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The Anatomy of the CDS Market

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Abstract

Using novel position and trading data for single-name corporate credit default swaps (CDSs), we provide evidence that CDS markets emerge as "alternative trading venues" that serve a standardization and liquidity role. CDS positions and trading volume are larger for firms with bonds that are fragmented into many separate issues and have heterogeneous contractual terms. Whereas hedging motives are associated with trading volume in the bond and CDS markets, speculative trading concentrates in the CDS. Cross-market arbitrage links the CDS and bond market via the basis trade, compressing the negative CDS-bond basis and reducing price impact in the bond market.

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Th market for credit default swaps (CDSs) has grown from an exotic niche market to a large and active venue for credit risk transfer—making it one of the most significant financial innovations of the last decades.[1] Concurrently, CDS markets have become the subject of a number of policy debates, including their role in the recent financial crisis (Stulz, 2010), their impact on the debtor-creditor relationship (Hu and Black, 2008; Bolton and Oehmke, 2011), as well as firms' costs of capital, financing choices, and credit risk (Ashcraft and Santos, 2009; Saretto and Tookes, 2013; Subrahmanyam et al., 2014).

However, despite their growing importance, relatively little is known about the motivations that determine trading and positions in CDS markets. This paper aims to fill this void: Using newly available, disaggregated data on single-name CDS positions and trading volume, we investigate the motivations for trading in CDS markets and, more broadly, the economic function these markets perform.

Our evidence suggests that CDS markets are "alternative trading venues" for hedging and speculation. CDS markets are larger when the reference entity's bonds are fragmented into many separate issues, suggesting a standardization and liquidity role of CDS markets: While investors can usually make the same economic trade in the underlying bond, the CDS market is attractive because trading frictions in the CDS market are smaller than in the underlying bond. This interpretation is supported by the finding that bond fragmentation is associated with both higher trading costs and lower turnover in the underlying reference bonds. We also show that, whereas hedging motives are reflected to a comparable extent in bond and CDS trading volume, speculative trading, which is likely to be more sensitive to the relative liquidity advantage of the CDS market, concentrates in the CDS market. Finally, we document arbitrage activity that links the CDS and the bond market via the basis trade. We provide evidence that basis traders compress the negative bond basis and, by acting as absorbers of bond supply shocks, reduce price impact in the bond market.

[1] 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. Credit events usually include bankruptcy, non-payment of debt, and, in some CDS contracts, debt restructuring.

The data underlying our analysis are newly-available CDS market statistics on net notional CDS amounts and CDS trading volume for individual reference entities from the Depository Trust & Clearing Corporation (DTCC). Because the DTCC provides disaggregated information at the reference entity level, the data allows a much more detailed investigation of motivations of trading in the CDS market than was previously possible. In our analysis, we focus on *net notional* CDS positions on individual reference entities, which is calculated as the sum of net protection bought (or sold) by counterparties that are net buyers (sellers) of protection for a particular reference entity. Intuitively speaking, the net notional amount captures the stock of credit risk that is transferred via the CDS market. In addition to the stock of credit risk transferred, we also investigate the flow of credit risk by examining *trading volume* in the CDS market and the underlying reference bonds.

We first provide evidence consistent with the view that CDSs are being used as instruments for hedging. Specifically, we show that firms that have more bonds outstanding also have larger net notional CDS positions. This positive relation between insurable interest and net notional amounts in the CDS market indicates that at least some market participants use the CDS market to hedge their bond exposure. Our baseline estimate of 7.77 cents of net CDS positions per dollar of outstanding bonds suggests that this hedging role is economically significant: A move from the 25th to the 75th percentile in bonds outstanding is associated with a 31.9% increase in CDS positions for the median firm. While non-bond debt (e.g., bank loans) is generally not associated with larger net notional CDS positions, some other proxies for insurable interest are. For example, net notional CDS positions are larger for firms that provide credit guarantees (e.g., monoline insurers) or have large amounts of accounts payable and therefore represent counterparty risk to other market participants. Turning to trading volume in the bond and CDS markets, we document a similar pattern in the sense that hedging motives are associated with comparable amounts of trading volume in the bond and the CDS market (8.62 cents on the dollar in monthly trading volume in the bond market, 2.83 cents on the dollar in the CDS market in our the baseline specification). Taken together, the documented link between insurable interest and net notional CDS amounts suggests that at least some market participants use the CDS market to hedge their debt, bond, or counterparty exposure.

Second, we document that proxies for speculative trading motives are associated with larger net CDS positions. Specifically, we show that disagreement about a reference entity's future earnings prospects (as measured by analyst earnings forecast dispersion) is associated with larger net notional CDS amounts, in an economically significant way: A one-standard deviation increase in disagreement is associated with an 18% increase in net notional CDS positions for the median firm in our baseline specification. This indicates that, in addition to hedging, investors use the CDS market to speculate by taking views on the default probabilities of traded reference entities. Interestingly, trading in response to speculative motives seems to occur almost exclusively in the CDS market, not in the underlying bonds: A one-standard deviation increase in disagreement is associated with 43.1% more CDS trading for the median firm, but no more trading (of statistical or economic significance) in the underlying bond. This finding is consistent with the view that speculators, who generally have shorter trading horizons, value the liquidity advantage of the CDS and thus take short-term views in the CDS market.

While taken together these results suggest that both hedging and speculation are determinants of CDS positions, they do not explain *why* investors choose to trade in the CDS market as opposed to trading directly in the underlying bond. This leads to the main finding of our paper, which suggests that CDS markets serve a standardization role: Holding constant the amount of bonds outstanding and speculative trading motives, net notional CDS amounts are larger for firms with bonds that are fragmented into many separate issues, as proxied by a Herfindahl index of bond issues. Above-median bond fragmentation is associated with $272m more in net notional CDS positions, an increase of 33% relative to the median firm. Similarly, when we replace bond fragmentation with a more direct measure of contractual heterogeneity among bond issues, we find that firms whose bond issues exhibit more heterogeneity in contractual terms (e.g., callable, puttable, etc.) haver larger net notional CDS positions. Contractual heterogeneity across bonds is associated with $291m more in net notional CDS positions, an increase of 36% relative to the median firm. The same pattern emerges when looking at trading volume. Bond fragmentation and contractual heterogeneity among bond issues are associated with more trading volume in the associated CDS and less trading in the underlying bond. Taken together, these findings lend strong support to the view that CDS markets serve a standardization role: CDS markets, which are relatively standardized, are attractive precisely when the underlying bonds are fragmented and have heterogeneous contractual terms.

What is the mechanism through which the standardized nature of the CDS market attracts investors? Here, our evidence suggests that this mechanism is related to liquidity. Specifically, we show that higher bond fragmentation and contractual heterogeneity among bond issues are associated with higher roundtrip trading costs and lower turnover in the underlying bonds. This result echoes the view, commonly held among bond market practitioners, that the fragmentation of the corporate bond market impedes its liquidity, thereby generating potential benefits from standardization (BlackRock, 2013). Our evidence suggests that, in the absence of more standardized bonds, the CDS market can step in to provide a standardized trading venue for credit risk.

Finally, we provide evidence that net notional CDS positions reflect arbitrage between the bond and CDS markets. In particular, net notional CDS positions are increasing in the negative CDS-bond basis, a measure of price differences between the underlying bond and the CDS. 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. Consistent with the predictions of the equilibrium model of Oehmke and Zawadowski (2015), we show that CDS positions are increasing in the negative basis, particularly when funding conditions for basis traders are favorable. This result suggests that arbitrageurs use CDSs to lean against the negative CDS-bond basis—an interpretation that is supported by the finding that the effect is larger during times when funding conditions for arbitrageurs are better. The presence of basis traders has major economic implications, because it affects pricing in the bond and CDS market: First, we show that the CDS-bond basis is, on average, less negative when basis traders are active. Second, we show that, by acting as absorbers of supply shocks, the presence of levered basis traders reduces price impact in bond market. These positive effects of CDSs complement the results of Saretto and Tookes (2013), who document that the presence of CDSs allows firms to borrow more and at longer maturities.

To our knowledge, this is the first comprehensive study of CDS positions and trading volume at the reference entity level. While our analysis is largely descriptive, the goal of the paper is to provide a set of descriptive results and tests that lay a foundation for future theoretical and empirical work on CDS markets. A few other recent empirical studies have investigated CDS positions or transaction volume, but are mostly based on less disaggregated data or shorter sample periods. 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 were the main source of position information before the DTCC data became available. Using three months of confidential trading data, Chen et al. (2011) document relatively low unconditional trading volume in CDSs, with spikes in trading around credit events. Consistent with the standardization function of CDS markets documented in this paper, they show that trading in CDS markets concentrates in the more standardized contracts that conform with the industry's "big bang" protocol change. Shachar (2011) uses transaction level data to investigate price effects of traded volume, order imbalances and dealer inventories in the CDS market. In addition, a number of recent papers investigate the CDS-bond basis (Blanco et al., 2005; Bai and Collin-Dufresne, 2013; Nashikkar et al., 2011; Fontana, 2011). Our paper contributes to this literature by linking the CDS-bond basis to quantities in the CDS market.[2]

[2] More broadly, our paper relates to a growing literature that investigates the effects of CDS markets on information transmission, risk transfer, and credit market outcomes (Acharya and Johnson (2007), Qiu and Yu (2012), Minton et al. (2009), Ashcraft and Santos (2009), Hirtle (2009), and Saretto and Tookes (2013)), as well as a growing theory literature on the uses of CDSs (Duffee and Zhou (2001), Parlour and Plantin (2008), Thompson (2009), Parlour and Winton (2013), Bolton and Oehmke (2011), Zawadowski (2013), Atkeson et al. (2015), Che and Sethi (2014), Fostel and Geanakoplos (2012), and Oehmke and Zawadowski (2015)). Du and Zhu (2013), Gupta and Sundaram (2012), and Chernov et al. (2013) investigate CDS settlement auctions.

1 Empirical Hypotheses

Taken together, the theory literature on credit default swaps suggests several economic motives for trading in the CDS market. We distill these motives into four main hypotheses. These hypotheses should be seen as broadly guiding our empirical analysis and allowing us to perform a number of descriptive tests that shed light on trading patterns in the CDS market. In particular, because of lack of natural experiments we are generally not able to identify causal effects. The aim of this paper is therefore to provide a set of descriptive results that can lay a foundation for future theoretical and empirical work on CDS markets.

First, to the extent that CDSs are used for hedging, insurable interest should play a role in determining net notional CDS amounts and CDS trading volume. For example, in a setting in which some fraction of investors insure their bond holdings, more bonds outstanding (i.e., larger insurable interest) is naturally associated with larger net notional CDSs amounts and, potentially, more trading volume in the CDS. Note that, whereas hedging demand is naturally related to insurable interest, there is no reason to believe that speculative trading activity (i.e., bets on future changes in credit quality) in the CDS market should be directly related to insurable interest.

Second, 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 other exposure to the reference entity (see, for example, Fostel and Geanakoplos, 2012; Che and Sethi, 2014). To the extent that CDSs are used as speculative instruments, reference entities on which investors' beliefs differ more should have larger outstanding CDS positions than reference entities with less disagreement. To the extent that speculative bets represent short-term views, they should also be associated with more CDS trading volume.

Third, because investors can choose between trading in the CDS market or directly in the underlying bond, CDS markets should be more attractive when there are frictions in the market for the underlying bonds. One of the main differences between bonds and CDSs is their level of standardization: While different bond issues usually differ significantly in their contractual terms (covenants, callability features, coupon, etc.), CDS are standardized products that generally follow a set of standardized contractual terms set forth in the ISDA protocol (see, for example BlackRock, 2013). The larger this standardization advantage of the CDS, the more attractive the CDS market should be for investors.

Fourth, CDS positions could be driven by arbitrage activity. No arbitrage implies that a long position in a bond hedged with the appropriate CDS should earn (approximately) the risk-free rate (Duffie, 1999). Deviations from this no-arbitrage relationship should be associated with larger net CDS positions, as arbitrageurs attempt to exploit these deviations through the basis trade. 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 will enter a negative basis trade where they purchase the bond and CDS protection, thereby increasing the amount of CDSs outstanding. Here we base our hypotheses on the theoretical framework of Oehmke and Zawadowski (2015), who show that in equilibrium such arbitrage trades lead to a positive correlation between a more negative CDS-bond basis (due to bond illiquidity or bond supply shocks) and the size of CDS positions taken by arbitrageurs. Their model also predicts that stronger arbitrage activity influences economic outcomes, by compressing the CDS-bond basis and reducing price impact in the bond market. (We develop more detailed hypotheses regarding the CDS-bond basis in Section 4.)

2 Data and Summary Statistics

Our data on CDS positions and CDS trading comes from the Trade Information Warehouse of the Depository Trust & Clearing Corporation (DTCC).[3] The position and trading data from the DTCC

[3] 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). The data is available on the DTCC's website at www.dtcc.com/repository-otc-data.aspx.

capture almost the entire market for standard single-name CDSs. According to the DTCC (2009), their data capture around 95% of globally traded CDSs, making it the most accurate and comprehensive publicly available dataset for CDS positions and trading.[4]

Weekly CDS position data is available from October 31, 2008 in Table 6 of Section I of the DTCC data. In its weekly reports on outstanding CDS positions, 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. In our analysis, we focus on the *net notional* amount, because it provides a more meaningful measure of the amount of credit risk transferred in the CDS market: The net notional amount outstanding adjusts the gross notional amount[5] for offsetting positions in order to better reflect the actual amount of credit risk transferred in the CDS market. Specifically, 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). Intuitively, one can thus interpret the net notional amount outstanding 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.[6] Figure 1 provides a simple example to illustrate the difference between gross notional and net notional.

[4] 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 available at www.bis.org/statistics/derstats.htm. 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.

[5] The gross notional amount outstanding is simply 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. The gross notional position increases even if a trade offsets an existing trade and thus reduces the overall amount of credit risk transfer in 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.

[6] 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.

Weekly CDS trading data is available starting July 16, 2010 in Section IVa of the DTCC data. These data capture all trades recorded with the DTCC that constitute *market risk activity*, which means that trades are recorded only if they result in a transfer of credit risk among market participants (this includes, for example, new trades, the termination of existing transactions, assignment of an existing transactions to a third party etc.). Trades that do not transfer risk are excluded (for example, the clearing of existing bilateral trades by central counterparties, portfolio compression trades, and backloaded trades). The resulting measure of CDS trading volume is therefore directly comparable to trading volume in the underlying bond.

Our sample is comprised of public U.S. (parent) companies in Compustat that are traded reference entities in the CDS market. We define existence of a CDS market as having at least 3 CDS dealers that provide quotes on a 5-year CDS in the Markit data and/or being one of the top 1,000 reference entities in the DTCC data (we hand-match Compustat firms to DTCC and Markit). We assume that once a CDS market exists for a reference entity, it continues to exist for the remainder of our sample. We include only firms which, in a given month, have at least one bond registered with the SEC and are rated by S&P (in order to control for credit quality). We also restrict our sample to public companies with at least 2 analysts to be able to control for disagreement. As data sources, we rely on Compustat (balance sheet data, credit ratings, and industry codes), Mergent FISD (data on outstanding bonds), TRACE Enhanced[7] (bond trading data), CRSP (stock price data), IBES (earnings forecasts), and Markit (CDS spreads). A detailed description of our sample construction and matching procedures can be found in Appendix A. We provide all variable definitions in Table 1.

Our final sample has 496 firms, out of which 302 appear in the DTCC data at least once during our sample period. We can calculate the CDS-bond basis for 123 of these companies, 97 of which appear in the DTCC data. We use monthly data as most controls, such as ratings and disagreement,

[7] TRACE Enhanced is preferable to TRACE because it contains transaction information, such as trade size, that is not always available in TRACE (for example, TRACE does not contain trade sizes for large trades). TRACE Enhanced also includes transactions that at the time of trading were not subject to reporting (for example, trades in non-investment grade corporate bonds. Using TRACE Enhanced (rather than TRACE) therefore allows us to more accurately calculate bond turnover and bond trading costs.

are only available on a monthly basis. Altogether the time series length of our baseline sample on net notional CDS is 52 months: October 2008 to December 2012. The length of the CDS trading data is somewhat shorter; these data are available for 29 months from August 2010 to December 2012.

Table 1 provides summary statistics for our baseline sample of firms that are traded reference entities in the CDS market. Overall, we have data on gross and net notional CDS positions for 13,441 firm-month observations. For those firms, the mean net notional CDS amount is given by $1.035bn. The mean gross notional amount of CDS outstanding on a reference entity in our sample is $13.13bn. The corresponding medians are $817m and $9.914bn, respectively. Hence, netting within counterparties on average reduces the amount of CDS outstanding by a factor of more than ten.

Firms in our sample have median assets of $10.63bn and $1.798bn of outstanding bonds. For firms in DTCC, normalizing the amount of CDS protection bought or sold by the total amount of bonds the reference entity has outstanding, we find that the median net notional amount of CDS as a fraction of bonds outstanding is equal to 26.1% of bonds when looking at bonds issued directly by that firm and 18.2% when we consolidate bonds to also include bonds issued by subsidiaries. The 90th percentiles given by 113.8% and 85.9%, respectively. One interesting observation is that, while these numbers suggest that significant amounts of credit risk are transferred through the CDS market, the data do 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 bonds outstanding.[8]

Figure 2 plots the evolution of total net notional CDS amounts over time. The top solid line depicts the total amount of net CDS outstanding on all single-name reference entities captured by the DTCC. This is essentially the entire single-name CDS market. As the figure illustrates, since the fall

[8]Nonetheless, there are some firms for which the amount of net notional of CDS outstanding significantly exceeds the amount of bonds the firm has outstanding. A typical example are potential buyout targets (with low current debt, but potentially large future debt), such as the clothing retailer Gap and the electronics distributer Arrow Electronics. Other types of companies with high net CDS amounts as a fraction of outstanding bonds are homebuilders, mortgage insurers and suppliers for the automobile industry.

of 2008 net notional CDS amounts have decreased by about 35%. Nonetheless, aggregate net notional in the single-name CDS market is still substantial at around $1tn at the end of 2012.[9] The dashed line depicts the total net notional 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 (in addition to firms, this includes sovereigns, states, and municipalities). Finally, the dotted line plots the total net notional CDS amounts for our final sample. After dropping sovereigns, states, municipalities, non-U.S. companies, non-rated companies, and other reference entities that we cannot match to Compustat, our sample still constitutes a significant fraction of the total single-name corporate CDS market.

Monthly turnover in the CDS market (trading volume divided by net notional CDS positions) is on average 50.6% (median 43.7%) and therefore substantially higher than bond turnover, which amounts to 7.16% for the average firm (median 4.62%). Note that this observation in itself lends preliminary support to our hypothesis that the CDS market is attractive because it is more liquid than the associated bond market. Figure 3 plots monthly trading volume in CDSs and the underlying bonds in our sample. As discussed above, trading volume for CDSs only includes trades that represent market risk transfer (i.e., trades that change the allocation of credit risk among market participants) and is available starting August 2010. The plot shows that for traded reference entities monthly trading volume in the CDS market (solid line) is comparable in size to trading volume in the associated bonds (dashed line). However, bond turnover is much smaller than CDS turnover because on average the amount of bonds outstanding is larger than the associated net notional CDS positions. Bonds of

[9]The decrease in net CDS positions does not necessarily imply that the CDS market has become less relevant over time. In particular, the DTCC data suggests that the downward trend in net CDS positions is primarily due to a decrease in interdealer positions, whereas customer positions have increased. Although net notional CDS positions are not available by the counterparty type, Table 1 in Section I of the DTCC TIW reports the gross positions by counterparty type. Over of our sample period, gross interdealer positions in single name CDSs decreased from $12.68tn to $9.23tn. At the same time, gross CDS positions bought by customers (non-dealers) from dealers increased from $1.43tn to $2.04tn, and gross CDS positions sold by customers to dealers increased from $1.26tn to $2.06tn.

companies that are not in the DTCC sample have significantly lower bond trading volume (dotted line).

3 CDSs as Alternative Trading Venues

In this section, we investigate the determinants of net notional CDS positions as well as trading volume in the CDS and bond markets. The main empirical result is that, controlling for hedging needs and speculative trading demand, net notional CDS positions and CDS trading volume are larger for firms whose bonds are fragmented into many separate issues and have heterogeneous contractual terms. We then provide evidence that these results reflect the economic role of the CDS market as an alternative trading venue that circumvents trading frictions in the underlying corporate bond market.

3.1 Measures of CDS demand and bond market frictions

Tables 2 and 3 contain our baseline specifications that investigate the determinants of net notional CDS positions and CDS and bond trading volume, respectively. In both tables, we are interested in hedging and speculation motives as determinants of CDS positions, as well as the role of frictions in the underlying bond market. We proxy for hedging motives with the amount of bonds that is outstanding, which captures insurable interest. We proxy for speculative trading motives using analyst forecast dispersion normalized by the stock price (disagreement) for the underlying company. To examine the role of trading frictions in the bond market, we focus on one of the main differences between bonds and CDSs: Whereas the CDS is a standardized contract with a standard set of contractual features and standardized maturities, a firm's bonds are usually split into a number of different issues with different maturities, coupons, covenants, and embedded options. Since the "big bang" protocol change of April 2009, CDSs also trade with standardized coupons and standardized accruals, further increasing standardization.

We construct two measures of the relative standardization advantage of CDSs. The first is based on the fragmentation of a firm's bonds into separate issues. Specifically, we calculate a Herfindahl index of bond issues for every firm in our sample.[10] We then take the natural logarithm of the Herfindahl in order to improve the distributional properties of the measure and adjust the measure for the mechanical relationship between total issuance and the number of bond issues (firms that have more bonds outstanding usually also have more separate bond issues). We do this by regressing the log Herfindahl on the log of bonds outstanding of the firm. Our measure of bond fragmentation is given by the residual of this regression. Finally, we multiply this measure by minus one, such that a higher value of bond fragmentation means just that. The resulting bond fragmentation measure therefore captures the fragmentation of a firm's bond issues controlling for the overall amount of bonds that a firm has outstanding. Our results are similar when we use a Herfindahl index that is not adjusted for the amount of bonds bonds a firm has outstanding.

This bond fragmentation measure is attractive for a number of reasons. First, it captures one of the first-order differences between bonds and CDSs. Whereas a firm's bonds are usually fragmented into a number of different issues with different contractual terms, the CDS is a standardized contract. Therefore, the more fragmented and diverse a company's bonds, the more attractive the CDS market should become as a venue for trading credit risk. Second, unlike other common measures of trading frictions, bond fragmentation is likely to be (relatively) exogenous to CDS trading: It is unlikely that managers choose the fragmentation of their bond issues to affect CDS trading on their bonds. Bond fragmentation is therefore a more attractive right hand side variable than direct measures of bond trading costs, which are usually highly endogenous. Third, while measures of liquidity that rely on trading costs or trading volume confound the effects of the ease of trading (i.e., how easy is it to trade

[10] This is done by summing, for each firm i, the squared shares that each bond issue j represents of the overall amount of bonds firm i has outstanding:

$$H_i = \sum_{j=1}^{N} \left(\frac{b_{i,j}}{B_i}\right)^2,$$

where $b_{i,j}$ denotes the dollar amount of bond issue j of firm i, and $B_i = \sum_j b_{i,j}$ denotes the total dollar amount of bonds that firm i has outstanding. For example, a firm that has issued \$1bn in bonds as one unified issue would have a Herfindahl of one, whereas a firm that has issued the same amount but in five separate issues would have a Herfindahl of 0.2.

the bond?) and the demand for trading (i.e., how strong are market participants' motives to trade?), the fragmentation of a reference entity's bonds is likely to be less affected by demand for trading and therefore provides a cleaner measure of how easy it is to trade the bonds.

On the other hand, one shortcoming of the bond fragmentation measure is that, while suggestive of a standardization role of CDSs, it does not directly measure contractual heterogeneity among bonds that the CDS serves to standardize. We therefore construct a second measure of standardization based directly on the heterogeneity of contractual features among bond issues of a given firm. Specifically, Mergent FISD provides dummy variable information on whether a particular bond is (i) puttable, (ii) callable, (iii) convertible, (iv) has a fixed coupon, (v) has covenants, and (vi) is subject to credit enhancement. We construct a contractual heterogeneity dummy which takes the value 0 for those firms for which all the above contractual features are the same across all issues and takes the value 1 for all other firms (i.e. for firms that have at least some heterogeneity in contractual features). The advantage of the contractual heterogeneity measure is that it captures directly the difference of contractual terms across bond issues and therefore allows us to draw sharper conclusions regarding a potential standardization role of CDS markets. The slight disadvantage of this measure is that contractual features of a particular bond issue are measured relatively imprecisely: Mergent FISD only provides dummy variables as to whether certain contractual features are present in a particular bond issue.

3.2 Determinants of net notional CDS positions

Table 2 shows the results of our baseline regression of net notional CDS amounts on proxies for insurable interest and speculative trading demand, as well as bond fragmentation and contractual heterogeneity. The regression specification is

$$NetCDS_{i,t} = \beta \cdot X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where the vector X contains explanatory variables (our proxies for hedging and speculation as well as measures of bond fragmentation and contractual heterogeneity), a set of controls, and a constant, and ϵ is an error term. Note that controls include credit quality proxied by S&P rating dummies. Note that we do not scale net CDS by assets. The reason is that neither net CDS nor the trading motives (e.g., speculation or the basis trade) scale naturally with assets or bonds outstanding. Because the DTCC provides net notional amounts only for the top 1,000 reference entities, our data is subject to a censoring problem. In particular, for traded reference entities that do not appear in the 1,000 largest reference entities provided by the DTCC we know that the CDS amount is positive but lies below the 1,000th largest reference entity. Because of this, estimates from a simple OLS estimation would be biased. We therefore run a maximum likelihood estimation that takes account of the censoring in the data. To mitigate the effect of outliers, we allow the error term to scale with bonds outstanding. Finally, because of autocorrelation of our regressors, we cluster standard errors at the firm level. The econometric details of our estimation procedure can be found in Appendix B.

Table 2 shows that, across a number of different specifications, both insurable interest and speculative trading demand are significant determinants of net CDS positions: First, the positive coefficient on *bonds outstanding*, significant at the 1% in most specifications, demonstrates that insurable interest is a significant determinant of the net notional positions in the CDS market. This finding supports the view that at least some traders in the CDS market use CDS to hedge bond exposure. Quantitatively, the coefficient of 0.0777 in the regression of column (1) that controls for ratings and includes time and industry fixed effects implies that for each additional dollar in bonds outstanding, net CDS positions are on average 7.77 cents larger. To gauge the economic magnitude of this effect, note that in our sample, a move from the 25th to the 75th percentile in terms of bonds outstanding is associated with an increase in net notional CDS positions of $261m, which raises the net notional for the median firm (which has $817m in net notional CDS) by about 31.9%.[11] When we include firm

[11] In our sample, the 25th percentile of bonds outstanding is $800m and the 75th percentile $4.15bn. For insurable interest, we use percentiles to gauge economic significance because bonds outstanding is strongly positively skewed. A one-standard deviation increase in bonds outstanding is associated with a $984m increase in net notional CDS amounts.

fixed effects in column (2), the magnitude of the effect is smaller and no longer statistically significant, but at 1.38 cents on the dollar remains economically significant.[12]

In addition to bonds outstanding (arguably the most natural proxy for insurable interest because CDSs directly reference a firm's bonds), specifications (3) and (4) control for firm size and a number of additional proxies for insurable interest that may capture relevant hedging motives in the CDS market. Three observations emerge. First, including other types of debt we find that it is bonds that matter for CDS positions. Bonds are not simply a proxy for other types of debt or the size of the firm. In column (3), we add total assets of a firm as an explanatory variable and find it both economically and statistically insignificant at 0.093 cents per dollar of assets. More importantly, bonds outstanding is almost unchanged compared to column (1) and remains statistically and economically significant. Column (4) includes bonds of subsidiaries and other non-bond debt. The coefficient on bonds of subsidiaries is statistically insignificant and economically small. While other borrowing is statistically significant, it is negative, which might be due to the fact that it is calculated as a residual quantity. Most importantly, the coefficient on bonds outstanding remains of similar magnitude and significant. The evidence is therefore consistent with the hypothesis that CDSs are mainly used to insure bonds and not other types debt, such as bank loans and debt of the subsidiaries.[13] Second, the large positive and statistically significant coefficient on the dummy variable *credit enhancement* in column (4) reflects that there is a large amount of net notional CDS protection written on companies that provide credit enhancement (e.g., monoline insurers): Firms that provide credit enhancement

[12]Given our relatively short time series and the fact that, at the firm level, neither the amount of bonds outstanding nor net notional CDS positions vary much over time, it is not surprising that the effect is weaker when we include firm fixed effects. It is reassuring, however, that even with firm fixed effects the result remains economically significant. In the trading volume regression below, where there is more time-series variation, bonds outstanding remains significant even with firm fixed effects. Finally, note that the sample size drops when we include firm fixed effects. The reason is that in order to identify the firm fixed effect, a firm has to be observed in the DTCC data at least once. Hence, we lose firms that have traded CDS contracts but are not part of the DTCC position data.

[13]This finding is perhaps not all that surprising given that CDS directly references a company's bonds. Recovery rates for other types of debt (e.g., loans) differ from those of bonds, such that a CDS is a less precise hedge. There is a separate market for loan credit default swaps (LCDSs), but according to the DTCC data this market is very small. For example, in December 2011, the net amount of LCDSs registered with the DTCC was \$7.2 billion for US companies and \$1.1 billion for European companies, compared to regular net CDS of \$1.1 trillion.

on average have an additional \$2bn in net notional CDS positions outstanding.[14] This suggests that investors who rely on insurance from monoline insurance companies and other providers of credit enhancement purchase CDSs in order to eliminate their counterparty risk, as in Zawadowski (2013). 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. Third, net notional CDS amounts tend to be larger for firms with large amounts of accounts payable (by 2.02 cents per dollar of accounts payable), suggesting that trade creditors use the CDS market to hedge exposures to their trading partners. These findings corroborate the role of insurable interest as a determinant of net notional CDS positions. We provide further robustness checks using additional hedging proxies and controls in Table 8 in the online appendix.

Second, to investigate the role of speculation, Table 2 includes analyst earnings disagreement as a proxy for speculative trading demand. The rationale for this proxy is that the more traders disagree on a firm's earnings prospects, the more they may want to take views on credit risk because disagreement about default probabilities should naturally be related to disagreement about earnings. Our disagreement measure divides earnings-per-share forecast dispersion by the share price.[15] This measure can be interpreted as the size of the firm's equity cushion relative to disagreement on earnings (one attractive feature of this measure is that, by dividing through the equity cushion, it automatically adjusts for the firm's leverage). We find that, across all specifications, higher analyst disagreement is associated with more net CDS outstanding for traded reference entities, mostly significant at the 1% level. Based on the baseline specification in column (1), which includes ratings controls and time and industry fixed effects, a one standard-deviation increase in earnings disagreement is associated with an increase in the net notional CDS amount of \$146m, which corresponds to 18% of the median net notional CDS amount. When controlling for firm fixed effects (column (2)), the magnitude of the

[14]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.

[15]We use IBES earnings analyst forecasts on two-year earnings per share to calculate the measure of disagreement. We divide the standard deviation of forecasts by the CRSP stock price if the stock price is above one dollar and set it to missing (and thus excluded from the sample) otherwise.

coefficient is smaller but still statistically significant at the 5% level. In Table 9 in the online appendix we show that these results continue to hold when using the ratio of CDS trading to bond trading as an alternative proxy for disagreement.

Third, consistent with the hypothesis that CDS markets are attractive when there are trading frictions in the underlying bonds, Table 2 shows that the fragmentation of a firm's bonds into separate issues is a highly significant determinant of net notional CDS positions.[16] Column (5) shows that, controlling for the total amount of bonds that a reference entity has outstanding, bond fragmentation is associated with larger net CDS positions. Column (6) repeats the same analysis but using a dummy variable for above-median bond fragmentation. In both specifications, bond fragmentation is significant at the 1% level and the effects are economically large. For example, the coefficient of 0.272 on the bond fragmentation dummy variable implies that firms above the 50th percentile of bond fragmentation on average have \$272m more net notional in CDSs outstanding. The coefficient of 0.272 on bond fragmentation in column (5) implies that a one-standard deviation increase in bond fragmentation is associated with an increase in net notional CDS positions of \$110m. Both of these effects are economically significant when compared to the median firm's net notional CDS amount of \$817m.

While the fragmentation of a firm's bonds is arguably more exogenous than other standard measures of trading frictions (such as trading volume or trading costs), bond fragmentation is ultimately also a choice variable for firms. For example, one may worry that firms change the fragmentation of their bonds depending on whether they are traded reference entities. To alleviate such endogeneity concerns, column (7) repeats the analysis using a predetermined bond fragmentation measure. We define predetermined bond fragmentation as the fragmentation of a firm's bonds at the moment that firm becomes a traded reference entity in the CDS market. In cases where the firm was already a traded CDS reference entity in January 2002 (when the CDS market was still in its infancy), we use

[16]All columns that include bond fragmentation and contractual heterogeneity of bond issues include time and industry fixed effects and ratings controls. Because for a given firm bond fragmentation and contractual heterogeneity is essentially constant over time, we cannot not include firm fixed effects in these specifications.

the bond fragmentation at that point. This robustness check confirms our results by showing that also predetermined bond fragmentation is a significant determinant of net CDS positions.

Columns (8) and (9) investigate contractual heterogeneity of outstanding bonds as a determinant of CDS positions. Column (8) shows that having bonds with different contractual terms is associated with an increase in CDS positions of $291m. The explicit measure of contractual heterogeneity therefore lends further support to the interpretation that the CDS market serves a standardization role. Column (9) shows that contractual heterogeneity remains significant when also controlling for bond fragmentation, although the coefficient is sightly reduced. This suggests that bond fragmentation and contractual heterogeneity capture related but not identical aspects of frictions in the bond market.

3.3 Determinants of CDS and bond trading volume

Table 3 examines trading volume in the bond and CDS markets. Investigating trading volume is interesting for two reasons. First, it allows us to examine whether the determinants of trading flow in the CDS market are the same as the determinants of the stock of credit risk that is transferred via the CDS market (i.e., the net notional). Second, looking at trading volume allows us to directly compare the determinants of trading volume in the CDS market to the determinants of trading in the underlying bond, thereby shedding light on the potentially different roles these two markets fulfill.

Table 3 shows the results of a joint regression of CDS and bond trading volume on insurable interest (bonds outstanding), speculative trading motives (analyst disagreement), bond fragmentation, and contractual heterogeneity on trading in the bond market and the CDS market. The regression specification is similar to the above specification for net notional, except that, unlike net notional, trading volume as an outcome variable is not censored. Rather, because trading volume can be zero both in the CDS and the bond market, we run a tobit regression. Moreover, because unobservable variables might lead to trading in both the bond and the CDS market, we estimate the two trading equations jointly, allowing the error term in the two equations to be correlated, see Appendix B for details.

The results indicate that, across all specifications, insurable interest is a significant determinant of trading volume, both in the bond market and the CDS market. Disagreement, on the other hand, is a strong determinant of trading volume in the CDS market but not in the bond market, where the estimated coefficient is much smaller (and insignificant across all specifications). Table 3 also shows that there are striking differences in the economic magnitudes of the effects across the two markets, the baseline specification is column (1). The effect of insurable interest (bonds outstanding) on trading volume in the bond and the CDS markets are of the same order of magnitude. In the bond market, an additional dollar of bonds outstanding is associated with an increase in monthly trading volume of 8.62 cents in the specification of column (1), significant at the 1% level. In the CDS market, an additional dollar of bonds outstanding is associated with an increase in monthly trading volume of around 2.83 cents, also significant at the 1% level. The difference between the two coefficients is statistically significant at the 1% level, but the economic magnitude of the effect is similar. This changes dramatically when we investigate the effect of disagreement on trading volume: Here, the effects are at least an order of magnitude larger in the CDS market. Taking the coefficient of 4.594, a one standard-deviation increase in disagreement is associated with an increase of $144m in monthly trading volume in the CDS market, which corresponds to 43.1% of median CDS trading volume. In contrast, in the bond market a one standard-deviation increase in disagreement is associated with a (statistically insignificant) increase of only $13.3m in monthly trading volume. Again, the difference between the coefficients is significant at the 1% level but, more importantly, the size of the two effects are of a different order of magnitude. In specification (2) we repeat the analysis with firm fixed effects.[17] Note that there is much more time variation in trading activity, so the coefficients are much better identified than in case of explaining net CDS. Both the size and the statistical and economic significance of the coefficients of bonds outstanding and disagreement are very similar to the case in column (1) both for bond and CDS trading.

[17] We had to exclude one firm from the sample in the specification that includes firm fixed effects because, for that firm, there are no bond transactions during our sample period, such that the firm fixed effect cannot be identified.

Hence, while insurable interest is associated with more trading volume in both the bond and the CDS market (with larger effects in the bond market), our evidence suggests that, conditional on the existence of a CDS market, trading due to speculative motives occurs predominantly in the CDS market. This finding is consistent with the view that, due to the liquidity advantage of the corporate CDS market, speculators (typically hedge funds with the ability to trade in both markets) take short-term views in the CDS market and not in the underlying bonds. On the other hand, irrespective of the fact that the bond is less liquid, bond investors (hedgers) might still use the bond market to trade for two reasons. First, liquidity traders who need cash still need to trade in the bond market since hedging in the CDS market does not necessarily free up the invested cash. Second, many hedgers that need to offload credit risk could be institutional investors that are restricted in their use of derivatives (e.g., mutual funds).

Columns (3) to (5) examine the effect of bond fragmentation and contractual heterogeneity of bond issues on trading volume in the bond and the CDS market. The coefficients on bond fragmentation and the bond fragmentation dummy indicate that for firms with more fragmented bonds we observe significantly less trading in the underlying bond and more trading in the CDS. The coefficient on the dummy variable for fragmentation in column (4) lends itself to a particularly easy interpretation: Above-median bond fragmentation is associated with \$20.1m less in monthly bond trading volume, which corresponds to a reduction of about 22% for the median firm. In the CDS market, above-median bond fragmentation is associated with higher trading volume of \$89.9m, an increase of about 27% for the median firm. The difference between the coefficients on fragmentation for CDS and bond trading is significant at the 1% level both for the continuous and the dummy measure. This finding indicates that for firms with more fragmented bonds, more trading of credit risk happens in the CDS market and less in the bond market, suggesting that the CDS market is a substitute trading venue for bonds. A similar picture emerges in column (5), which investigates the contractual heterogeneity of bond issues as a determinant of trading volume. Contractual heterogeneity is associated with \$84m more monthly trading volume in the CDS and a reduction of \$17.3m of trading volume in the underlying bonds, the difference is again significant at the 1% level. Tables 10 and 11 in the online appendix show that these results continue to hold when using alternative hedging proxies, size controls, and controls for lagged CDS returns and volatility.

3.4 CDS markets and trading frictions in the bond market

Taken together, the evidence in Tables 2 and 3 therefore confirms the hypothesis that CDS reference entities have larger net notional CDS amounts and more CDS trading when the underlying bonds are fragmented into separate issues and heterogeneous in their contractual terms. We now provide evidence that the mechanism behind this result is indeed related to trading costs and liquidity.[18] Specifically, Table 4 investigates the link between bond fragmentation and two commonly used measures of liquidity: bond trading costs and bond turnover. We measure bond trading costs as the "implied spread" that traders pay on a roundtrip bond transaction, following Feldhütter (2012).[19]

The results show that higher bond fragmentation and more contractual heterogeneity among bonds are both associated with higher trading costs and lower turnover in the associated bonds. The specification in column (1) implies that a one-standard deviation increase in bond fragmentation is associated with a 6.2% increase in roundtrip trading costs and a reduction of 17.5% in bond turnover (column (4)) relative to the median firm. Similarly, roundtrip trading costs are 8.8% higher (column (2)) and monthly bond turnover 21.9% lower (column (5)) for firms with bonds that are contractually heterogeneous when compared to the median firm. When adding both bond fragmentation and contractual heterogeneity in columns (3) and (6) fragmentation drives out the effect of contractual heterogeneity to a substantial degree. To eliminate potential worries that these results are driven by firms with very

[18] Because bond trading costs and bond turnover are highly endogenous variables, we did not include them as regressors in our regressions above. However, in order to investigate the mechanism behind the association between activity in the CDS market and bond fragmentation, we now use roundtrip trading costs and bond turnover as left-hand-side variables in Table 4.

[19] Specifically, we match bond trades of the same size that are at most 15 minutes and 10 trades apart and then calculate the roundtrip trading cost, expressed as a spread. Half roundtrip spreads (customer to dealer) are multiplied by 2 to get the full implied roundtrip cost. We only consider trades with par value of at least $1 million to capture institutional trades.

few bond issues, Table 12 in the online appendix show that these results continue to hold when we restrict the sample to firms with at least three bond issues.

The control variables enter as expected. Firms that have more bonds outstanding have more liquid bonds, both in terms of lower trading costs and higher turnover.[20] Disagreement is associated with higher implied trading cost (consistent with higher levels of asymmetric information) and higher turnover (most likely reflecting trading demand created by disagreement). This finding highlights that turnover is an imperfect measure of liquidity, because it confounds the ease of trading with the demand for trading.

Overall, our evidence supports the view of the CDS market as an alternative trading venue that circumvents trading frictions in the underlying bond market. The CDS market is particularly active for firms with bonds that are fragmented and contractually heterogeneous, making them illiquid and costly to trade. This finding echoes the view, held among bond market practitioners, that the fragmentation of the corporate bond market impedes its liquidity, thereby generating potential benefits to the introduction of more standardized securities. While some market participants have proposed increasing standardization in the corporate bond market itself (e.g., BlackRock, 2013), our results indicate that, in the absence of more standardized bonds, the CDS market can step in as a more standardized trading venue.[21]

[20]One interpretation of this result is that, in an OTC market, a larger asset float makes it easier to find trading partners, reducing trading cost. In contrast, as discussed above, the coefficient on bond fragmentation is positive because, for a given amount of bonds outstanding (recall that bond fragmentation is orthogonalized to size), a more fragmented bond market is associated with smaller individual issuances, which increases frictions in the bond markets and thus increase trading costs.

[21]The finding that bond fragmentation is associated with higher trading costs is consistent with the predictions of theories of corporate bond markets as OTC markets. Weill (2008) shows that, in a search-based model of OTC markets, bid-ask spreads are larger for assets with smaller outstanding supply. Empirically, our finding that bond fragmentation is associated with bond liquidity is consistent with the findings 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, such that firms that split their bonds into multiple smaller issues tend to have less liquid bonds.

4 CDSs and Arbitrage

Another major implication of CDS markets is that they allow arbitrage activity between the underlying bond market and the associated CDS. In this section, we examine this arbitrage role of CDS markets. The main idea is that arbitrage activity across bond and CDS markets should be reflected in CDS positions. Moreover, to the extent that such arbitrage activity is present, it may have economic consequences. Consistent with the theoretical predictions of Oehmke and Zawadowski (2015), our evidence shows that more arbitrage activity helps eliminate relative mispricing between the bond and the CDS and, by facilitating the absorption of bond supply shocks, is associated with lower price impact in the bond market.

4.1 Documenting arbitrage activity

The main quantity of interest for arbitrageurs that connect the bond and CDS markets is the CDS-bond basis, which has received considerable attention over the last few years (especially during the financial turmoil of 2008-09). The CDS-bond basis is defined as the CDS spread minus the spread of the underlying bond over the risk-free rate. Because a hedged portfolio consisting of a long bond position and a CDS that insures the default risk of the bond should yield the risk-free rate, no arbitrage implies that the CDS-bond basis should be approximately zero.[22]

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 (2013) and Fontana (2011). A negative CDS-bond basis means that the CDS spread is lower than the spread of the underlying bond over the risk-free rate. Intuitively speaking, this price difference implies that one can earn a positive return by purchasing the bond and entering a CDS contract to hedge the bond's default risk—a so-called negative basis trade. Because this arbitrage trade involves a long position in the

[22] Absent limits-to-arbitrage frictions, the CDS-bond basis should be approximately zero (see Duffie, 1999). 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).

CDS, negative-basis arbitrage activity should be associated with larger net notional CDS positions. Analogously, in a positive basis trade an arbitrageur would short the reference bond and sell credit protection in order to profit from a situation where the bond spread is higher than the associated CDS spread. Therefore, also the positive basis trade could lead to an increase in net notional CDS amounts.

To generate crisp hypotheses regarding CDS positions and the CDS-bond basis, we draw on the equilibrium model of bond and CDS markets in Oehmke and Zawadowski (2015).[23] In particular, their framework generates four main hypotheses on the relation between CDS positions and the negative basis. To avoid confusion: In the hypotheses and in the tables that follow, we define the negative basis as a positive number (i.e., the absolute value of the negative basis). The first hypothesis is that basis trader positions are increasing in the negative basis. This suggests that in a regression of net notional CDS positions on the (absolute value of) the negative basis, the coefficient on the negative basis is predicted to be positive. The second hypothesis is that the coefficient on the negative basis should be smaller when funding conditions are tough, because tough funding conditions make it more difficult for basis traders to lever their arbitrage trades. We therefore expect a negative coefficient on the interaction term of the negative basis with the TED spread (where the TED spread proxies for tough funding conditions for arbitrageurs). Third, the relation between CDS positions and the negative basis should be weaker when bond trading costs are high, because this makes it more expensive to set up a basis trade position. This predicts a negative coefficient on an interaction term of the negative basis and bond trading costs. Fourth, the relation between the negative basis and CDS positions is predicted to be weaker for firms with significant disagreement, because in this case it becomes more attractive for investors to take directional bets rather than join the basis trade. We therefore expect a negative coefficient on the interaction term of the negative basis and our disagreement proxy.

[23]In Oehmke and Zawadowski (2015), leverage-constrained arbitrageurs lean against the negative CDS-bond basis that results from differences in trading costs between the bond and the CDS. The model yields joint predictions on the negative CDS-bond basis and the size of the positions that arbitrageurs hold as part of the basis trade. For the theoretical details on which the following hypotheses are based, see Section 3.2 and, in particular, Corollary 1.

We investigate these predictions in Table 5, which, in addition to disagreement and bonds outstanding, includes the CDS-bond basis as a determinant of net notional CDS positions. We calculate the CDS-bond basis using bonds with remaining maturities of 1–30 years, which we match to the associated CDS spread of equivalent maturity, interpolating where necessary. We eliminate bonds with embedded options (puttable, redeemable, callable, exchangeable, or convertible), and floating-rate coupons. To calculate the profitability of a negative basis trade that is implementable (buy bond and buy CDS) on a large enough scale, we use the realized weighted average bond purchase (ask) price for transactions over \$1 million in face value from TRACE.[24] We use the overnight indexed swap (OIS) rate as the risk-free rate. This procedure yields data on the CDS-bond basis data for 123 companies. For each company, we use the bond issue with the largest negative or positive basis on a given day, because the bond issue with the most extreme basis represents the most profitable opportunity for an arbitrageur. For each firm, we then average these basis values over the given month. If, for a given issuer, there is no bond with an implementable negative basis, *negative basis* takes value zero (and analogously for the positive basis). For robustness, Table 13 in the online appendix shows that all results continue to hold if instead of the largest negative or positive basis we use the average basis.

Table 5 confirms all four of these hypotheses laid out above. First, the estimated coefficient on the negative CDS-bond basis is significantly positive across all specifications, which means that a negative CDS-bond basis is indeed associated with larger net CDS positions, confirming the first hypothesis. In terms of economic magnitudes, the coefficient of 0.0888 of column (1) in Table 5 indicates that for bonds with a negative basis, a one standard deviation increase in the negative basis (i.e., a more negative basis of 149.6 basis points) is associated with an increase in net notional CDS outstanding of \$133m, which, for the median firm in the DTCC data, corresponds to a 16% increase in net notional CDS positions. In contrast, a positive basis is generally not associated with larger CDS positions, indicating that the effect of the CDS-bond basis on net notional CDS positions is asymmetric. While

[24] In a positive basis trade, the arbitrageur has to short sell the bond. We therefore use the bond's bid price, using transactions over \$1 million in face value. While in principle one would also like to use realized ask prices for the CDS leg of the trade, these are generally not available (Markit does not even report quoted bid-ask spreads). We therefore use the midpoint for the CDS leg.

this apparent asymmetry could partially be driven by lack of data (during our sample period positive CDS-bond bases occur less often than negative CDS-bond bases), the finding is consistent with the interpretation that there is an asymmetry in the effect of negative and positive CDS-bond bases on net notional amounts of CDS outstanding: Profiting from a positive CDS-bond basis requires short selling the bond, which is often difficult and potentially costly. In column (2) we repeat the analysis with firm fixed effects. Here the sample drops to 97 firms, but the coefficient on the negative basis remains statistically significant at the 1% level, although the point estimate is slightly smaller. The coefficient on the positive basis remains insignificant.

To test the second hypothesis, column (3) includes an interaction term between the absolute value of the negative basis and the TED spread. As predicted, the coefficient on this interaction term is negative. This corroborates the interpretation that the positive association between net notional CDS positions and the negative CDS-bond basis reflect arbitrage activity that links bond and CDS markets. When arbitrageur funding conditions are tough (as proxied by a higher TED spread), the link between the negative basis and net notional CDS positions is less strong.[25]

Finally, the results also confirm the third and fourth hypotheses. Columns (4) and (5) show that the interaction of the negative basis with bond illiquidity is negative as predicted, suggesting that basis traders are less active when bond trading costs are high. We measure illiquidity of the bond market two ways, using bond fragmentation in column (4) and implied roundtrip cost in column (5). Whereas the roundtrip trading cost interaction is significant both by itself (column (5)) and when all other interactions are included (column (7)), the interaction between bond fragmentation and the negative basis is significant when all other interaction terms are included (column (7)), but not by itself (column (4)). Column (6) shows that the interaction term of the negative basis with disagreement is negative as predicted, reflecting a less active basis trade when market participants have more directional views.

[25] The observation that the basis coefficient is lower when funding conditions are difficult makes it unlikely that the association between the negative CDS-bond basis and net CDS positions is driven by CDS dealer inventory concerns. Dealers would react to CDS demand shocks (i.e., increases in net notional) by charging higher CDS spreads, thereby decreasing the negative basis. In contrast, we find that larger net CDS positions are associated with a more negative basis.

4.2 Economic effects of CDS-bond arbitrage

What are the economic implications of the arbitrage activity documented above? Here, the model in Oehmke and Zawadowski (2015) predicts that more active basis traders are associated with a smaller negative basis and lower price impact in the bond market (for details, see Corollary 1 and Proposition 3 of that paper). In Tables 6 and 7 we investigate these predictions and examine the effect of arbitrage activity on the relative pricing of bonds and CDSs and on price impact in the bond market. In both of these tables, we proxy for the "strength of the basis trade" over time by constructing a time series of the sensitivity of CDS positions to the negative CDS-bond basis. The basis trade is stronger when this sensitivity is high. To obtain this time series of the "strength of the basis trade" we rerun the analysis of column (1) in Table 5 but allow the coefficient on the negative basis to vary over time. Specifically, we estimate a different cross-sectional regression every month but set the coefficients on the controls to be the same across months (allowing the coefficients on bonds outstanding and disagreement to also vary over time yields similar results). Because Tables 6 and 7 are from a two-stage estimation, we bootstrap standard errors, taking into account that the "strength of the basis trade" is a generated regressor.[26]

4.2.1 Leaning against the CDS-bond basis

Figure 5 plots a time series of the "strength of the basis trade" (i.e., the estimated monthly basis coefficient) with 95% confidence intervals. The figure shows that, at the beginning of our sample period, the coefficient is essentially zero, reflecting the extremely difficult funding conditions of a basis trade in late 2008 and early 2009, as also illustrated by the high TED-spread (dashed line). Consistent with this interpretation, Choi and Shachar (2014) document significant unwinding of the basis trade after the Lehman default in the fall of 2008. As funding conditions improve later on in the sample, the basis coefficient becomes positive and statistically different from zero. Finally, towards the end

[26] Bootstrapped standard errors calculated the following way: We draw 1,000 bootstrap samples by first resampling dates and then resampling firms within each date. We then apply the two-step estimation procedure to each bootstrapped sample and calculate the standard deviation of the estimated coefficients.

of the sample, the basis coefficient seems to decline, potentially reflecting diminished opportunities in the basis trade. Note that the strength of the basis trade is measured relatively precisely in the earlier part of our sample, but is measured more imprecisely in the latter half of the sample. Because this proxy is an estimated coefficient (from a finite cross section), there is an errors-in-variables issue when using it as a regressor. However, note that this results in a downward bias in the estimated coefficient on the strength of the basis trade, therefore biasing the analysis that follows against finding significant effects. We performed Monte Carlo analysis to confirm that the inferences drawn based on this coefficient are indeed conservative.[27]

Table 6 investigates the implications of the strength of the basis trade for the relative pricing of the bond and the CDS (i.e., the level of the negative CDS-bond basis). The table contains the results of an OLS regression of the negative CDS-bond basis on the proxy for the strength of the basis trade and a number of other control variables. The significantly negative coefficient on the "strength of the basis trade" reported in Columns (1)-(3) show that the negative basis is smaller (in absolute value) when basis trader positions are more sensitive to changes in the CDS-bond basis. Column (1) shows this in the context of a univariate regression; column (2) adds a number of controls and industry fixed effects, column (3) adds firm fixed effects. The effect of the strength of the basis trade on the negative CDS-bond basis is economically significant. Using the results from column (2), a one-standard deviation increase in the strength of the basis trade is associated with a reduction of the negative basis of 52 basis points. Again, the control variables enter as expected. Disagreement is associated with a more negative basis in all specifications, as predicted by Oehmke and Zawadowski (2015), even after controlling for credit quality. Bond fragmentation is associated with a more negative CDS-bond basis, but is not statistically significant. No clear pattern emerges with respect to the amount of bonds outstanding, which is insignificant in some specifications and significant in others, with changing sign.

[27]Specifically, using generated data broadly consistent with the true data, we ran a Monte Carlo analysis of the two-stage estimation procedure used in Tables 6 and 7. The results confirm that the estimated second-stage coefficient is downward biased and, importantly, that the standard error of the second-stage coefficient is not downward biased. The inferences drawn in Tables 6 and 7 therefore seem conservative.

In columns (4)-(6) we add interaction terms to investigate the role of the strength of the basis trade during the crisis (defined as October 2008 to December 2009) and after the crisis (January 2010 to December 2012). This sample split shows that (i) the basis was much more negative during the crisis, as shown by the significant positive coefficient on the crisis dummy; (ii) unconditionally, the strength of the basis trade is still a significant determinant of the basis, but with smaller economic magnitude and somewhat less statistical significance, as shown by the coefficients on the negative basis; and (iii) the strength of the basis trade has a particularly large influence in reducing the negative basis during the crisis, as shown by the large and statistically significant coefficient on the interaction of the basis coefficient and the crisis dummy. Finally, columns (7)-(9) show that these results survive even after controlling for the TED spread both during and after the crisis. This finding suggests that the results in columns (1)-(6) are not merely driven by general funding conditions, but work through the CDS market.

Economically, this evidence on arbitrage activity points to another potentially important role of CDS markets. By allowing arbitrageurs to lean against price differences between the bond and the CDS and absorb supply shocks, CDS markets may help to compress spreads for bond issuers. The presence of CDSs may thereby improve firms' access to financing. This interpretation echoes the empirical findings of Saretto and Tookes (2013), who document that the presence of CDSs allows firms to borrow more and at longer maturities. The finding is also consistent with the theoretical predictions in Oehmke and Zawadowski (2015), who show that the introduction of CDSs can reduce bond spreads for issuers via the emergence of levered basis traders.

Note also that the observation that the negative basis is an economically significant determinant of net notional CDS amounts is a potential explanation for the relation between bond fragmentation and net notional CDS positions documented in Section 3: It is well known that smaller bond issuances and more illiquid bonds tend to have more negative CDS-bond bases (see, for example, Longstaff et al., 2005; Bai and Collin-Dufresne, 2013), which, through the arbitrage channel documented in this section, is translated into larger net notional CDS positions.

4.2.2 Price impact in the bond market

In Table 7 we investigate the effect of basis traders on price impact with respect to bond supply shocks. The main theoretical prediction that we are after here is that levered basis traders can act as "shock absorbers" and lower price impact in the bond market (see Proposition 3 in Oehmke and Zawadowski, 2015). To test this prediction, we calculate a bond-market Amihud (2002) price impact measure for each firm in our sample.[28] Table 7 presents the results of an OLS regression of the Amihud price impact of the bonds of the firms in our sample on the strength of the basis trade and liquidity and size controls. The results show that when CDS positions are sensitive to changes in the negative basis (i.e., basis traders provide significant cushioning), price impact in the bond market is significantly lower. The coefficient of -2.954 in column (2) implies that a one-standard deviation increase in the strength of the basis trade is associated with a reduction in the Amihud price impact measure of 28.9% for the median firm. Hence, a potentially important economic implication of CDSs is that they make the bond market more resilient to supply shocks because, in the presence of CDSs, levered basis traders can act as shock absorbers.

Column (1) presents the univariate regression, column (2) adds controls, column (3) firm fixed effects, columns (4)-(6) repeat the same analysis but with a different coefficient in and out of crisis, columns (7)-(9) also control for the TED spread in and out of crisis. The results indicate that price impact in the bond market is significantly lower during times when CDS positions are particularly sensitive to the negative basis (columns (1)-(3)) and that this effect is concentrated during the financial crisis (columns (4)-(6)). The finding that the effect is concentrated during the financial crisis lends

[28]For every bond, we calculate the monthly Amihud price impact as the absolute value of the percentage change in the bond price divided by volume. More specifically, we calculate the mid-price for every trading day using the average of value-weighted bid and ask transaction prices for that day. If these are not available, we use the value-weighted transaction price of inter-dealer trades. For every trading day t and every bond issue, we then calculate the absolute value of the percentage change in this mid-price from the previous trading day $t-1$ to the next trading day $t+1$ and divide by bond trading volume on day t. To reduce noise and to concentrate on trades of institutional size, we use only days with volume of at least \$1 million on trading day t. We then average across bond issues and days in a particular month to generate a monthly Amihud measure at the firm level. This measure can be computed for $15,639$ out of $22,229$ firm-month observations, based on an average of 26.3 issue-day observations. While the measure is noisy, it seems to capture illiquidity well both in the time series and cross section.

itself to two interpretations. One interpretation is that the presence of basis traders is more important during times of dislocations. The other possibility is that the estimated coefficient for the strength of the basis trade is estimated imprecisely for the second half of our sample (where there is much less variation in the basis), leading to attenuation bias. Finally, note that also in Table 7 the main result remains after controlling for the TED spread: the interaction of the basis coefficient with the crisis dummy remains significant in columns (7)-(8) and is similar in magnitude but insignificant in column (9), which includes firm fixed effects (as discussed above, insignificance could be due to the downward bias in the coefficient). The control variables enter as expected. We find that both bond fragmentation (a proxy for trading costs) and disagreement are associated with a significantly larger price impact in all specifications, consistent with the predictions in Oehmke and Zawadowski (2015). More bonds outstanding, on the other hand, are associated with lower price impact, suggesting that larger supply increases the liquidity of a firm's bonds.

The result that basis traders can act as shock absorbers in the bond market complement the findings in Massa and Zhang (2012), who provide evidence—based on event studies around Hurricane Katrina and downgrades from investment grade to non-investment grade—that the presence of CDSs can reduce fire sales. However, whereas in Massa and Zhang (2012) CDSs reduce fire sale risk by reducing the need of investors to sell bonds when credit conditions deteriorate, our evidence suggests that even conditional on selling pressure in the bond market, CDSs help reduce price impact by allowing levered basis traders to step in as absorbers of supply shocks.

5 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). Our analysis, based on novel data on net notional CDS positions and CDS trading volume from the Depository Trust & Clearing Corporation (DTCC), suggests that CDS markets function as "alternative trading venues" for both hedging and speculation in the underlying bond. In particular, net notional CDS positions are larger and CDS trading volume higher when the underlying bonds are fragmented into separate issues and differ in their contractual terms. The evidence therefore supports a standardization and liquidity role of the CDS market. This interpretation is supported by the finding that bond fragmentation and contractual heterogeneity among bond issues are associated with higher trading costs and lower trading volume in the underlying bonds.

Our analysis also points to economically important arbitrage activity that links the CDS and the bond market via the basis trade: 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 price differences between the bond and the CDS. This has economic consequences. At times during which basis traders are more active, the discount of the underlying bond relative to the CDS is smaller, potentially improving firms' access to financing. Moreover, price impact in the bond market is lower when basis traders are more active, suggesting that levered arbitrageurs help absorb supply shocks in the bond market.

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A Sample Construction

When matching Compustat to DTCC companies, we only took into account exact matches. Thus the CDS of a subsidiary was not matched to that of the parent. If we found more than one possible DTCC match for a Compustat firm, we dropped it. We exclude companies once they enter bankruptcy and/or once a CDS settlement auction takes place. The CDS settlement auction data is available at www.creditfixings.com.

Given the complicated legal structure of companies, we construct two different measures of bonds outstanding. The first measure, *bonds outstanding (direct issue)*, includes all bonds issued directly by the parent company, including all bonds issued by companies that have been acquired and fully dissolved (in case of mergers and acquisitions, the new parent inherits the bonds of the old company). The second measure, *bonds issued by subsidiaries*, includes all bonds issued by all subsidiaries of the parent company. Parent companies are not be liable for the bonds of their subsidiaries unless they explicitly guarantee them. 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.

Bonds outstanding are from 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. Retail notes (average issue size is only $7 million in the sample) and bonds with face value of less than $1000 are excluded since these are small issues catered to retail investors who do not participate in the CDS market. Pass-through notes and foreign currency bonds are also excluded. 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 Enhanced and match the two using the CUSIP of the bond issues. Bond turnover is then winsorized at the top 99% at the issuance level.

Matching between bond issues and Compustat companies is done along two dimensions. First, since the firms in our sample are public, 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. We also hand-search for parent companies using internet resourses (Bloomberg BusinessWeek and Wikipedia). We then use the first six digits of CUSIP (which identifies the issuer) to match Compustat 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 then hand-match Compustat companies to the Markit CDS spread database.

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 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 based on their dominant area of business. In every month, we winsorize all unbounded variables at the 1% and 99% level. We winsorize the CDS-bond basis at the 2% and 98% level because of the few observation (typically less than 100 per month). 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.

B Regression Specification and Censoring

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. On the other hand we do observe the trading activity for all of these reference entities regardless of the amount of trading, i.e. there is no direct censoring in the amount traded.

The censoring issue in notional CDS outstanding is illustrated in Figure 4. The figure plots the 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. We can thus infer that, conditional on a CDS market existing, 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 an OLS regression of net CDS on log assets, illustrated in Figure 4, 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 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. 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 to net notional amounts equals the mean of the empirical gross-net relation of firms for which we observe CDS positions in the same month. Adjusting for the uncertainty of this cutoff does not have a significant impact on our estimates so it is omitted for simplicity.

For net notional, we 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 $y_i = Net\_CDS_{i,t}$ for all firms for which $y_{i,t}$ exceeds the threshold $\tilde{y}_{i,t}$, where

$$L_t = \prod_{i=1}^{n} \left[\frac{1}{\sigma_{i,t}} \cdot \phi\left(\frac{y_{i,t} - \beta \cdot X_{i,t}}{\sigma_{i,t}}\right)\right]^{d_{i,t}} \cdot \left[\Phi\left(\frac{NetCutoff_t - \beta \cdot X_{i,t}}{\sigma_{i,t}}\right)\right]^{1-d_{i,t}}, \tag{B.1}$$

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

$$d_{i,t} = \begin{cases} 1 & \text{if} \quad y_{i,t} \geq NetCutoff_t \\ 0 & \text{if} \quad y_{i,t} < NetCutoff_t. \end{cases} \tag{B.2}$$

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. We jointly estimate

$$\sigma_{i,t} = \text{const} + \gamma \cdot \text{bonds outstanding}_{i,t} \tag{B.3}$$

to allow the error term to scale with amount of bonds a firm has outstanding. For example, this type of scaling is natural if a fraction of outstanding bonds is insured using CDSs. Our main results are robust to alternative scaling variables, such as alternative measures of debt or total assets.

For CDS trading, we run a maximum likelihood tobit estimation that corrects for the fact that some reference entities have zero trading volume. Zero trading volume can be inferred from the fact that the firm is missing from the DTCC or Trace trading report. Note, however, that this issue is not particularly common. In the data, less than 1% of firms have zero CDS trading and less than 5% of firms have zero bond trading over a full month.

The likelihood function for the tobit estimation is given by

$$L_t = \prod_{i=1}^{n} \left[\frac{1}{\sigma_{i,t}} \cdot \phi \left(\frac{y_{i,t} - \beta \cdot X_{i,t}}{\sigma_{i,t}} \right) \right]^{d_{i,t}} \cdot \left[\Phi \left(\frac{0 - \beta \cdot X_{i,t}}{\sigma_{i,t}} \right) \right]^{1-d_{i,t}}, \tag{B.4}$$

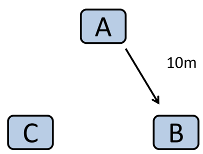
where y_i, t is monthly trading volume for firm i (in the CDS or the underlying bonds) and $d_{i,t}$ is an indicator variable that takes value one when trading volume is positive for firm i in month t,

$$d_{i,t} = \begin{cases} 1 & \text{if} \quad y_{i,t} > 0 \\ 0 & \text{if} \quad y_{i,t} = 0. \end{cases} \tag{B.5}$$

X is a vector that contains our explanatory variables and a constant. $\sigma_{i,t}$ is jointly estimated using the specification B.3.

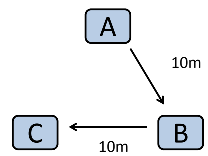
Figure 1: **Gross notional and net notional CDS amounts**

Example (a): Gross and net notional positions



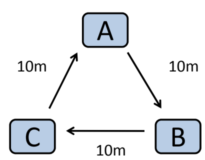
	Gross CDS bought	Gross CDS sold	Net CDS
A	0	10	(10)
B	10	0	10
C	0	0	0
Total	Gross Notional Bought =10	Gross Notional Sold =10	Net Notional Bought/Sold=10

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

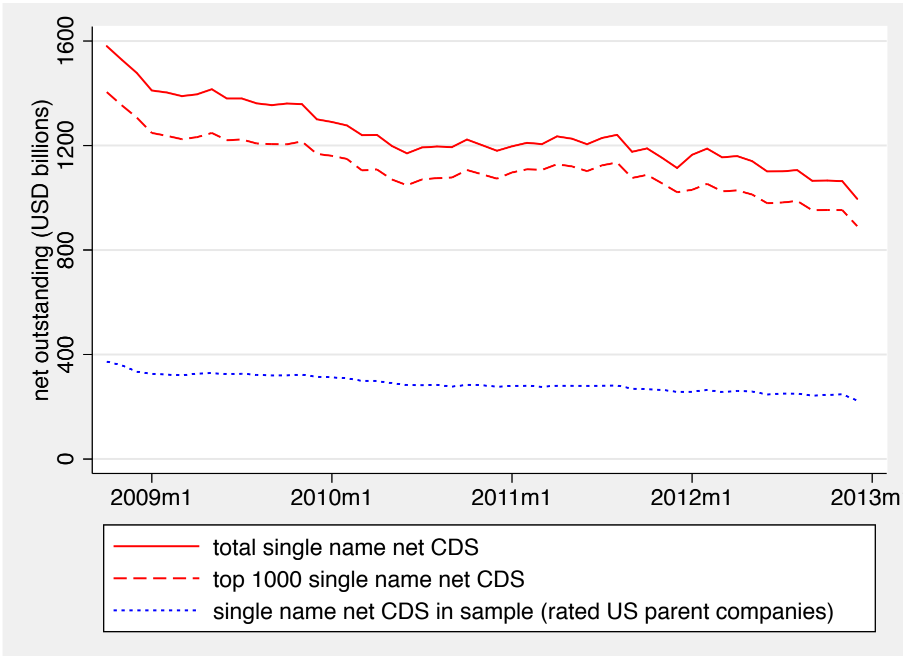
Example (c): Gross and net notional positions



	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

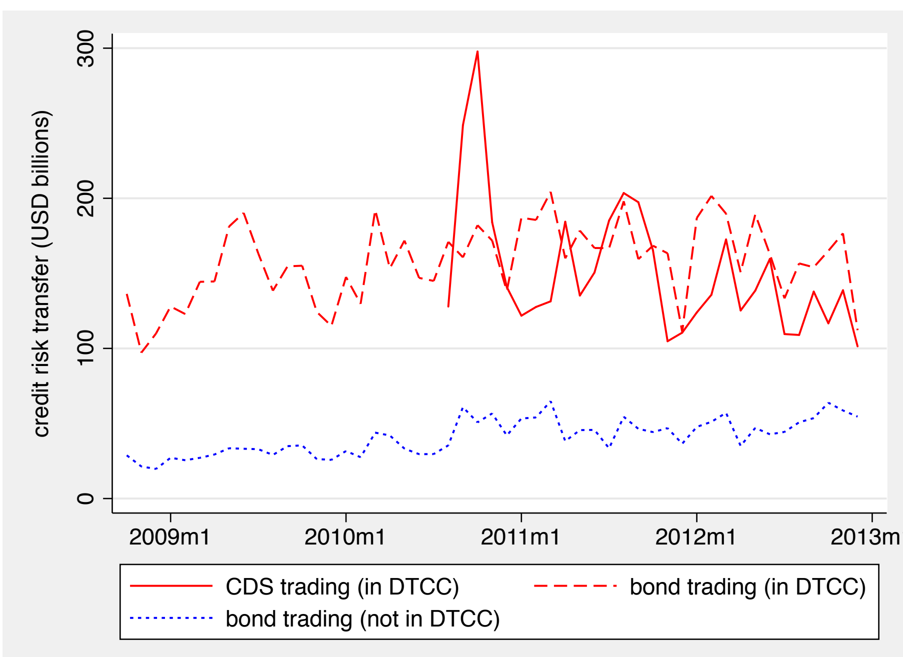
This figure illustrates the difference between gross notional and net notional amounts in the DTCC data. In Example (a), B has purchased \$10m in protection from A. Both the gross notional and the net notional amount outstanding are \$10m. In Example (b), B offsets the initial trade by selling \$10m 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 net notional CDS amounts over time**



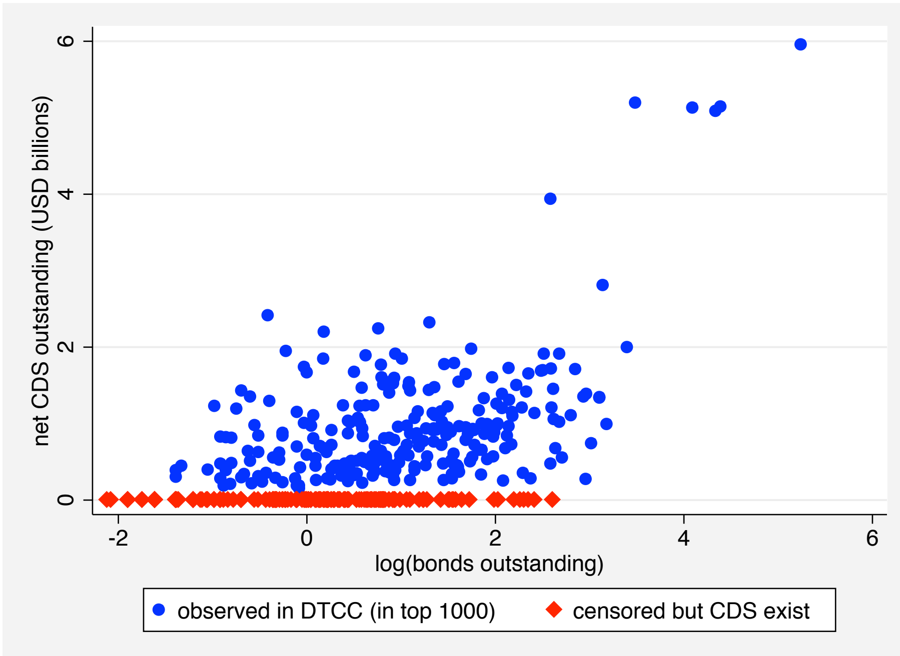
This figure plots single-name net notional CDS amounts over time. The top solid line plots the total net notional CDS amount on all single-name reference entities, as reported by the DTCC. It thus captures the entire single-name CDS market. The dashed line plots the total net notional amount of CDS protection written on the top 1,000 single-name reference 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 single-name CDS market when measured in terms of net notional outstanding. The dotted line plots the total net notional CDS amount for reference entities in our sample: public rated U.S. (parent) companies that are in Compustat and have at least one bond outstanding.

Figure 3: **Trading volume in CDSs and bonds**



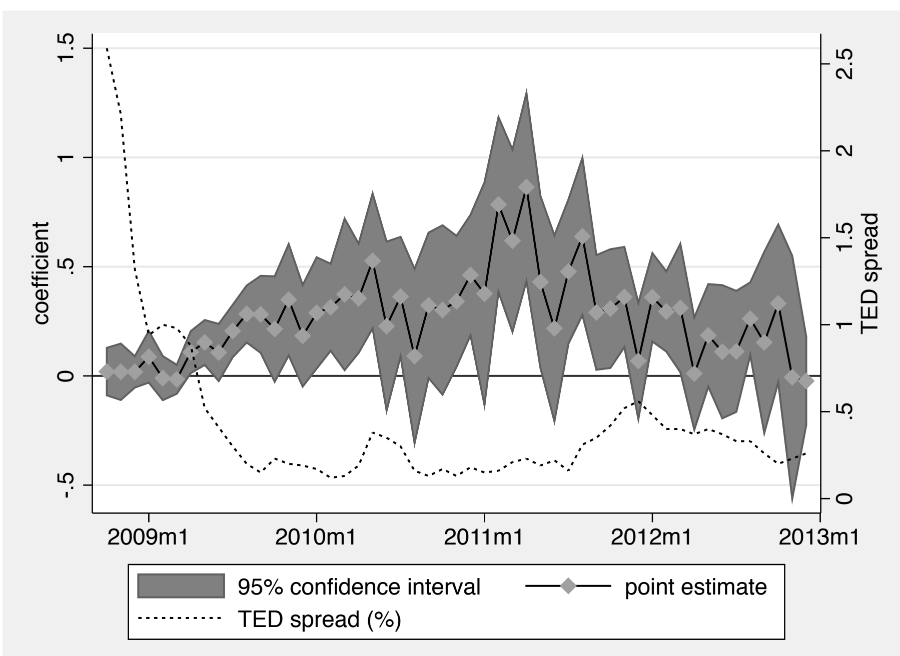
The figure plots trading volume in the bond market and the CDS market. The solid line depicts monthly trading volume in the CDS market as measured by trades that represent market risk activity according to the DTCC. The dashed line depicts monthly trading of directly issued bonds in our sample for firms for which we also have CDS trading volume (DTCC companies). The dotted line represents trading of directly issued bonds in our sample for non-DTCC companies.

Figure 4: **Censoring in net notional CDS amounts**



This figure illustrates the censoring in our sample based on one example month, December 2009. We plot the net CDS for *all* companies for which we know that the CDS market exists: companies that we observe in the DTCC data and/or for which we can find a Markit CDS quote from at least 3 dealers. Firms in the DTCC data are denoted by circles, firms not in DTCC by diamonds. For expositional purposes, for firms not in DTCC we set the net notional CDS amount to zero in the figure. However, we know that these firms have positive net notional CDS amounts but do not make it into the top 1,000 reference entities.

Figure 5: **The "strength of the basis trade"**



This figure plots the "strength of the basis trade" which is defined as the time-series of the cross-sectional coefficient of net notional CDS amounts on the negative CDS-bond basis (left axis). The regression specification is the same as column (1) of Table 5, but allows for time variation in the coefficient of both the negative and the positive basis. The grey shaded region denotes the 95% confidence interval. The mean of "strength of the basis trade" is 0.265 and the standard deviation 0.198. The dashed line plots funding conditions as measured by the TED spread (right axis).

Table 1: **Summary Statistics**

This table provides summary statistics for our data: number of observations, mean, standard deviation, 10th, 50th and 90th percentile. Our sample consists of U.S. public parent companies that are in Compustat, are traded reference entities in the CDS market, have at least one bond outstanding, are rated by S&P, and for which the *disagreement* measure can be calculated. Data is monthly from October 2008 to December 2012, with CDS trading data starting only August 2010. The CDS market is assumed to exist once and for all if in a month the firm is in the DTCC data or has at least 3 dealers in the Markit data. The variables are defined as follows. *assets* is total assets from Compustat. *debt* is total long and short-term debt from Compustat. *bonds outstanding (direct issue)* is the total amount of bonds issued directly by the parent company with at least 1 year of maturity at issuance from Mergent FISD. *bonds issued by subsidiaries* is the total amount of bonds issued by subsidiaries of the parent with at least 1 year of maturity at issuance from Mergent FISD. *other borrowing* is non-bond debt defined as *debt* minus the sum of *bonds outstanding* and *bonds issued by subsidiaries*. *accounts payable* is from Compustat. We set accounts payable to zero for financial firms, because it includes deposits and is thus not comparable to non-financials. *credit enhancement (dummy)* is dummy variable indicating firms providing credit enhancement.*net CDS* and *gross CDS* are the net and gross notional CDS amounts, respectively, as reported by the DTCC. *5y CDS spread (bps)* is the CDS spread from Markit in basis points. *negative basis* and *positive basis* are the absolute value of the smallest daily negative CDS-bond basis and the largest daily positive CDS-bond basis across issuances of the same firm calculated using implementable trades of at least $1 million notional, averaged over the month. Firm-months for which a basis can be calculated but there is no positive maximum or negative minimum are set to zero. *CDS volume (monthly)* is total monthly CDS trading volume that constitute market risk activity, in dollars of notional as reported by the DTCC. *CDS turnover (monthly)* is *CDS volume* divided by *net CDS*. *bond volume (monthly)* is the total monthly bond trading volume in dollars of notional for all bonds a company has issued, taken from Trace Enhanced. *bond turnover (monthly)* is *bond volume* divided by *bonds outstanding*. *implied bond roundtrip cost* is the implied roundtrip cost of paired bond trades from Trace Enhanced with trade volume above $1 million. *issuer bond Herfindahl* is the Herfindahl measure of a firm's bond issues based on Mergent FISD. *bond fragmentation* is negative *log(issuer bond Herfindahl)* orthogonalized to *log(bonds outstanding)*. *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. *disagreement: analyst std/price* is defined as the standard deviation of analyst earnings forecast from IBES normalized by stock price from CRSP if it is above $1. *contractual heterogeneity (dummy)* is an indicator variable of whether all bonds of the issuer have the same contractual features along 6 dimensions: callable, puttable, convertible, fixed coupon, covenants, credit enhancement. *Amihud price impact* is the change in value-weighted bond mid-price from the previous trading day to the next trading day divided by the bond volume on that day (in billions), averaged across issuances and days of the month for a firm. All dollar amounts are in billions. Continuous variables are winsorized at the 1% level (basis measures at the 2% level) every month.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	std	p10	p50	p90
assets	22,229	51.22	191.3	2.641	10.63	79.55
debt	22,229	14.13	65.82	0.690	3.005	17.08
bonds outstanding (direct issue)	22,229	4.505	12.66	0.400	1.798	9.252
bonds issued by subsidiaries	22,229	2.452	9.046	0	0	4.908
other borrowing	22,229	7.861	50.63	0	0.321	5.670
accounts payable	22,229	1.462	3.876	0	0.355	3.379
credit enhancement (dummy)	22,229	0.00787	0.0884	0	0	0
net CDS	13,411	1.035	0.869	0.317	0.817	1.870
gross CDS	13,411	13.13	12.19	2.890	9.914	25.40
net CDS / bonds (direct issue)	13,411	0.503	0.713	0.0758	0.261	1.138
net CDS / bonds (incl. subsidiary)	13,411	0.364	0.535	0.0505	0.182	0.859
5y CDS spread (bps)	19,705	249.2	369.0	50.71	138.8	541.3
negative basis (%)	3,012	0.917	1.496	0	0.496	2.206
positive basis (%)	3,012	0.206	0.575	0	0	0.554
CDS volume (monthly)	7,781	0.516	0.646	0.0594	0.334	1.097
CDS turnover (monthly)	7,781	0.506	0.344	0.142	0.437	0.950
bond volume (monthly)	22,229	0.370	1.094	0.00261	0.0916	0.766
bond turnover (monthly)	22,229	0.0716	0.0873	0.00456	0.0462	0.159
implied bond roundtrip cost (%)	15,405	0.369	0.323	0.105	0.280	0.723
issuer bond Herfindahl	22,229	0.330	0.271	0.0903	0.240	1
bond fragmentation	22,229	0.0191	0.406	-0.525	0.0447	0.495
S&P rating (notch)	22,229	9.212	3.042	6	9	13
disagreement: analyst std/price	22,229	0.0135	0.0313	0.00147	0.00552	0.0260
contractual heterogeneity (dummy)	22,229	0.671	0.470	0	1	1
Amihud price impact	15,639	3.132	4.056	0.677	2.023	6.522

Table 2: **Net notional CDS amounts**

This table presents the results of a censored regression of *net CDS* on proxies for hedging, speculation, bond market liquidity and controls. For variable definitions see Table 1. *high fragmentation (dummy)* is an indicator variable if fragmentation is above median. All regressions include time and rating dummies. The *rating controls* are dummies for: AA and above, A, BBB, B, CCC and below, while BB is omitted. Column (2) includes firm fixed effects, all other columns include industry dummies based on first-digit SIC codes. Note that the constant is subsumed by the control dummies. When including firm fixed effects, we only include companies that appear in the DTCC data at least once. The sample period is October 2008 to December 2012. We jointly estimate heteroskedasticity of the error term in the functional form of constant plus a coefficient times *bonds outstanding*. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) net CDS	(2) net CDS	(3) net CDS	(4) net CDS	(5) net CDS	(6) net CDS	(7) net CDS	(8) net CDS	(9) net CDS
disagreement: analyst std/price	4.672***	0.928**	4.645***	2.697***	4.622***	4.595***	4.945***	4.789***	4.734***
	(4.74)	(2.31)	(4.68)	(3.00)	(4.77)	(4.70)	(4.32)	(4.82)	(4.83)
bonds outstanding (direct issue)	0.0777***	0.0138	0.0651***	0.0874***	0.0772***	0.0764***	0.0875***	0.0692***	0.0705***
	(7.30)	(1.36)	(5.34)	(7.15)	(7.43)	(7.40)	(6.91)	(7.13)	(7.16)
bond fragmentation					0.272***				0.181**
					(3.41)				(2.16)
high fragmentation (dummy)						0.272***			
						(4.27)			
predetermined bond fragmentation							0.165**		
							(2.29)		
contractual heterogeneity (dummy)								0.291***	0.235***
								(3.97)	(3.04)
assets			0.000936						
			(1.21)						
bonds issued by subsidiaries				0.00732					
				(1.10)					
other borrowing				-0.00535**					
				(-2.06)					
accounts payable				0.0163**					
				(2.52)					
credit enhancement (dummy)				2.215***					
				(4.63)					
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	No	Yes	No	No	No	No	No	No	No
Number of Firms	496	302	496	496	496	496	431	496	496
Number of Observations	22229	13946	22229	22229	22229	22229	19606	22229	22229

Table 3: **Bond and CDS trading volume**

Each pair of column reports the results of a joint tobit regression of *CDS volume* (left column) and *bond volume* (right column) on proxies for hedging, speculation, bond market liquidity and controls. For variable definitions see Table 1, for control definitions see Table 2. The sample consists of firms with net CDS reported in the DTCC data. Note that the constant is subsumed by the control dummies. The sample period is August 2010 to December 2012. We jointly estimate heteroskedasticity of the error term in both regressions in the functional form of constant plus a coefficient times *bonds outstanding*. The error terms in the two regressions are allowed to be correlated. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. **At the bottom of the table we present the probability (p-value) of the hypothesis that the regressor has the same coefficient in both the CDS and the bond market.**

	(1)		(2)		(3)		(4)		(5)	
	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume
bonds outstanding (direct issue)	0.0283***	0.0862***	0.0156***	0.164***	0.0284***	0.0896***	0.0281***	0.0881***	0.0269***	0.0893***
	(8.94)	(29.72)	(2.79)	(11.90)	(9.06)	(28.54)	(9.01)	(29.61)	(8.52)	(29.38)
disagreement: analyst std/price	4.594***	0.427	3.352***	0.208	4.831***	0.350	4.890***	0.391	4.825***	0.367
	(3.29)	(1.14)	(2.94)	(1.08)	(3.42)	(0.90)	(3.44)	(1.08)	(3.55)	(1.04)
bond fragmentation					0.0825**	-0.0377***				
					(2.05)	(-3.88)				
high fragmentation (dummy)							0.0899***	-0.0201***		
							(2.74)	(-3.45)		
contractual heterogeneity (dummy)									0.0843**	-0.0173***
									(2.52)	(-2.97)
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	No	No	Yes	Yes	No	No	No	No	No	No
Number of Firms	288		287		288		288		288	
Number of Observations	8041		8029		8041		8041		8041	
p-value: larger coeff. on disagreement for CDS	0.005		0.007		0.002		0.003		0.002	
p-value: larger coeff. on bonds outst. for bonds	0.000		0.000		0.000		0.000		0.000	
p-value: larger coeff. on fragmentation for CDS					0.004		0.001			
p-value: larger coeff. on contr. heter. for CDS									0.002	

Table 4: **Bond fragmentation and bond liquidity**

Columns (1)-(3) present results of an OLS regression of bond roundtrip trading costs. Columns (4)-(6) are tobit regressions of monthly bond market turnover. The right hand side variables are measures of bond market fragmentation, contractual heterogeneity and controls. For variable definitions see Table 1, for control definitions see Table 2. Note that the constant is subsumed by the control dummies. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on heteroskedasticity-consistent standard errors clustered by firms. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) roundtrip cost	(2) roundtrip cost	(3) roundtrip cost	(4) turnover	(5) turnover	(6) turnover
bond fragmentation	0.0426***		0.0388***	-0.0199***		-0.0186***
	(3.90)		(3.45)	(-3.98)		(-3.85)
contractual heterogeneity (dummy)		0.0246**	0.0121		-0.0101**	-0.00398
		(2.46)	(1.17)		(-2.54)	(-1.13)
log(bonds outstanding)	-0.00881*	-0.0124**	-0.0108**	0.0154***	0.0171***	0.0162***
	(-1.70)	(-2.25)	(-1.99)	(8.98)	(9.60)	(9.07)
disagreement: analyst std/price	2.145***	2.146***	2.146***	0.0948**	0.0911**	0.0933**
	(7.26)	(7.41)	(7.28)	(2.14)	(1.99)	(2.12)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
rating controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	487	487	487	496	496	496
Number of Observations	15405	15405	15405	22229	22229	22229
R-squared	0.240	0.238	0.240			

Table 5: **Net notional CDS amounts and the CDS-bond basis**

This table presents the results of a censored regression of *net CDS* on the *positive basis* and *negative basis* and proxies for hedging, speculation, bond liquidity and controls. For variable definitions see Table 1, for control definitions see Table 2. We calculate the basis for firms with CDS quotes from at least 3 dealers in Markit and at least one fixed coupon bond without embedded options that matures within 1-30 years. We calculate the basis using an implementable basis trade: First, we use only bond trades of at least $1m in notional size. Second, we calculate the positive basis based on the bond bid price and and the negative basis based on the bond ask price. Third, for the negative basis we take the minimum among bonds of the firm every day, for the positive basis the maximum. We then average over the month. Note that the constant is subsumed by the control dummies. The sample period is October 2008 to December 2012. We jointly estimate heteroskedasticity of the error term in both regressions in the functional form of constant plus a coefficient times *bonds outstanding*. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) net CDS	(2) net CDS	(3) net CDS	(4) net CDS	(5) net CDS	(6) net CDS	(7) net CDS
negative basis (implementable)	0.0888***	0.0290***	0.203***	0.0923***	0.179***	0.127***	0.267***
	(2.61)	(2.86)	(4.16)	(2.88)	(3.39)	(3.11)	(4.40)
TED spread * neg. basis			-0.104***				-0.0840***
			(-3.87)				(-3.73)
fragmentation * neg. basis				-0.104			-0.158**
				(-1.34)			(-2.08)
roundtrip cost * neg. basis					-0.123**		-0.0729**
					(-2.48)		(-2.12)
disagreement * neg. basis						-1.029***	-0.721
						(-2.90)	(-1.29)
positive basis (implementable)	-0.0291	0.00230	0.0523	-0.0700	0.0280	-0.000358	-0.0495
	(-0.23)	(0.09)	(0.39)	(-0.49)	(0.13)	(-0.00)	(-0.18)
TED spread * pos. basis			-0.0926				0.103
			(-1.12)				(1.20)
fragmentation * pos. basis				0.490*			0.420
				(1.70)			(1.23)
roundtrip cost * pos. basis					-0.0794		-0.0473
					(-0.88)		(-0.54)
disagreement * pos. basis						-0.238	-0.270
						(-0.34)	(-0.36)
bond fragmentation				0.258			0.275
				(1.35)			(1.42)
implied bond roundtrip cost for large trades (%)					0.329**		0.204*
					(2.47)		(1.67)
disagreement: analyst std/price	7.656***	2.354***	7.767***	7.054***	7.902***	9.047***	8.825***
	(4.95)	(4.66)	(5.29)	(4.85)	(3.15)	(7.13)	(2.63)
bonds outstanding (direct issue)	0.0524***	0.0000943	0.0523***	0.0542***	0.0516***	0.0527***	0.0525***
	(5.14)	(0.01)	(5.14)	(5.15)	(4.75)	(5.11)	(4.72)
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
firm fixed effects	No	Yes	No	No	No	No	No
Number of Firms	123	97	123	123	120	123	120
Number of Observations	2730	2422	2730	2730	2423	2730	2423

Table 6: **The negative basis and the strength of the basis trade**

This table presents the results of an OLS regression of the *negative basis* on the *strength of the basis trade* and proxies for hedging, speculation, bond liquidity and controls. Since the *negative basis* is an estimated variable, this regression is the second step in a two-step estimation. The sample only includes firm-month observations for firms with at least one bond with a negative basis that month. The *strength of the basis trade* is graphed and described in Figure 5. For variable definitions see Table 1, for control definitions see Table 2, for the definition of the basis see Table 5. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on bootstrapped standard errors based on 1,000 bootstrapped samples drawn by first resampling dates and then resampling firms within each date. We then apply the two-step estimation procedure to each bootstrapped sample to calculate the standard deviation of the estimated coefficients. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	neg. basis	neg. basis	neg. basis	neg. basis	neg. basis	neg. basis	neg. basis	neg. basis	neg. basis
strength of basis trade	-2.895***	-2.624***	-2.210***	-0.282**	-0.291***	-0.242*	-0.273**	-0.279***	-0.229*
	(-4.75)	(-4.91)	(-5.09)	(-2.51)	(-2.74)	(-1.94)	(-2.35)	(-2.58)	(-1.80)
strength of basis trade * crisis				-7.004***	-7.128***	-6.873***	-6.128***	-5.676***	-5.096***
				(-4.27)	(-4.40)	(-4.60)	(-2.94)	(-2.91)	(-2.74)
TED spread							0.0594	0.0759	0.0871
							(0.25)	(0.33)	(0.38)
TED spread * crisis							0.130	0.238	0.310
							(0.17)	(0.32)	(0.43)
crisis (dummy)				2.478***	2.398***	2.376***	2.230***	1.979***	1.860***
				(7.00)	(6.91)	(6.76)	(3.24)	(3.08)	(2.88)
log(bonds outstanding)		-0.0909	-0.301*		0.0151	0.452**		0.0173	0.461**
		(-1.51)	(-1.68)		(0.34)	(2.32)		(0.39)	(2.29)
disagreement: analyst std/price		15.34**	20.43**		7.737	10.87		7.930	11.35*
		(2.19)	(2.39)		(1.45)	(1.61)		(1.48)	(1.68)
bond fragmentation		0.173			0.220**			0.227	
		(1.56)			(2.26)			(1.43)	
constant	2.046***	2.374***		0.828***	1.306***		0.809***	1.276***	
	(8.08)	(7.67)		(18.81)	(7.42)		(9.09)	(8.13)	
industry fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
rating controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
firm fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Number of Dates	51	51	51	51	51	51	51	51	51
Number of Firms	120	120	120	120	120	120	120	120	120
Number of Observations	2112	2112	2112	2112	2112	2112	2112	2112	2112
R-squared	0.116	0.239	0.439	0.303	0.397	0.561	0.304	0.400	0.565

Table 7: **Price impact in the bond market and the strength of the basis trade**

This table presents the results of an OLS regression of price impact in the bond market on the strength of the basis trade. The left-hand side variable is the *Amihud price impact* measure of illiquidity of the bond market for a given firm in a given month. The right-hand side variables are the *strength of the basis trade* and proxies for hedging, speculation, bond liquidity and controls. Since the *negative basis* is an estimated variable, this regression is the second step in a two-step estimation. To define *Amihud price impact* we first calculate the absolute value of the percentage change in the mid-price of a firm's specific bond issue from the previous day $t-1$ to the next trading day $t+1$ divided by bond trading volume on that trading day t (in \$ billions if volume exceeds \$ 1 million). We then aggregate (average) this across all days and bond issues of a given firm in a given month. This results in a similar measure of illiquidity as the one introduced by Amihud (2002) for stocks. The *strength of the basis trade* is graphed and described in Figure 5. For variable definitions see Table 1, for control definitions see Table 2. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on bootstrapped standard errors based on 1,000 bootstrapped samples drawn by first resampling dates and then resampling firms within each date. We then apply the two-step estimation procedure to each bootstrapped sample to calculate the standard deviation of the estimated coefficients. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Amihud	Amihud	Amihud	Amihud	Amihud	Amihud	Amihud	Amihud	Amihud
strength of basis trade	-3.597***	-2.954***	-2.677***	0.126	0.0753	-0.0214	0.374	0.348	0.258
	(-3.70)	(-3.60)	(-3.95)	(0.33)	(0.20)	(-0.06)	(1.04)	(1.02)	(0.77)
strength of basis trade * crisis				-14.23***	-12.67***	-12.28***	-5.221**	-3.390*	-2.870
				(-4.46)	(-4.11)	(-4.17)	(-2.54)	(-1.87)	(-1.52)
TED spread							1.617**	1.792***	1.850***
							(2.38)	(2.79)	(2.85)
TED spread * crisis							0.426	0.325	0.323
							(0.44)	(0.37)	(0.38)
crisis (dummy)				4.675***	4.060***	3.842***	2.369***	1.714***	1.462**
				(6.50)	(5.77)	(5.38)	(3.39)	(2.85)	(2.37)
log(bonds outstanding)		-0.648***	-1.615***		-0.553***	-0.624***		-0.560***	-0.581**
		(-9.97)	(-6.14)		(-10.63)	(-2.67)		(-10.98)	(-2.33)
disagreement: analyst std/price		35.05***	39.56***		25.61***	27.37***		25.43***	27.38***
		(8.07)	(7.32)		(6.56)	(5.32)		(6.72)	(5.73)
bond fragmentation		0.693***	-0.194		0.735***	0.131		0.751***	0.108
		(5.06)	(-0.36)		(5.83)	(0.26)		(6.77)	(0.22)
constant	4.112***	3.894***		2.373***	2.639***		1.848***	2.053***	
	(9.91)	(10.91)		(18.25)	(15.34)		(8.36)	(14.26)	
industry fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
rating controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
firm fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Number of Dates	51	51	51	51	51	51	51	51	51
Number of Firms	469	469	469	469	469	469	469	469	469
Number of Observations	15639	15639	15639	15639	15639	15639	15639	15639	15639
R-squared	0.0305	0.133	0.259	0.126	0.200	0.311	0.142	0.218	0.328

Online Appendix: Additional Robustness Checks

Table 8: **Net notional CDS amounts with different hedging proxies and size controls**

This table repeats the censored regression analysis of Table 2 column (1) (repeated in this table as column (1)) using different proxies for hedging and additional controls. *net debt* is defined as debt minus cash and cash equivalents. *book leverage* is defined as debt over assets. *idiosyncratic stock volatility* is the standard deviation of the residual of 3 factor Fama-French regression of the monthly stock return of the firm using a 5 year rolling window. *CDX NA IG index* is an indicator variable whether the CDS of the firm is a constituent of the CDX North America Investment Grade index. *CDX NA HY index* is an indicator variable whether the CDS of the firm is a constituent of the CDX North America High Yield index. *CDS volatility (%, lagged)* is defined as the % standard deviation of daily CDS spread changes over 60 days before the start of the month. *CDS spread increase (%, lagged)* is the % change of the CDS spread over the previous month over the CDS spread at the beginning of the previous month if the change is positive, zero otherwise. *CDS spread drop (%, lagged)* is the change of CDS spread over the previous month over the CDS spread at the beginning of the previous month if the change is negative, zero otherwise. For additional variable definitions see Table 1, for control definitions see Table 2. We jointly estimate heteroskedasticity of the error term in the functional form of constant plus a coefficient times *bonds outstanding*. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	alternative size & debt measures, controls											
	(1) net CDS	(2) net CDS	(3) net CDS	(4) net CDS	(5) net CDS	(6) net CDS	(7) net CDS	(8) net CDS	(9) net CDS	(10) net CDS	(11) net CDS	(12) net CDS
bonds outstanding (direct issue)	0.0777***		0.0831***		0.0825***		0.0623***	0.0787***	0.0650***	0.0810***	0.0528***	0.0739***
	(7.30)		(6.79)		(6.97)		(5.43)	(7.53)	(5.57)	(6.35)	(7.67)	(7.27)
debt		0.00609	-0.00151									
		(1.46)	(-1.06)									
net debt				0.00515	-0.00241							
				(0.94)	(-1.24)							
assets						0.00334***	0.00113		0.00101			
						(5.86)	(1.52)		(1.38)			
book leverage								-0.372*	-0.309			
								(-1.80)	(-1.44)			
disagreement: analyst std/price	4.672***	4.942***	4.625***	4.971***	4.624***	4.783***	4.585***	4.556***	4.535***	5.581***	3.810***	4.464***
	(4.74)	(5.20)	(4.76)	(5.17)	(4.76)	(4.86)	(4.70)	(4.74)	(4.68)	(6.58)	(4.03)	(4.55)
bond fragmentation		0.324***	0.262***	0.308***	0.261***	0.334***	0.291***	0.289***	0.303***	0.252***	0.175**	0.235***
		(3.74)	(3.29)	(3.56)	(3.26)	(3.77)	(3.61)	(3.58)	(3.70)	(2.86)	(2.53)	(2.93)
idiosyncratic (stock) volatility										2.987***		
										(2.63)		
CDX NA IG index (dummy)											0.967***	
											(12.95)	
CDX NA HY index (dummy)											0.746***	
											(6.92)	
CDS volatility (%, lagged)												0.0913
												(0.12)
CDS spread increase (%, lagged)												1.034***
												(10.84)
CDS spread drop (%, lagged)												-1.939***
												(-11.82)
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	496	496	496	496	496	496	496	496	496	407	496	450
Number of Observations	22229	22229	22229	22229	22229	22229	22229	22229	22229	15679	22229	18599

Table 9: **Net notional CDS amounts with a different proxy for speculative demand**

Columns (1)-(3) of this table repeat the censored regression analysis of Table 2 column (1), while columns (4)-(6) repeat the analysis of Table 2 column (2) using a different proxy for speculation. The original regressions are repeated here in columns (1) and (4) over the same subsample where the new proxy is available starting August 2010. *log(CDS volume/bond volume)* measures the log of *CDS volume* to *bond volume*. For further variable definitions see Table 1, for control definitions see Table 2. We jointly estimate heteroskedasticity of the error term in the functional form of constant plus a coefficient times *bonds outstanding*. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	alternative disagreement measures					
	(1) net CDS	(2) net CDS	(3) net CDS	(4) net CDS	(5) net CDS	(6) net CDS
log(CDS volume/bond volume)		0.112***	0.112***		0.00765***	0.00766***
		(9.79)	(9.74)		(2.73)	(2.72)
disagreement: analyst std/price	3.853***		3.552***	0.418		0.419
	(2.80)		(3.05)	(0.67)		(0.66)
bonds outstanding (direct issue)	0.0474***	0.0690***	0.0687***	0.00705	0.00899	0.00900
	(6.60)	(6.22)	(6.23)	(1.12)	(1.42)	(1.42)
bond fragmentation	0.146**	0.118**	0.133**			
	(2.37)	(2.16)	(2.47)			
rating controls	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	No	No	No
firm fixed effects	No	No	No	Yes	Yes	Yes
Number of Firms	287	287	287	287	287	287
Number of Observations	7735	7735	7735	7735	7735	7735

Table 10: **Bond and CDS trading volume with different hedging proxies and size controls**

Columns (1)-(4) in this table repeat the tobit regression analysis of Table 3 specification (3), while column (5) repeats the analysis of Table 3 specification (2), using different proxies for hedging and additional controls for size. For variable definitions see Table 1, for control definitions see Table 2. The sample consists of firms with net CDS reported in the DTCC data. The sample period is August 2010 to December 2012. We jointly estimate heteroskedasticity of the error term in both regressions in the functional form of constant plus a coefficient times *bonds outstanding*. The error terms in the two regressions are allowed to be correlated. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. **At the bottom of the table we present the probability (p-value) of the hypothesis that the regressor has the same coefficient in both the CDS and the bond market.**

	(1)		(2)		(3)		(4)		(5)	
	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume
bonds outstanding (direct issue)	0.0208***	0.0894***	0.0261***	0.0896***	0.0174***	0.0893***	0.0161***	0.0892***	0.0206***	0.164***
	(5.56)	(28.14)	(8.35)	(28.59)	(4.64)	(28.20)	(4.30)	(28.15)	(3.64)	(11.97)
bonds issued by subsidiaries			0.00977**	-0.000507			0.00587*	-0.00130*	0.0147***	0.00721*
			(2.54)	(-0.73)			(1.78)	(-1.90)	(3.50)	(1.72)
other borrowing	0.00305***	0.00108					0.00116	0.000831	0.00478	-0.00752**
	(4.16)	(0.92)					(1.16)	(0.68)	(1.60)	(-2.46)
assets					0.000961***	0.000183*	0.000696***	0.000208*	0.000458	0.000175
					(4.99)	(1.66)	(2.62)	(1.74)	(0.79)	(0.65)
disagreement: analyst std/price	4.888***	0.362	4.983***	0.342	4.851***	0.350	4.958***	0.339	3.311***	0.223
	(3.49)	(0.95)	(3.54)	(0.89)	(3.45)	(0.94)	(3.54)	(0.95)	(2.89)	(1.08)
bond fragmentation	0.0887**	-0.0368***	0.100**	-0.0377***	0.0972**	-0.0369***	0.106***	-0.0367***		
	(2.20)	(-3.84)	(2.49)	(-3.89)	(2.42)	(-3.88)	(2.64)	(-3.86)		
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
firm fixed effects	No	No	No	No	No	No	No	No	Yes	Yes
Number of Firms	288		288		288		288		287	
Number of Observations	8041		8041		8041		8041		8029	
p-value: larger coeff. on disagreement for CDS	0.002		0.001		0.002		0.001		0.008	
p-value: larger coeff. on bonds outst. for bonds	0.000		0.000		0.000		0.000		0.000	
p-value: larger coeff. on fragmentation for CDS	0.002		0.001		0.001		0.001			

Table 11: **Bond and CDS trading volume with volatility controls**

This table repeats the tobit regression analysis of Table 3 including volatility and return controls. *CDS volatility (%, lagged)* is defined as the % standard deviation of daily CDS spread changes over 60 days before the start of the month. *CDS spread increase (%, lagged)* is the % change of the CDS spread over the previous month over the CDS spread at the beginning of the previous month if the change is positive, zero otherwise. *CDS spread drop (%, lagged)* is the change of CDS spread over the previous month over the CDS spread at the beginning of the previous month if the change is negative, zero otherwise. For variable definitions see Table 1, for control definitions see Table 2. The sample period is August 2010 to December 2012. We jointly estimate heteroskedasticity of the error term in both regressions in the functional form of constant plus a coefficient times *bonds outstanding*. The error terms in the two regressions are allowed to be correlated. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. **At the bottom of the table we present the probability (p-value) of the hypothesis that the regressor has the same coefficient in both the CDS and the bond market.**

	(1)		(2)		(3)		(4)		(5)	
	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume	CDS volume	bond volume
bonds outstanding (direct issue)	0.0292***	0.0865***	0.0143**	0.166***	0.0292***	0.0898***	0.0290***	0.0884***	0.0280***	0.0890***
	(9.15)	(28.47)	(2.52)	(12.23)	(9.24)	(27.92)	(9.26)	(28.50)	(8.84)	(28.42)
disagreement: analyst std/price	3.450***	0.523	3.349***	0.158	3.672***	0.414	3.751***	0.475	3.745***	0.457
	(2.86)	(1.28)	(2.78)	(0.78)	(3.02)	(1.12)	(3.11)	(1.25)	(3.22)	(1.20)
bond fragmentation					0.0629	-0.0375***				
					(1.53)	(-3.39)				
high fragmentation (dummy)							0.0822**	-0.0210***		
							(2.46)	(-3.28)		
contractual heterogeneity (dummy)									0.0753**	-0.0146***
									(2.17)	(-2.70)
CDS volatility (%, lagged)	2.899	0.0643	0.590	0.391*	2.860	0.111	2.971	0.0846	2.697	0.0703
	(1.47)	(0.59)	(1.06)	(1.86)	(1.43)	(0.52)	(1.47)	(0.62)	(1.38)	(0.59)
CDS spread increase (%, lagged)	0.457***	0.0315	0.218***	0.0296	0.450***	0.0271	0.444***	0.0285	0.454***	0.0336
	(4.47)	(0.68)	(4.80)	(1.12)	(4.35)	(0.51)	(4.28)	(0.61)	(4.55)	(0.68)
CDS spread drop (%, lagged)	-0.310**	0.0336	-0.0290	0.0476*	-0.308**	0.0298	-0.305**	0.0336	-0.307***	0.0283
	(-2.58)	(0.86)	(-0.49)	(1.70)	(-2.54)	(0.70)	(-2.52)	(0.84)	(-2.58)	(0.71)
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	No	No	Yes	Yes	No	No	No	No	No	No
Number of Firms	269		268		269		269		269	
Number of Observations	7488		7476		7488		7488		7488	
p-value: larger coeff. on disagreement for CDS	0.027		0.009		0.012		0.012		0.009	
p-value: larger coeff. on bonds outst. for bonds	0.000		0.000		0.000		0.000		0.000	
p-value: larger coeff. on fragmentation for CDS					0.020		0.002			
p-value: larger coeff. on contr. heter. for CDS									0.009	

Table 12: **Bond fragmentation and bond liquidity: using firms with at least 3 bonds**

This table repeats the analysis of Table 4 using only firms which have at least 3 bonds outstanding. Columns (1)-(3) present results of an OLS regression of bond roundtrip trading costs. Columns (4)-(6) are tobit regressions of monthly bond market turnover. For variable definitions see Table 1, for control definitions see Table 2. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on heteroskedasticity-consistent standard errors clustered by firms. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) roundtrip cost	(2) roundtrip cost	(3) roundtrip cost	(4) turnover	(5) turnover	(6) turnover
bond fragmentation	0.0425***		0.0395***	-0.0169***		-0.0161***
	(3.33)		(3.09)	(-3.37)		(-3.21)
contractual heterogeneity (dummy)		0.0254**	0.0191*		-0.00706**	-0.00504
		(2.20)	(1.66)		(-2.21)	(-1.62)
log(bonds outstanding)	-0.00905	-0.0146**	-0.0111*	0.0140***	0.0162***	0.0146***
	(-1.45)	(-2.25)	(-1.74)	(7.19)	(8.00)	(7.18)
disagreement: analyst std/price	2.044***	2.061***	2.049***	0.129***	0.124***	0.127***
	(6.32)	(6.46)	(6.35)	(2.83)	(2.66)	(2.78)
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
rating controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	422	422	422	427	427	427
Number of Observations	13327	13327	13327	17444	17444	17444
R-squared	0.248	0.246	0.248			

Table 13: **Net notional CDS amounts: CDS-bond basis using average basis**

This table repeats the censored regression analysis of Table 5 using a different definition of the basis. *negative avg. basis* is the average basis of all the bonds of a firm every day and then averaged over the month if this number is negative and zero otherwise. *positive avg. basis* is the average basis of all the bonds of a firm every day and then averaged over the month if this number is positive and zero otherwise. For both, the bond yield is defined as the average yield for trades over $ 1 million (irrespective of being bid, ask or interdealer price). For variable definitions see Table 1, for control definitions see Table 2. We jointly estimate heteroskedasticity of the error term in the functional form of constant plus a coefficient times *bonds outstanding*. The sample period is October 2008 to December 2012. T-stats are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

	(1) net CDS	(2) net CDS	(3) net CDS	(4) net CDS	(5) net CDS	(6) net CDS	(7) net CDS
negative avg. basis	0.107**	0.0275*	0.238***	0.121***	0.189***	0.157***	0.326***
	(2.46)	(1.71)	(4.23)	(2.90)	(2.84)	(3.13)	(4.47)
negative avg. basis * TED spread			-0.126***				-0.122***
			(-3.78)				(-3.67)
fragmentation * neg. basis				-0.135*			-0.203**
				(-1.65)			(-2.51)
roundtrip cost * neg. basis					-0.124**		-0.0683*
					(-2.39)		(-1.89)
disagreement * neg. basis						-1.536***	-0.949**
						(-3.11)	(-2.03)
positive avg. basis	-0.0457	-0.00967	0.0960	0.0523	-0.0863	0.0137	0.0262
	(-0.74)	(-0.97)	(0.62)	(0.76)	(-0.37)	(0.07)	(0.09)
positive avg. basis * TED spread			-0.141				-0.0703
			(-1.27)				(-1.33)
fragmentation * pos. basis				0.383**			0.308
				(2.17)			(0.93)
roundtrip cost * pos. basis					-0.00413		0.0298
					(-0.07)		(0.49)
disagreement * pos. basis						-0.343	-0.171
						(-0.71)	(-0.44)
bond fragmentation				0.302			0.316
				(1.53)			(1.63)
implied bond roundtrip cost for large trades (%)					0.340**		0.183
					(2.48)		(1.49)
disagreement: analyst std/price	7.782***	2.373***	7.867***	7.326***	7.992***	11.08***	9.163***
	(5.76)	(4.63)	(6.07)	(5.48)	(3.28)	(5.71)	(3.48)
bonds outstanding (direct issue)	0.0522***	0.00180	0.0528***	0.0548***	0.0512***	0.0525***	0.0533***
	(5.22)	(0.22)	(5.29)	(5.23)	(4.85)	(5.30)	(4.93)
rating controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
firm fixed effects	No	Yes	No	No	No	No	No
Number of Firms	123	97	123	123	120	123	120
Number of Observations	2759	2451	2759	2759	2445	2759	2445