8.60)	(-5.60)	(-2.53)	(-3.06)	(-2.72)	(-3.31)	(-5.63)
industry: agricultural	0.159	-0.149	-0.0216	-0.0190	-0.262**	-0.291***	-0.0761	-0.214	0.253
	(0.50)	(-0.51)	(-0.05)	(-0.07)	(-2.44)	(-2.89)	(-0.67)	(-1.64)	(0.27)
industry: service	-0.394***	-0.185**	-0.461***	-0.329***	-0.176*	-0.172*	-0.168*	-0.199**	-0.259*
	(-4.22)	(-2.49)	(-4.70)	(-2.69)	(-1.79)	(-1.75)	(-1.69)	(-1.97)	(-1.75)
industry: cons. & mining	0.0940	-0.00902	0.00358	-0.00873	0.0387	0.0346	-0.0220	-0.0459	-0.163
	(0.67)	(-0.09)	(0.02)	(-0.05)	(0.33)	(0.30)	(-0.18)	(-0.38)	(-0.77)
Constant	-3.648***	-1.599***	-1.416***	-2.972***	-1.474***	-1.533***	-1.650***	-1.585***	-0.802***
	(-23.14)	(-9.45)	(-10.92)	(-14.18)	(-6.88)	(-7.53)	(-7.88)	(-7.12)	(-3.62)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	1784	609	1784	685	378	355	360	335	685
Number of Observations	57220	21095	57220	19966	12767	11967	12152	11101	19966

Table A.2: **Baseline Results: using net CDS as dependent variable**

This table presents the determinants of the size and existence of the CDS market using Compustat companies with S&P ratings. Columns (1)-(3) use all rated companies; columns (3)-(9) only US companies with at least one bond issue in Mergent FISD. Within every sample the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the middle column(s) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the last column runs a probit regression on a dummy variable indicating the existence of a CDS market. *credit enhancement* is an indicator dummy that is one for firms that provide credit enhancement. *systemic* is a dummy for the top 30 most systemic financial institutions. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	Baseline: US and international			US firms in FISD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	all	if exist	probit	all	if exist	if exist	if exist	if exist	probit
log(assets)	0.179***	0.0985**	0.262***	0.170**	0.109*	0.142**	0.0767	0.144**	0.250**
	(3.78)	(2.25)	(4.17)	(2.53)	(1.77)	(2.12)	(1.29)	(2.21)	(2.33)
log(debt)	0.270***	0.256***	0.171***	0.184*	0.273***	0.287***	0.300***	0.428***	-0.192
	(6.48)	(6.25)	(3.32)	(1.73)	(2.84)	(2.81)	(3.07)	(3.32)	(-1.60)
log(bonds outstanding)				0.331***	0.147***	0.0771	0.149***	0.242***	0.501***
				(3.31)	(3.05)	(1.19)	(3.10)	(2.73)	(3.13)
log(consol'd bonds outstanding)				-0.0534				-0.281**	0.215
				(-0.47)				(-2.15)	(1.15)
bond turnover (last 12 months)				-0.0494	-0.137			-0.201*	0.328*
				(-0.50)	(-1.59)			(-1.94)	(1.94)
adj. log(bond Herfindahl)				-0.326***		-0.281***		-0.170*	-0.559***
				(-3.52)		(-2.93)		(-1.79)	(-3.59)
disagree: analyst std/price				2.623**			3.131***	3.148***	1.224
				(2.36)			(2.95)	(2.79)	(1.07)
AA or higher rating	0.286*	-0.102	0.697***	0.368	0.0195	-0.0194	0.147	0.0829	0.283
	(1.80)	(-0.64)	(3.04)	(1.48)	(0.08)	(-0.08)	(0.63)	(0.35)	(0.72)
A rating	0.542***	0.0904	0.960***	0.464***	0.0642	0.0581	0.202	0.161	0.651***
	(5.18)	(0.77)	(6.31)	(2.79)	(0.39)	(0.35)	(1.23)	(0.93)	(2.91)
BBB rating	0.672***	0.295***	0.978***	0.654***	0.244*	0.222	0.360**	0.328**	1.002***
	(7.08)	(2.65)	(7.82)	(4.97)	(1.69)	(1.54)	(2.54)	(2.23)	(5.71)
B rating	-0.164*	-0.206**	-0.0803	-0.108	-0.126	-0.147	-0.155	-0.115	0.172
	(-1.79)	(-2.19)	(-0.63)	(-0.90)	(-1.10)	(-1.30)	(-1.36)	(-0.97)	(1.06)
CCC or lower rating	0.115	0.107	-0.00786	0.762***	0.348	0.393	0.548***	0.644***	0.786***
	(0.53)	(0.43)	(-0.04)	(2.96)	(1.02)	(1.14)	(2.68)	(3.05)	(2.91)
lost inv. grade in last 5 years	1.109***	0.777***	1.348***	1.217***	0.849***	0.880***	0.926***	0.899***	1.570***
	(10.17)	(7.33)	(8.29)	(8.90)	(6.32)	(6.76)	(7.36)	(6.77)	(6.86)
credit enhancement (dummy)	1.755***	1.406***	perfect +						
	(2.93)	(2.86)	(omitted)						
systemic	2.592***	2.335***	perfect +						
	(5.09)	(4.78)	(omitted)						
CDX NA IG index (dummy)	1.188***	0.774***	2.249***	0.844***	0.613***	0.592***	0.607***	0.621***	perfect +
	(14.54)	(10.83)	(5.61)	(7.16)	(5.64)	(5.36)	(5.40)	(5.75)	(omitted)
CDX NA HY index (dummy)	1.272***	0.521***	3.571***	1.108***	0.501***	0.478***	0.564***	0.547***	perfect +
	(15.07)	(5.40)	(8.92)	(9.47)	(3.79)	(3.61)	(4.55)	(4.31)	(omitted)
iTraxx Europe index (dummy)	1.098***	0.816***	2.335***						
	(10.03)	(7.68)	(7.91)						
industry: finance	-0.772***	-0.270***	-1.136***	-0.506***	-0.0474	-0.106	-0.0542	-0.122	-1.129***
	(-8.48)	(-2.97)	(-8.60)	(-4.38)	(-0.39)	(-0.84)	(-0.47)	(-0.97)	(-5.63)
industry: agricultural	0.0430	-0.128	-0.0216	0.0970	-0.0487	-0.0336	0.136	-0.0552	0.253
	(0.24)	(-0.59)	(-0.05)	(0.57)	(-0.50)	(-0.36)	(1.22)	(-0.47)	(0.27)
industry: service	-0.240***	-0.142**	-0.461***	-0.226**	-0.167*	-0.169*	-0.148*	-0.146	-0.259*
	(-3.87)	(-2.29)	(-4.70)	(-2.41)	(-1.95)	(-1.91)	(-1.69)	(-1.64)	(-1.75)
industry: cons. & mining	0.0190	-0.0536	0.00358	-0.0580	-0.00872	-0.0122	-0.0573	-0.0615	-0.163
	(0.21)	(-0.64)	(0.02)	(-0.49)	(-0.09)	(-0.12)	(-0.56)	(-0.58)	(-0.77)
Constant	-1.125***	-0.0543	-1.416***	-0.907***	-0.0290	-0.110	-0.209	-0.197	-0.802***
	(-8.95)	(-0.41)	(-10.92)	(-4.80)	(-0.16)	(-0.60)	(-1.13)	(-0.99)	(-3.62)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	1784	609	1784	685	378	355	360	335	685
Number of Observations	57220	21095	57220	19966	12767	11967	12152	11101	19966

Table A.3: **Disagreement and Bond Market Liquidity: using equity turnover**

This table presents the effect of the interaction of disagreement and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure, the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * disagree* and *low liquidity * disagree* measure the additional effect of disagreement on medium and low liquidity companies beyond the unconditional effect measured by *equity turnover*. In the interaction terms *disagree* refers to *equity turnover*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
equity turnover (monthly)	0.0905***	0.0671***	0.0416	0.0994***	0.0645***	0.0518**	0.0735*	0.0683**	0.0443
	(3.89)	(4.13)	(1.41)	(3.97)	(4.00)	(1.99)	(1.94)	(2.25)	(1.28)
medium liquidity * disagree	0.0191	0.0720***	-0.00970	0.0251	0.0505**	-0.0141	0.0279	0.0292	-0.0223
	(0.60)	(2.64)	(-0.30)	(0.77)	(2.42)	(-0.42)	(0.69)	(0.81)	(-0.59)
low liquidity * disagree	0.101*	0.128*	0.0378	0.0971**	0.102**	0.0452	0.0705	0.0314	0.0606
	(1.89)	(1.70)	(0.90)	(2.26)	(2.36)	(1.18)	(1.56)	(0.92)	(1.27)
lost inv. grade in last 5 years	2.128***	1.069***	1.663***	2.059***	1.010***	1.552***	1.980***	1.090***	1.518***
	(9.94)	(6.56)	(8.39)	(9.36)	(6.16)	(8.04)	(9.33)	(6.79)	(7.03)
medium liquidity (dummy)	-0.536***	-0.357**	-0.421***	0.204	-0.0542	0.318**	0.353**	0.0277	0.531***
	(-3.38)	(-2.56)	(-2.80)	(1.64)	(-0.57)	(2.47)	(2.02)	(0.19)	(3.25)
low liquidity (dummy)	-1.407***	-0.900***	-0.905***	-0.402**	-0.408**	-0.130	0.396**	0.123	0.488**
	(-5.96)	(-3.23)	(-4.74)	(-2.16)	(-2.42)	(-0.83)	(2.07)	(0.78)	(2.48)
log(assets)	0.255***	0.175**	0.170*	0.311***	0.183**	0.226**	0.368***	0.214***	0.242**
	(2.75)	(2.41)	(1.85)	(3.24)	(2.49)	(2.50)	(3.79)	(2.87)	(2.40)
log(debt)	0.0239	0.110	-0.00685	0.0206	0.0986	0.00399	-0.0441	0.0814	-0.0651
	(0.23)	(1.32)	(-0.07)	(0.20)	(1.18)	(0.04)	(-0.40)	(0.94)	(-0.59)
log(bonds outstanding)	0.559***	0.281***	0.358***	0.772***	0.361***	0.512***	0.702***	0.313***	0.626***
	(5.73)	(3.98)	(3.97)	(8.54)	(5.46)	(6.26)	(6.41)	(3.91)	(6.27)
AA or higher rating	0.547*	0.0514	0.688*	0.305	-0.0208	0.427	0.277	0.0338	0.384
	(1.76)	(0.24)	(1.93)	(0.94)	(-0.10)	(1.20)	(0.86)	(0.15)	(0.98)
A rating	0.891***	0.233	0.988***	0.730***	0.161	0.810***	0.665***	0.220	0.718***
	(3.72)	(1.26)	(4.89)	(2.96)	(0.88)	(4.13)	(2.67)	(1.16)	(3.34)
BBB rating	1.238***	0.460***	1.231***	1.138***	0.390***	1.093***	1.036***	0.410***	1.051***
	(6.34)	(3.03)	(7.65)	(5.85)	(2.64)	(7.22)	(5.26)	(2.65)	(6.36)
B rating	0.133	-0.000543	0.132	0.168	-0.0155	0.168	0.170	-0.00865	0.207
	(0.74)	(-0.00)	(0.91)	(0.96)	(-0.11)	(1.24)	(0.94)	(-0.06)	(1.32)
CCC or lower rating	0.875***	0.570**	0.380	0.986***	0.617***	0.508**	1.058***	0.751***	0.476*
	(2.84)	(2.35)	(1.58)	(3.19)	(2.62)	(2.11)	(3.43)	(3.76)	(1.80)
Constant	-3.002***	-1.653***	-0.711***	-3.601***	-1.762***	-1.223***	-3.657***	-1.906***	-1.361***
	(-11.70)	(-7.90)	(-3.19)	(-13.86)	(-8.35)	(-5.79)	(-12.71)	(-7.56)	(-5.52)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	910	368	910	945	369	945	752	345	752
Number of Observations	27634	12505	27634	30045	12691	30045	21921	11705	21921

Table A.4: **Disagreement and Bond Market Liquidity: using disagreement scaled by mean**

This table presents the effect of the interaction of disagreement and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure, the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * disagree* and *low liquidity * disagree* measure the additional effect of disagreement on medium and low liquidity companies beyond the unconditional effect measured by *analyst disagreement: std/mean*. In the interaction terms *disagree* refers to *analyst disagreement: std*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
disagree: analyst std/abs(mean)	0.00408	0.225**	-0.222	0.0218	0.101	-0.0299	-0.0602	0.168	-0.0904
	(0.02)	(2.05)	(-1.14)	(0.12)	(0.70)	(-0.18)	(-0.26)	(0.70)	(-0.35)
medium liquidity * disagree	0.300	0.204	0.252	0.0959	0.335*	-0.233	0.173	0.180	-0.158
	(1.36)	(1.02)	(1.12)	(0.40)	(1.86)	(-1.07)	(0.63)	(0.63)	(-0.56)
low liquidity * disagree	1.021***	1.365***	0.389	0.944***	0.871***	0.345	0.505*	0.259	0.280
	(3.58)	(4.94)	(1.47)	(3.73)	(3.84)	(1.58)	(1.67)	(0.92)	(0.85)
lost inv. grade in last 5 years	2.011***	0.966***	1.590***	1.926***	0.854***	1.494***	1.840***	0.915***	1.456***
	(8.47)	(4.98)	(7.37)	(8.00)	(4.36)	(7.04)	(7.82)	(4.77)	(6.06)
medium liquidity (dummy)	-0.590***	-0.215*	-0.538***	0.234**	0.0317	0.299***	0.380***	0.0492	0.497***
	(-4.17)	(-1.75)	(-4.27)	(2.25)	(0.38)	(3.01)	(2.66)	(0.43)	(3.87)
low liquidity (dummy)	-1.459***	-0.857***	-0.944***	-0.369**	-0.256*	-0.150	0.503***	0.184	0.560***
	(-7.03)	(-4.05)	(-5.51)	(-2.35)	(-1.89)	(-1.18)	(3.14)	(1.43)	(3.57)
log(assets)	0.311***	0.181**	0.225**	0.375***	0.189**	0.281***	0.431***	0.222***	0.299***
	(3.20)	(2.40)	(2.36)	(3.72)	(2.48)	(3.00)	(4.18)	(2.86)	(2.89)
log(debt)	0.0628	0.141	-0.0201	0.0373	0.123	-0.0180	-0.0259	0.103	-0.0776
	(0.59)	(1.61)	(-0.21)	(0.35)	(1.41)	(-0.19)	(-0.23)	(1.13)	(-0.68)
log(bonds outstanding)	0.476***	0.261***	0.315***	0.733***	0.366***	0.492***	0.675***	0.321***	0.585***
	(4.88)	(3.66)	(3.49)	(7.83)	(5.40)	(5.93)	(6.01)	(3.82)	(5.76)
AA or higher rating	0.176	-0.192	0.489	-0.114	-0.318	0.220	-0.126	-0.284	0.188
	(0.60)	(-0.93)	(1.39)	(-0.36)	(-1.53)	(0.62)	(-0.39)	(-1.31)	(0.49)
A rating	0.652***	0.0905	0.844***	0.457*	-0.0270	0.666***	0.397	0.00252	0.576***
	(2.80)	(0.51)	(4.24)	(1.83)	(-0.15)	(3.39)	(1.59)	(0.01)	(2.69)
BBB rating	1.087***	0.348**	1.150***	0.959***	0.235	1.011***	0.862***	0.242	0.968***
	(5.84)	(2.35)	(7.25)	(4.98)	(1.58)	(6.66)	(4.41)	(1.54)	(5.86)
B rating	0.107	-0.0173	0.119	0.163	-0.0275	0.179	0.205	0.00366	0.236
	(0.54)	(-0.10)	(0.78)	(0.85)	(-0.17)	(1.25)	(1.04)	(0.02)	(1.41)
CCC or lower rating	0.795	1.320***	0.0295	0.970*	1.219***	0.302	1.161**	1.356***	0.286
	(1.28)	(5.55)	(0.07)	(1.75)	(3.81)	(0.83)	(2.23)	(5.55)	(0.77)
Constant	-2.463***	-1.222***	-0.449**	-3.026***	-1.315***	-0.950***	-3.196***	-1.444***	-1.142***
	(-10.79)	(-6.56)	(-2.25)	(-12.98)	(-6.87)	(-4.96)	(-12.18)	(-6.87)	(-5.15)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	848	352	848	884	353	884	697	331	697
Number of Observations	24237	11348	24237	26316	11525	26316	19466	10606	19466

Table A.5: **Disagreement and Bond Market Liquidity: including CDX dummies**

This table presents the effect of the interaction of disagreement and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure, the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * disagree* and *low liquidity * disagree* measure the additional effect of disagreement on medium and low liquidity companies beyond the unconditional effect measured by *analyst disagreement: std/mean*. In the interaction terms *disagree* refers to *analyst disagreement: std*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
disagree: analyst std/price	0.276	1.191*	0.997	2.403**	2.264***	2.092*	-3.089*	-1.018	-0.329
	(0.25)	(1.85)	(0.72)	(2.12)	(2.73)	(1.88)	(-1.75)	(-0.77)	(-0.14)
medium liquidity * disagree	5.779***	4.858***	0.448	0.671	2.206**	-2.156	7.605***	6.099***	1.141
	(2.98)	(3.36)	(0.25)	(0.44)	(2.31)	(-1.47)	(3.11)	(3.41)	(0.42)
low liquidity * disagree	6.960***	12.29***	-0.941	4.008*	4.407**	0.420	5.534**	2.962*	2.886
	(2.84)	(2.90)	(-0.39)	(1.92)	(2.31)	(0.18)	(2.52)	(1.84)	(0.94)
lost inv. grade in last 5 years	1.823***	1.083***	1.676***	1.746***	1.018***	1.577***	1.651***	1.039***	1.507***
	(10.12)	(7.41)	(7.98)	(9.57)	(6.89)	(7.71)	(9.37)	(7.07)	(6.66)
medium liquidity (dummy)	-0.314***	-0.110	-0.483***	0.274***	0.101	0.304***	0.211*	0.0238	0.441***
	(-2.88)	(-1.20)	(-4.00)	(3.30)	(1.54)	(3.17)	(1.84)	(0.25)	(3.58)
low liquidity (dummy)	-0.868***	-0.546***	-0.839***	-0.0870	-0.0358	-0.0557	0.394***	0.182*	0.579***
	(-5.08)	(-2.98)	(-5.03)	(-0.70)	(-0.33)	(-0.44)	(3.08)	(1.73)	(3.82)
log(assets)	0.188**	0.114*	0.190**	0.232***	0.128*	0.254***	0.264***	0.151**	0.265***
	(2.22)	(1.72)	(2.03)	(2.65)	(1.89)	(2.77)	(2.94)	(2.20)	(2.60)
log(debt)	0.0779	0.182**	-0.0149	0.0601	0.164**	-0.0140	0.0499	0.177**	-0.0871
	(0.88)	(2.36)	(-0.16)	(0.68)	(2.13)	(-0.15)	(0.53)	(2.22)	(-0.78)
log(bonds outstanding)	0.354***	0.166***	0.349***	0.486***	0.225***	0.514***	0.405***	0.146**	0.637***
	(4.69)	(2.87)	(3.79)	(6.85)	(4.17)	(6.11)	(4.72)	(2.14)	(6.24)
AA or higher rating	0.950***	0.297	0.567	0.794***	0.222	0.285	0.691**	0.201	0.238
	(3.36)	(1.24)	(1.60)	(2.71)	(0.92)	(0.80)	(2.41)	(0.84)	(0.61)
A rating	0.992***	0.307	0.893***	0.866***	0.221	0.706***	0.751***	0.210	0.604***
	(4.71)	(1.50)	(4.41)	(3.98)	(1.07)	(3.55)	(3.45)	(1.00)	(2.79)
BBB rating	1.237***	0.489***	1.164***	1.155***	0.416**	1.024***	1.017***	0.383**	0.974***
	(6.96)	(2.66)	(7.16)	(6.51)	(2.26)	(6.63)	(5.68)	(2.03)	(5.78)
B rating	-0.159	-0.213*	0.118	-0.135	-0.223*	0.160	-0.150	-0.199	0.196
	(-1.01)	(-1.69)	(0.80)	(-0.87)	(-1.75)	(1.16)	(-0.96)	(-1.56)	(1.23)
CCC or lower rating	0.779***	0.650***	0.526*	0.801***	0.600***	0.624**	0.854***	0.554***	0.743***
	(2.65)	(3.47)	(1.92)	(2.68)	(2.91)	(2.30)	(2.87)	(2.65)	(2.72)
CDX NA IG index (dummy)	1.271***	0.865***	perfect +	1.355***	0.896***	perfect +	1.322***	0.889***	perfect +
	(9.94)	(8.80)	(omitted)	(10.32)	(9.06)	(omitted)	(10.06)	(8.98)	(omitted)
CDX NA HY index (dummy)	1.840***	0.768***	perfect +	1.953***	0.774***	perfect +	1.782***	0.735***	perfect +
	(11.80)	(5.05)	(omitted)	(12.88)	(5.20)	(omitted)	(11.86)	(4.86)	(omitted)
Constant	-2.845***	-1.557***	-0.461**	-3.287***	-1.690***	-0.954***	-3.175***	-1.654***	-1.056***
	(-14.16)	(-7.20)	(-2.35)	(-16.95)	(-8.02)	(-5.01)	(-15.71)	(-7.48)	(-4.76)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table A.6: **Disagreement and Bond Market Liquidity: using net CDS as dependent variable**

This table presents the effect of the interaction of disagreement and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure, the first column uses all companies, the left hand side variable is net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * disagree* and *low liquidity * disagree* measure the additional effect of disagreement on medium and low liquidity companies beyond the unconditional effect measured by *analyst disagreement: std/price*. In the interaction terms *disagree* refers to *analyst disagreement: std/price*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
disagree: analyst std/price	2.123**	1.807**	0.997	2.854***	2.402**	2.092*	-0.293	0.425	-0.329
	(2.41)	(1.99)	(0.72)	(2.94)	(2.31)	(1.88)	(-0.18)	(0.26)	(-0.14)
medium liquidity * disagree	3.124*	4.824**	0.448	1.774	3.587***	-2.156	6.042***	6.404***	1.141
	(1.69)	(2.58)	(0.25)	(1.40)	(3.25)	(-1.47)	(2.74)	(3.03)	(0.42)
low liquidity * disagree	2.539	10.61***	-0.941	1.868	3.642*	0.420	2.311	0.820	2.886
	(1.08)	(3.49)	(-0.39)	(1.02)	(1.82)	(0.18)	(1.30)	(0.43)	(0.94)
lost inv. grade in last 5 years	1.383***	0.815***	1.676***	1.345***	0.803***	1.577***	1.287***	0.860***	1.507***
	(9.02)	(6.01)	(7.98)	(8.56)	(5.82)	(7.71)	(8.56)	(6.19)	(6.66)
medium liquidity (dummy)	-0.229**	-0.0390	-0.483***	0.105	-0.00638	0.304***	0.166*	-0.0284	0.441***
	(-2.34)	(-0.40)	(-4.00)	(1.53)	(-0.10)	(3.17)	(1.80)	(-0.32)	(3.58)
low liquidity (dummy)	-0.603***	-0.308*	-0.839***	-0.123	-0.0835	-0.0557	0.388***	0.200*	0.579***
	(-4.00)	(-1.85)	(-5.03)	(-1.20)	(-0.86)	(-0.44)	(3.55)	(1.95)	(3.82)
log(assets)	0.165***	0.114*	0.190**	0.189***	0.118*	0.254***	0.216***	0.126**	0.265***
	(2.59)	(1.83)	(2.03)	(2.96)	(1.87)	(2.77)	(3.28)	(1.97)	(2.60)
log(debt)	0.146*	0.285***	-0.0149	0.134	0.267***	-0.0140	0.133	0.294***	-0.0871
	(1.71)	(3.00)	(-0.16)	(1.62)	(2.79)	(-0.15)	(1.48)	(2.89)	(-0.78)
log(bonds outstanding)	0.407***	0.214***	0.349***	0.503***	0.235***	0.514***	0.463***	0.193***	0.637***
	(5.74)	(3.70)	(3.79)	(8.23)	(4.57)	(6.11)	(6.46)	(2.92)	(6.24)
AA or higher rating	0.0445	-0.223	0.567	-0.0754	-0.231	0.285	-0.120	-0.213	0.238
	(0.18)	(-1.02)	(1.60)	(-0.31)	(-1.08)	(0.80)	(-0.50)	(-0.99)	(0.61)
A rating	0.366**	0.0199	0.893***	0.293*	0.00761	0.706***	0.235	0.0281	0.604***
	(2.26)	(0.13)	(4.41)	(1.76)	(0.05)	(3.55)	(1.39)	(0.18)	(2.79)
BBB rating	0.650***	0.235*	1.164***	0.598***	0.217*	1.024***	0.534***	0.237*	0.974***
	(4.96)	(1.93)	(7.16)	(4.57)	(1.83)	(6.63)	(4.03)	(1.90)	(5.78)
B rating	0.0202	-0.0563	0.118	0.0401	-0.0726	0.160	0.0722	-0.0127	0.196
	(0.17)	(-0.47)	(0.80)	(0.34)	(-0.59)	(1.16)	(0.60)	(-0.10)	(1.23)
CCC or lower rating	0.811***	0.701***	0.526*	0.800***	0.613***	0.624**	0.896***	0.565***	0.743***
	(3.61)	(4.14)	(1.92)	(3.51)	(3.32)	(2.30)	(4.34)	(2.96)	(2.72)
Constant	-0.550***	0.0955	-0.461**	-0.786***	0.0590	-0.954***	-0.876***	-0.0262	-1.056***
	(-3.14)	(0.57)	(-2.35)	(-4.74)	(0.37)	(-5.01)	(-4.66)	(-0.14)	(-4.76)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table A.7: **Losing Investment Grade and Bond Market Liquidity: including CDX dummies**

This table presents the effect of the interaction of losing investment grade status and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure the first column uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * lost IG* and *low liquidity * lost IG* measure the additional effect of losing investment grade on medium and low liquidity companies beyond the unconditional effect measured by *lost inv. grade in last 5 years*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	all	if exist	probit	all	if exist	probit	all	if exist	probit
lost inv. grade in last 5 years	1.271***	0.860***	1.310***	1.269***	0.655***	1.329***	1.575***	0.866***	1.540***
	(7.15)	(5.58)	(4.96)	(6.34)	(3.80)	(4.98)	(6.04)	(4.06)	(4.82)
medium liquidity * 5yr lost IG	0.792***	0.325	0.515*	0.380*	0.316*	0.301	0.00814	0.186	-0.384
	(3.18)	(1.54)	(1.73)	(1.82)	(1.77)	(0.98)	(0.03)	(0.78)	(-1.07)
low liquidity * 5yr lost IG	1.309***	1.022***	0.441	0.987***	0.806***	0.392	0.231	0.284	0.677
	(3.47)	(3.03)	(1.16)	(3.47)	(3.42)	(1.10)	(0.65)	(1.08)	(1.53)
disagree: analyst std/price	2.843***	3.070***	1.106	3.115***	3.241***	1.553	2.606**	2.766***	1.259
	(2.65)	(3.92)	(1.08)	(2.89)	(3.99)	(1.52)	(2.30)	(3.38)	(1.12)
medium liquidity (dummy)	-0.313***	-0.0805	-0.514***	0.266***	0.119*	0.252***	0.318***	0.0872	0.490***
	(-2.90)	(-0.89)	(-4.26)	(3.35)	(1.87)	(2.79)	(2.88)	(0.93)	(4.33)
low liquidity (dummy)	-0.983***	-0.606***	-0.887***	-0.159	-0.0975	-0.0853	0.441***	0.186*	0.588***
	(-5.72)	(-3.39)	(-5.49)	(-1.28)	(-0.89)	(-0.71)	(3.51)	(1.79)	(4.01)
log(assets)	0.182**	0.118*	0.186**	0.232***	0.129*	0.254***	0.269***	0.158**	0.269***
	(2.16)	(1.78)	(1.99)	(2.67)	(1.92)	(2.77)	(2.99)	(2.30)	(2.64)
log(debt)	0.0945	0.190**	-0.0121	0.0765	0.178**	-0.00990	0.0358	0.167**	-0.0956
	(1.06)	(2.46)	(-0.13)	(0.87)	(2.31)	(-0.11)	(0.37)	(2.06)	(-0.85)
log(bonds outstanding)	0.327***	0.144**	0.343***	0.463***	0.205***	0.509***	0.410***	0.145**	0.644***
	(4.34)	(2.53)	(3.74)	(6.51)	(3.71)	(6.07)	(4.76)	(2.11)	(6.26)
AA or higher rating	0.987***	0.353	0.564	0.802***	0.243	0.285	0.698**	0.196	0.237
	(3.48)	(1.48)	(1.58)	(2.74)	(1.02)	(0.80)	(2.43)	(0.81)	(0.60)
A rating	1.029***	0.364*	0.893***	0.886***	0.247	0.712***	0.759***	0.208	0.605***
	(4.86)	(1.78)	(4.41)	(4.07)	(1.20)	(3.60)	(3.49)	(0.99)	(2.80)
BBB rating	1.278***	0.553***	1.165***	1.174***	0.447**	1.025***	1.017***	0.377**	0.977***
	(7.17)	(2.99)	(7.18)	(6.64)	(2.45)	(6.67)	(5.68)	(2.00)	(5.79)
B rating	-0.167	-0.195	0.105	-0.140	-0.221*	0.156	-0.161	-0.207	0.182
	(-1.06)	(-1.49)	(0.70)	(-0.91)	(-1.82)	(1.12)	(-1.02)	(-1.64)	(1.14)
CCC or lower rating	0.799***	0.675***	0.508*	0.867***	0.705***	0.638**	0.915***	0.675***	0.812***
	(2.79)	(3.30)	(1.87)	(2.79)	(3.19)	(2.37)	(3.09)	(3.50)	(2.86)
CDX NA IG index (dummy)	1.255***	0.854***	perfect +	1.338***	0.880***	perfect +	1.321***	0.888***	perfect +
	(9.85)	(8.75)	(omitted)	(10.24)	(8.95)	(omitted)	(10.05)	(8.97)	(omitted)
CDX NA HY index (dummy)	1.854***	0.785***	perfect +	1.951***	0.782***	perfect +	1.764***	0.722***	perfect +
	(12.48)	(5.26)	(omitted)	(13.12)	(5.36)	(omitted)	(11.73)	(4.73)	(omitted)
Constant	-2.864***	-1.618***	-0.434**	-3.295***	-1.714***	-0.937***	-3.247***	-1.683***	-1.087***
	(-14.09)	(-7.63)	(-2.20)	(-17.07)	(-8.36)	(-4.94)	(-16.13)	(-7.52)	(-5.01)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table A.8: **Losing Investment Grade and Bond Market Liquidity: using net CDS as dependent variable**

This table presents the effect of the interaction of losing investment grade status and bond market liquidity on the size and existence of the CDS market using US Compustat companies with S&P ratings that have at least bond issue according to Mergent FISD. *low liquidity*, *medium liquidity*, and *high liquidity* are assigned based on the liquidity terciles in each given month. Columns (1)-(3) uses *number of bond trades* to measure liquidity, columns (4)-(6) use *bond turnover (last 12 months)*, while columns (7)-(9) use *adjusted log(bond Herfindahl)*. Within every liquidity measure the first column uses all companies, the left hand side variable is net notional CDS and applies a censored regression approach as described in Section 5.2; the second column restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the third column runs a probit regression on a dummy variable indicating the existence of a CDS market. The coefficients on the interaction terms *medium liquidity * lost IG* and *low liquidity * lost IG* measure the additional effect of losing investment grade on medium and low liquidity companies beyond the unconditional effect measured by *lost inv. grade in last 5 years*. All other variables are defined in Table 1. The number of observations refers to firm-month observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	liquidity: # of bond trades			liquidity: bond turnover			liquidity: adj. bond Herfindahl		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
lost inv. grade in last 5 years	1.134***	0.724***	1.310***	0.976***	0.439***	1.329***	1.186***	0.666***	1.540***
	(6.27)	(4.23)	(4.96)	(5.13)	(2.59)	(4.98)	(5.35)	(3.16)	(4.82)
medium liquidity * 5yr lost IG	0.302	0.100	0.515*	0.348*	0.399**	0.301	0.0588	0.324	-0.384
	(1.32)	(0.46)	(1.73)	(1.84)	(2.25)	(0.98)	(0.22)	(1.31)	(-1.07)
low liquidity * 5yr lost IG	0.709**	0.705**	0.441	0.716***	0.705***	0.392	0.261	0.246	0.677
	(2.11)	(2.17)	(1.16)	(2.80)	(3.01)	(1.10)	(0.97)	(0.92)	(1.53)
disagree: analyst std/price	3.431***	3.585***	1.106	3.592***	3.657***	1.553	3.286***	3.240***	1.259
	(3.62)	(3.45)	(1.08)	(3.86)	(3.45)	(1.52)	(3.16)	(2.95)	(1.12)
medium liquidity (dummy)	-0.212**	0.0215	-0.514***	0.114*	0.0213	0.252***	0.256***	0.0288	0.490***
	(-2.19)	(0.22)	(-4.26)	(1.71)	(0.33)	(2.79)	(2.88)	(0.34)	(4.33)
low liquidity (dummy)	-0.692***	-0.332**	-0.887***	-0.186*	-0.131	-0.0853	0.392***	0.179*	0.588***
	(-4.75)	(-2.09)	(-5.49)	(-1.81)	(-1.35)	(-0.71)	(3.60)	(1.77)	(4.01)
log(assets)	0.162**	0.119*	0.186**	0.188***	0.117*	0.254***	0.225***	0.138**	0.269***
	(2.52)	(1.89)	(1.99)	(2.94)	(1.86)	(2.77)	(3.39)	(2.11)	(2.64)
log(debt)	0.156*	0.288***	-0.0121	0.147*	0.282***	-0.00990	0.117	0.280***	-0.0956
	(1.79)	(3.00)	(-0.13)	(1.75)	(2.92)	(-0.11)	(1.29)	(2.71)	(-0.85)
log(bonds outstanding)	0.393***	0.199***	0.343***	0.487***	0.216***	0.509***	0.466***	0.191***	0.644***
	(5.56)	(3.45)	(3.74)	(7.92)	(4.13)	(6.07)	(6.43)	(2.85)	(6.26)
AA or higher rating	0.0640	-0.180	0.564	-0.0679	-0.215	0.285	-0.114	-0.218	0.237
	(0.26)	(-0.82)	(1.58)	(-0.28)	(-1.01)	(0.80)	(-0.47)	(-1.01)	(0.60)
A rating	0.383**	0.0596	0.893***	0.305*	0.0237	0.712***	0.244	0.0271	0.605***
	(2.35)	(0.40)	(4.41)	(1.82)	(0.16)	(3.60)	(1.44)	(0.17)	(2.80)
BBB rating	0.669***	0.277**	1.165***	0.610***	0.239**	1.025***	0.539***	0.234*	0.977***
	(5.06)	(2.26)	(7.18)	(4.66)	(2.02)	(6.67)	(4.05)	(1.88)	(5.79)
B rating	0.0266	-0.0284	0.105	0.0353	-0.0644	0.156	0.0597	-0.0268	0.182
	(0.22)	(-0.23)	(0.70)	(0.30)	(-0.55)	(1.12)	(0.49)	(-0.22)	(1.14)
CCC or lower rating	0.841***	0.738***	0.508*	0.854***	0.732***	0.638**	0.959***	0.710***	0.812***
	(3.64)	(3.85)	(1.87)	(3.61)	(3.73)	(2.37)	(4.40)	(4.23)	(2.86)
Constant	-0.565***	0.0348	-0.434**	-0.795***	0.0353	-0.937***	-0.931***	-0.0509	-1.087***
	(-3.21)	(0.21)	(-2.20)	(-4.82)	(0.22)	(-4.94)	(-4.89)	(-0.28)	(-5.01)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	865	359	865	900	360	900	710	337	710
Number of Observations	25700	11972	25700	27884	12152	27884	20664	11195	20664

Table A.9: **Detailed Debt Structure: including CDS index dummies**

This table presents how different types of debt affects the size and existence of the CDS market using Compustat companies with S&P ratings for which we have detailed balance sheet information from Capital IQ using annual data 2008-2011. In columns (1)-(9) we take logs of all components of debt (after adding 10 million USD). Column (1) uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the column (2) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the column (3) runs a probit regression on a dummy variable indicating the existence of a CDS market. In columns (4)-(6) we restrict the sample to US bonds with at least one bond issue in FISD-Mergent, while in columns (7)-(9) we add further controls to the regressions in columns (4)-(6). The number of observations refer to firm-year observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	US and international			US firms in FISD			US firms in FISD w/ controls		
	(1) all	(2) if exist	(3) probit	(4) all	(5) if exist	(6) probit	(7) all	(8) if exist	(9) probit
log(bonds+0.01)	0.323***	0.179***	0.243***	0.431***	0.280***	0.313***	0.354***	0.231***	0.262**
	(6.02)	(4.41)	(4.71)	(4.53)	(4.29)	(3.43)	(3.64)	(3.62)	(2.47)
log(accounts payable+0.01)	-0.00471	0.0190	0.0606	0.0344	0.0271	0.103	0.0197	0.0141	0.137
	(-0.10)	(0.56)	(0.66)	(0.54)	(0.64)	(0.83)	(0.28)	(0.28)	(0.91)
log(term loans+0.01)	-0.0259	0.0120	-0.0588**	-0.0531*	0.0104	-0.113***	-0.0480	0.0139	-0.0994**
	(-1.26)	(0.84)	(-2.11)	(-1.73)	(0.54)	(-2.72)	(-1.54)	(0.68)	(-2.18)
log(comm. paper+0.01)	0.0362*	-0.0168	0.109***	0.00907	-0.0431**	0.0428	0.00426	-0.0303*	0.0167
	(1.75)	(-1.24)	(2.85)	(0.32)	(-2.46)	(0.80)	(0.16)	(-1.66)	(0.27)
log(other borrowing+0.01)	-0.00606	0.0529***	-0.103***	0.0267	0.0784***	-0.0900**	0.00914	0.0696***	-0.152***
	(-0.28)	(3.52)	(-3.18)	(0.81)	(3.69)	(-2.07)	(0.28)	(3.36)	(-2.97)
log(capital lease+0.01)	0.0000674	0.00217	0.0320	-0.0656	-0.0239	0.0488	-0.0530	-0.0174	0.0902
	(0.00)	(0.09)	(0.51)	(-1.31)	(-0.68)	(0.49)	(-1.09)	(-0.51)	(0.80)
log(revolving credit+0.01)	-0.00832	0.0316**	-0.0562	0.0260	0.0238	0.0306	0.0229	0.0242	0.0373
	(-0.37)	(2.29)	(-1.57)	(0.82)	(1.27)	(0.64)	(0.71)	(1.21)	(0.68)
log(trust preferred+0.01)	-0.0428	0.0639**	-0.107**	-0.0624	0.0651**	-0.153**	-0.0757	0.0609*	-0.222***
	(-0.98)	(2.13)	(-2.36)	(-1.19)	(1.98)	(-2.53)	(-1.46)	(1.71)	(-3.08)
log(assets)	0.280***	0.131**	0.353***	0.250*	0.0522	0.382**	0.323**	0.0652	0.639***
	(3.06)	(2.01)	(3.17)	(1.84)	(0.57)	(2.38)	(2.46)	(0.70)	(3.01)
lost inv. grade in last 5 years	0.868***	0.865***	0.521	0.536*	0.892***	-0.0203	0.412	0.988***	-0.590
	(3.35)	(5.15)	(1.21)	(1.86)	(5.78)	(-0.04)	(1.38)	(6.30)	(-1.06)
bond turnover (last 12 months)							-0.0857	0.0351	-0.0482
							(-0.47)	(0.23)	(-0.18)
adj. log(bond Herfindahl)							-0.560***	-0.225*	-1.130***
							(-3.83)	(-1.92)	(-4.21)
disagree: analyst std/price							2.315*	1.102	3.082
							(1.65)	(1.15)	(0.75)
CDX NA IG index (dummy)	1.309***	0.811***	1.654***	1.195***	0.779***	perfect +	0.995***	0.695***	perfect +
	(10.95)	(10.27)	(3.38)	(8.03)	(7.96)	(omitted)	(6.89)	(7.25)	(omitted)
CDX NA HY index (dummy)	1.464***	0.557***	2.410***	1.400***	0.605***	perfect +	1.288***	0.480**	perfect +
	(7.65)	(3.45)	(4.82)	(5.70)	(3.05)	(omitted)	(4.92)	(2.25)	(omitted)
iTraxx Europe index (dummy)	1.255***	0.759***	perfect +						
	(10.70)	(9.45)	(omitted)						
Constant	-3.261***	-1.226***	-1.467**	-3.275***	-1.230***	-0.685	-3.311***	-1.130**	-1.377
	(-7.09)	(-3.66)	(-2.37)	(-5.29)	(-2.69)	(-0.80)	(-5.46)	(-2.43)	(-1.46)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rating fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	478	325	477	255	181	255	215	160	215
Number of Observations	1734	1168	1730	918	643	918	739	562	739

Table A.10: **Detailed Debt Structure: using net CDS as dependent variable**

This table presents how different types of debt affects the size and existence of the CDS market using Compustat companies with S&P ratings for which we have detailed balance sheet information from Capital IQ using annual data 2008-2011. In columns (1)-(9) we take logs of all components of debt (after adding 10 million USD). Column (1) uses all companies, the left hand side variable is log net notional CDS and applies a censored regression approach as described in Section 5.2; the column (2) restricts the sample to those companies with a CDS market (in the DTCC database or with a Bloomberg quote) and also applies a censored regression approach; the column (3) runs a probit regression on a dummy variable indicating the existence of a CDS market. In columns (4)-(6) we restrict the sample to US bonds with at least one bond issue in FISD-Mergent, while in columns (7)-(9) we add further controls to the regressions in columns (4)-(6). The number of observations refer to firm-year observations. Industry effects controlled for using first digit SIC codes. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	US and international			US firms in FISD			US firms in FISD w/ controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	all	if exist	probit	all	if exist	probit	all	if exist	probit
log(bonds+0.01)	0.376***	0.209***	0.300***	0.511***	0.340***	0.313***	0.438***	0.305***	0.262**
	(6.21)	(4.54)	(5.65)	(4.73)	(4.54)	(3.43)	(3.87)	(3.95)	(2.47)
log(accounts payable+0.01)	-0.00736	0.00494	0.0495	0.00361	0.00307	0.103	-0.0143	0.00562	0.137
	(-0.14)	(0.11)	(0.61)	(0.05)	(0.06)	(0.83)	(-0.19)	(0.09)	(0.91)
log(term loans+0.01)	-0.0266	0.0149	-0.0777***	-0.0552	0.0120	-0.113***	-0.0435	0.0245	-0.0994**
	(-1.29)	(0.91)	(-2.96)	(-1.60)	(0.53)	(-2.72)	(-1.19)	(1.03)	(-2.18)
log(comm. paper+0.01)	0.0332	-0.0225	0.0892**	-0.000719	-0.0545***	0.0428	0.000682	-0.0365*	0.0167
	(1.48)	(-1.14)	(2.34)	(-0.02)	(-2.69)	(0.80)	(0.02)	(-1.66)	(0.27)
log(other borrowing+0.01)	0.0247	0.0882***	-0.109***	0.0344	0.102***	-0.0900**	0.0214	0.0958***	-0.152***
	(1.10)	(4.42)	(-3.39)	(1.07)	(3.91)	(-2.07)	(0.65)	(3.68)	(-2.97)
log(capital lease+0.01)	0.0137	0.0172	0.0550	-0.0262	0.00992	0.0488	-0.0204	0.0117	0.0902
	(0.39)	(0.57)	(0.96)	(-0.50)	(0.23)	(0.49)	(-0.38)	(0.27)	(0.80)
log(revolving credit+0.01)	-0.0209	0.0284	-0.0541	0.00463	0.00985	0.0306	-0.00211	0.0130	0.0373
	(-0.78)	(1.47)	(-1.58)	(0.13)	(0.40)	(0.64)	(-0.05)	(0.51)	(0.68)
log(trust preferred+0.01)	0.0108	0.172***	-0.115***	-0.00960	0.182***	-0.153**	0.00725	0.201***	-0.222***
	(0.19)	(2.92)	(-2.61)	(-0.16)	(3.32)	(-2.53)	(0.11)	(3.45)	(-3.08)
log(assets)	0.385***	0.257***	0.343***	0.349**	0.139	0.382**	0.369**	0.101	0.639***
	(3.73)	(3.47)	(3.16)	(2.47)	(1.43)	(2.38)	(2.56)	(0.98)	(3.01)
lost inv. grade in last 5 years	0.744***	0.756***	0.468	0.603**	0.954***	-0.0203	0.559*	1.087***	-0.590
	(2.92)	(3.78)	(1.32)	(2.27)	(5.89)	(-0.04)	(1.87)	(5.40)	(-1.06)
bond turnover (last 12 months)							0.0744	0.154	-0.0482
							(0.44)	(0.89)	(-0.18)
adj. log(bond Herfindahl)							-0.532***	-0.203	-1.130***
							(-3.67)	(-1.60)	(-4.21)
disagree: analyst std/price							3.078**	1.162	3.082
							(2.20)	(0.86)	(0.75)
Constant	-1.317***	0.519	-1.159**	-1.286**	0.697	-0.685	-1.245**	0.863*	-1.377
	(-2.89)	(1.33)	(-2.04)	(-2.40)	(1.51)	(-0.80)	(-2.20)	(1.80)	(-1.46)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rating fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	478	325	477	255	181	255	215	160	215
Number of Observations	1734	1168	1730	918	643	918	739	562	739

Table A.11: **The CDS-bond basis: including CDX dummies and using net CDS as dependent variable**

This table presents the results of a regression with the dependent variable of log net notional CDS (or net notional CDS) using US companies for which we have S&P ratings and there is at least one bond issue in FISD-Mergent. Columns (1)-(2) constrain the coefficient on positive and negative basis to be equal, while columns (3)-(4) allow them to differ. The *CDS-bond basis (mly avg, bps)* from Bloomberg is the difference between the CDS spread and the Z-spread of the most liquid fixed-coupon uncollateralized senior bond of the given company that does not have any embedded options. All other variables are defined in Table 1. The number of observations refers to firm-month observations. The CDS basis is winsorized at the 5% and the 95% level to avoid outliers driving the result. Time fixed effects are included. T-stats are given in parentheses based on clustered standard errors (by firm). ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	log(net_CDS)		net_CDS	
	(1) pooled	(2) split	(3) pooled	(4) split
abs. value of CDS-bond basis (mly avg, %)	0.207***		0.312***	
	(3.13)		(4.12)	
abs. value of neg. CDS-bond basis (mly avg, %)		0.206***		0.308***
		(3.12)		(4.04)
abs. value of pos. CDS-bond basis (mly avg, %)		-0.0866		-0.197*
		(-0.97)		(-1.73)
log(assets)	0.106	0.111	-0.000694	0.00591
	(1.00)	(1.08)	(-0.00)	(0.04)
log(debt)	0.334***	0.327***	0.804***	0.795***
	(4.06)	(4.08)	(5.33)	(5.55)
investment grade	0.479	0.476	0.236	0.192
	(1.17)	(1.18)	(0.87)	(0.72)
CDX NA IG index (dummy)	0.446***	0.426***		
	(2.99)	(2.84)		
CDX NA HY index (dummy)	0.436	0.455		
	(1.09)	(1.17)		
industry: finance	-0.146	-0.139	-0.0595	-0.0403
	(-0.99)	(-0.96)	(-0.29)	(-0.21)
Constant	-1.885***	-1.814***	-0.835**	-0.681**
	(-4.76)	(-4.68)	(-2.45)	(-1.99)
time fixed effects	Yes	Yes	Yes	Yes
Number of Firms	56	56	56	56
Number of Observations	1773	1773	1773	1773