

The Anatomy of the CDS Market

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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” serving a standardization and liquidity role. CDS positions and trading volume are larger for firms with bonds fragmented into many separate issues and with 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. (*JEL* G10, G12, G13)

Received September 24, 2014; accepted January 17, 2016 by Editor Andrew Karolyi.

The 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. For example, recent work has investigated the role of CDSs during the financial crisis (Stulz 2010), the impact of CDSs on the debtor-creditor relationship (Hu and Black 2008; Bolton and Oehmke 2011), and consequences of CDS markets for firms’

We thank the DTCC for providing the data on which this research is based. For comments and suggestions, we are grateful to three anonymous referees, Viral Acharya, Tobias Berg, András Danis, Merritt Fox, Larry Glosten, Valentin Haddad, Jing-Zhi Huang, Andrew Karolyi (the editor), Dino Palazzo, Or Shachar, Kumar Sivakumar, René Stulz, Raghu Sundaram, and Suresh Sundaresan. We also thank conference participants at the Econometric Society 2012 Winter Meeting (Chicago), European Finance Association 2012 Annual Meeting (Copenhagen), ESSFM 2012 (Gerzensee), American Economic Association 2013 Annual Meeting (San Diego), the Oxford/Columbia Conference on Derivatives Regulation after the Crisis, the 2013 Five Star Conference at NYU, and the 3rd Annual ITAM Finance Conference, as well as seminar participants at the Bank of England, Boston University, Central European University, FGV Sao Paolo, UNC, University of Houston, CU Boulder, UT Dallas, Goethe Universität Frankfurt, the Frankfurt School of Finance and Management, and the CFTC. We thank the Program for Financial Studies at Columbia University for support, and Adam Laiacano, Aditya Dugar, Shyam Iyer, and Tim Scully for assistance with the data. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Martin Oehmke, Columbia Business School, 420 Uris Hall, 3022 Broadway, New York, NY 10027. E-mail: moehmke@columbia.edu.

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, nonpayment of debt, and, in some CDS contracts, debt restructuring.

cost of capital, financing choices, and credit risk (Ashcraft and Santos 2009; Saretto and Tookes 2013; Subrahmanyam, Tang, and Wang 2014).

However, despite their growing importance, relatively little is known about what motivates trading and positions in CDS markets. This paper aims to fill this void: drawing on 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 for CDS markets: although 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, is concentrated 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.

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 allow 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 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 outstanding bonds 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 outstanding bonds is associated with a 31.9% increase in CDS positions for the median firm.

While nonbond 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.

Taken together, these results suggest that both hedging and speculation are determinants of CDS positions. However, 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 outstanding bonds 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 \$272 m 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 have larger net notional CDS positions. Contractual heterogeneity across bonds is associated with \$291 m 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 of 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 fragmented nature 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. This result suggests that arbitrageurs use CDSs to lean against the negative CDS-bond basis. This interpretation is supported by the finding that the effect is larger during times when funding conditions for arbitrageurs are favorable. Basis traders have major economic implications, because their presence 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 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. [Siriwardane \(2015\)](#) shows that capital fluctuations of large CDS sellers affect the pricing of CDSs. In addition, a number of recent papers investigate the CDS-bond basis ([Blanco, Brennan, and Marsh 2005](#); [Bai and Collin-Dufresne 2013](#); [Nashikkar, Subrahmanyam, and Mahanti 2011](#); [Fontana 2011](#)). Our paper contributes to this literature by linking the CDS-bond basis to quantities in the CDS market.²

1. Empirical Hypotheses

Taken together, the theoretical 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 a 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 laying 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 outstanding bonds (i.e., larger insurable interest) are 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.

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, Stulz, and Williamson 2009](#); [Ashcraft and Santos 2009](#); [Hirtle 2009](#); [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, Eisfeldt, and Weill 2015](#); [Che and Sethi 2014](#); [Fostel and Geanakoplos 2012](#); [Oehmke and Zawadowski 2015](#)). [Du and Zhu \(2013\)](#), [Gupta and Sundaram \(2012\)](#), and [Chernov, Gorbenko, and Makarov \(2013\)](#) investigate CDS settlement auctions.

Second, investors may use CDS contracts as speculative vehicles 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. If such 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 and trading 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.), CDSs 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 in which they purchase the bond and CDS protection, thereby increasing the amount of outstanding CDSs. 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 come from the Trade Information Warehouse of the Depository Trust & Clearing Corporation (DTCC).³ The

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.

position and trading data from the DTCC 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 are 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 CDS positions 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 adjusts the gross notional amount for offsetting positions to better reflect the actual amount of credit risk transferred in the CDS market.⁵ Specifically, the DTCC calculates the net notional amount 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.

Weekly CDS trading data are 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, or assignment of an existing transactions to a third party). Trades that do not

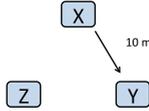
The DTCC then enters these trades into a Trade Information Warehouse (TIW). The data are available on the DTCC’s Web site at www.dtcc.com/repository-otc-data.aspx.

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 have a number of disadvantages. First, the BIS data only provide aggregate market statistics, while the DTCC data provide positioning at the reference entity level. Second, the BIS data are based on surveys as opposed to actual registered positions in the market. Third, because of its survey-based nature, the BIS data are 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 is simply the sum of all CDS contracts on a given reference entity. It therefore reflects the total par amount of credit protection bought (or, equivalently, sold). The gross notional amount is defined as either the sum of all long or, equivalently, the sum of all short CDS contracts on a particular reference entity. With the exception of occasional compression trades, in which offsetting CDS positions are eliminated, the gross notional amount increases with every trade. The gross notional amount increases even if a trade offsets an existing trade and thereby reduces the amount of credit risk transfer in the CDS market. This makes the gross notional amount an imprecise proxy for the amount of credit risk transferred in the CDS market.

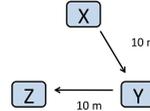
⁶ It is the maximum amount of payments, because actual payments will usually be less than the par value of the CDS, reflecting nonzero recovery rates on the defaulted bonds, as well as previous marking-to-market by counterparties.

A Gross and net notional positions



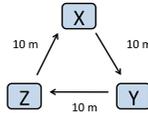
	Gross CDS bought	Gross CDS sold	Net CDS
X	0	10	(10)
Y	10	0	10
Z	0	0	0
Total	Gross Notional Bought=10	Gross Notional Sold=10	Net Notional Bought/Sold=10

B Gross and net notional positions



	Gross CDS bought	Gross CDS sold	Net CDS
X	0	10	(10)
Y	10	10	0
Z	10	0	10
Total	Gross Notional Bought=20	Gross Notional Sold=20	Net Notional Bought/Sold=10

C Gross and net notional positions



	Gross CDS bought	Gross CDS sold	Net CDS
X	10	10	0
Y	10	10	0
Z	10	10	0
Total	Gross Notional Bought=30	Gross Notional Sold=30	Net Notional Bought/Sold=0

Figure 1
Gross notional and net notional CDS positions

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

transfer risk are excluded (for example, the clearing of existing bilateral trades by central counterparties, portfolio compression trades, and backloaded trades). The resultant 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 three CDS dealers that provide quotes on a five-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 that, in a given month, have at least one bond registered with the SEC and are rated by S&P (to control for credit quality). We also restrict our sample to public companies with at least two 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 (bond trading data), CRSP (stock price data), IBES (earnings forecasts), and

Markit (CDS spreads).⁷ 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, 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, of which 97 appear in the DTCC data. We use monthly data because many controls are only available on a monthly basis. Altogether the time-series length of our baseline sample on net notional CDS positions is fifty-two months: October 2008 to December 2012. The length of the CDS trading data is somewhat shorter; these data are available for twenty-nine 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 \$1.035 bn. The mean gross notional CDS amount is \$13.13 bn. The corresponding medians are \$817 m and \$9.914 bn, respectively. Hence, on average, netting within counterparties reduces outstanding CDS amounts by a factor of more than ten.

Firms in our sample have median assets of \$10.63 bn and \$1.798 bn 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 outstanding bonds is equal to 26.1% of bonds when looking at bonds directly issued by that firm and 18.2% when we consolidate bonds to also include bonds issued by subsidiaries. The 90th percentile is 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 CDS positions often 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 are significantly smaller than outstanding bonds.⁸

Figure 2 plots the evolution of total net notional CDS amounts over time. The top solid line depicts total net notional CDS amounts 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 of 2008, net

⁷ TRACE Enhanced is preferable to TRACE because it contains transaction information not 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.

⁸ Nonetheless, for some firms net notional CDS amounts significantly exceed the amount of bonds the firm has outstanding. Potential buyout targets (with low current debt, but potentially large future debt), such as the clothing retailer Gap and the electronics distributor Arrow Electronics, are a typical example. Homebuilders, mortgage insurers, and suppliers for the automobile industry are other types of companies with high net notional CDS amounts as a fraction of outstanding bonds.

Table 1
Summary statistics

VARIABLES	(1) N	(2) Mean	(3) SD	(4) p10	(5) p50	(6) 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	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 SD/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

This table provides the summary statistics for our data: the number of observations, mean, standard deviation, and 10th, 50th, and 90th percentile. Our sample consists of U.S. public parent companies in Compustat that are traded reference entities in the CDS market, have at least one outstanding bond, are rated by S&P, and for which the *Disagreement: analyst SD/price* measure can be calculated. Data are monthly from October 2008 to December 2012, with CDS trading data starting in August 2010. We categorize a firm as a traded reference entity in the CDS market once the firm appears in the DTCC data or, in a given month, has at least three quotes from dealers in the Markit data. The variables are defined as follows. *Assets* is total assets from Compustat. *Debt* is the sum of long-term and short-term debt from Compustat. *Bonds* is the total face value of bonds issued directly by the parent company with at least one year of maturity at issuance from Mergent FISD. *Bonds issued by subsidiaries* is the total face value of bonds issued by subsidiaries of the parent with at least one year of maturity at issuance from Mergent FISD. *Other borrowing* is nonbond debt defined as *debt*, minus the sum of *bonds* 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 nonfinancials. *Credit enhancement (dummy)* is a 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 five-year 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 in face value, averaged for the month. Firm-months for which a basis can be calculated but without a positive maximum or negative minimum are set to zero. *CDS volume (monthly)* is total monthly CDS trading volume that constitutes market risk activity, in billions of 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 billions of dollars of notional for all bonds a company has issued, taken from Trace Enhanced. *Bond turnover (monthly)* is *bond volume*, divided by *bonds*. *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 $\log(\text{issuer bond Herfindahl})$ orthogonalized with respect to $\log(\text{bonds})$. *S&P rating (notch)* captures a firm's S&P rating; it takes a value of 1 for AAA, 2 for AA+, etc. The maximum value, 22, indicates that the bond has defaulted. *Disagreement: analyst SD/price* is defined as the standard deviation of analyst earnings forecasts from IBES, normalized by the stock price from CRSP. *Contractual heterogeneity (dummy)* is an indicator variable of whether all bonds of an issuer have the same contractual features along six dimensions: callable, puttable, convertible, fixed coupon, covenants, and credit enhancement. *Amihud price impact* is 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), averaged across all days and bond issues of a given firm in a given month. All dollar amounts are in billions.

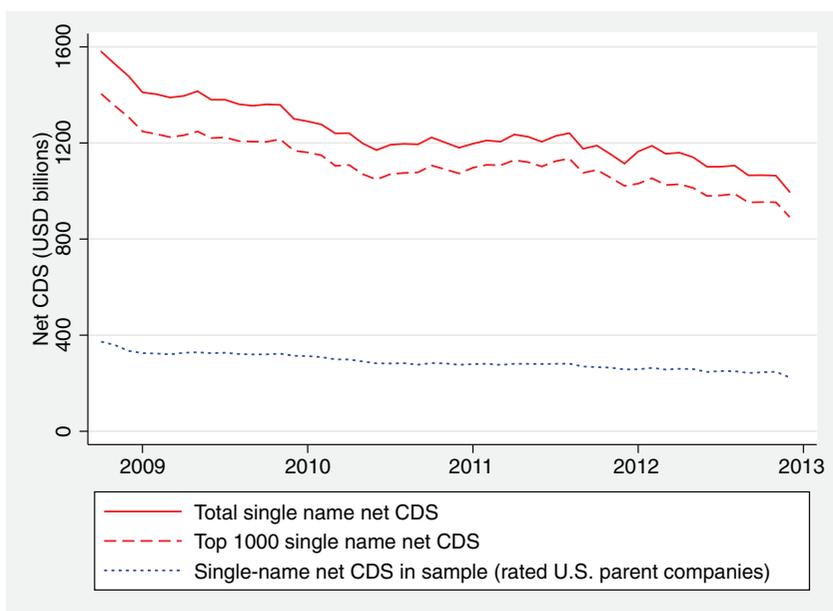


Figure 2
Single-name net notional CDS amounts over time

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 with 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. The dotted line plots the total net notional CDS amount for reference entities in our sample: rated public U.S. parent companies in Compustat with at least one outstanding bond.

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,

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 suggest 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. For 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 (nondealers) 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.

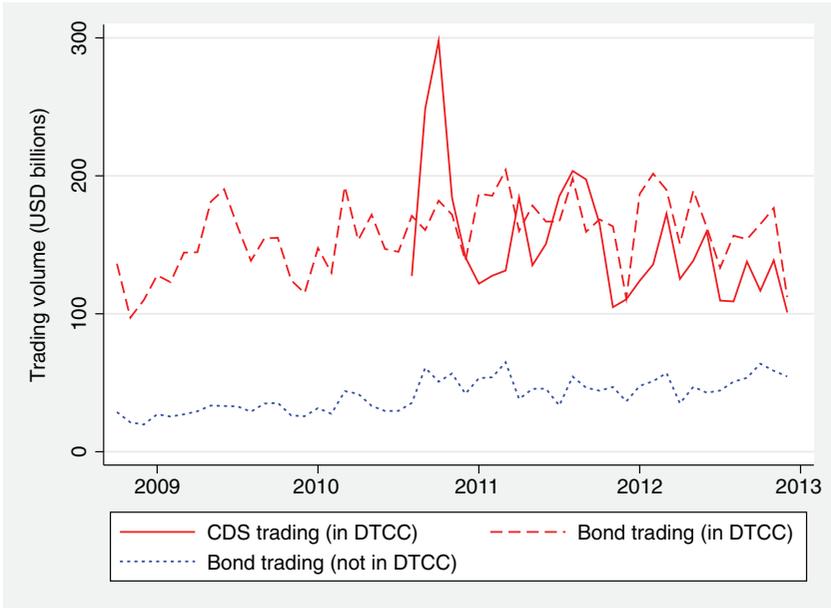


Figure 3
Trading volume in CDSs and bonds

This 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 volume of directly issued bonds for firms for which we also have CDS trading volume (DTCC companies). The dotted line represents trading volume of directly issued bonds for non-DTCC companies.

states, municipalities, non-U.S. companies, nonrated companies, and other nonmatched reference entities, 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 in 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 outstanding bonds is larger than the associated net notional CDS positions.

Bonds of companies 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 outstanding bonds, which captures insurable interest. We proxy for speculative trading motives using a measure of disagreement, which we calculate as analyst earnings forecast dispersion normalized by the stock price of 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 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 to

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 \$1 bn 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.

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 outstanding bonds usually have more separate bond issues). We do this by regressing the log Herfindahl on the log of the firm's outstanding bonds. 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 resultant 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 do not adjust the Herfindahl index for the amount of 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 are 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 the bond?) and the demand for trading (i.e., how strong are market participants' motives to trade?), fragmentation of a reference entity's bonds is likely to be less affected by the 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 directly based 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 (1) is puttable, (2) is callable, (3) is convertible, (4) has a fixed coupon, (5) has covenants, and (6) is subject to credit enhancement. We construct a contractual heterogeneity dummy that is zero for those firms for which all the above contractual features are the same across all issues, and one for all other firms (i.e., for firms that have at least some heterogeneity in contractual features of bond issues). The contractual heterogeneity measure has the advantage that it directly captures the difference of contractual terms across bond issues. It therefore allows us to draw sharper conclusions regarding a potential standardization role of CDS markets. The 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

$$NetCDS_{i,t} = \beta \cdot X_{i,t} + \epsilon_{i,t}, \quad (1)$$

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. Controls include credit quality proxied by S&P rating dummies. Note that we do not scale net CDS by assets. Neither net CDS nor the trading motives (e.g., speculation or the basis trade) naturally scale with assets or outstanding bonds. Because the DTCC provides net notional amounts for only the top 1,000 reference entities, the data are 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 (see Figure 4). Because of this, estimates from a simple ordinary least-squares (OLS) estimation would be biased. We therefore run a maximum likelihood estimation that takes into account the censoring in the data. To mitigate the effect of outliers, we allow the error term to scale with outstanding bonds. 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 outstanding bonds, significant at the 1% level in most specifications, demonstrates that insurable interest is a significant determinant of 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 outstanding bonds, net CDS positions are on average 7.77 cents larger. To gauge the economic magnitude of this effect, note that a move from the 25th to the 75th percentile in terms of outstanding bonds is associated with an increase in net notional CDS positions of \$261 m, which raises the net notional for the median firm (which has \$817 m in net notional CDS) by 31.9%.¹¹ When we include firm fixed effects in Column (2),

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

Table 2
Net notional CDS amounts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS
Bonds	0.0777*** (7.30)	0.0138 (1.36)	0.0651*** (5.34)	0.0874*** (7.15)	0.0772*** (7.43)	0.0764*** (7.40)	0.0875*** (6.91)	0.0692*** (7.13)	0.0705*** (7.16)
Disagreement: analyst SD/price	4.672*** (4.74)	0.928** (2.31)	4.645*** (4.68)	2.697*** (3.00)	4.622*** (4.77)	4.595*** (4.70)	4.945*** (4.32)	4.789*** (4.82)	4.734*** (4.83)
Bond fragmentation					0.272*** (3.41)				0.181** (2.16)
High fragmentation (dummy)						0.272*** (4.27)			
Predetermined bond fragmentation							0.165** (2.29)		
Contractual heterogeneity (dummy)								0.291*** (3.97)	0.235*** (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	22,229	13,946	22,229	22,229	22,229	22,229	19,606	22,229	22,229

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 bond fragmentation is above the median. *Predetermined bond fragmentation* is defined as *Bond fragmentation* in the month that the firm becomes a traded reference entity in the CDS market or in January 2002 (whichever is later). All regressions include time and rating dummies. The *Rating controls* are dummies for AA and above, A, BBB, B, CCC, and below. BB is the omitted control. 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 heteroscedasticity of the error term in the functional form of constant, plus a coefficient times *bonds*. *t*-statistics are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

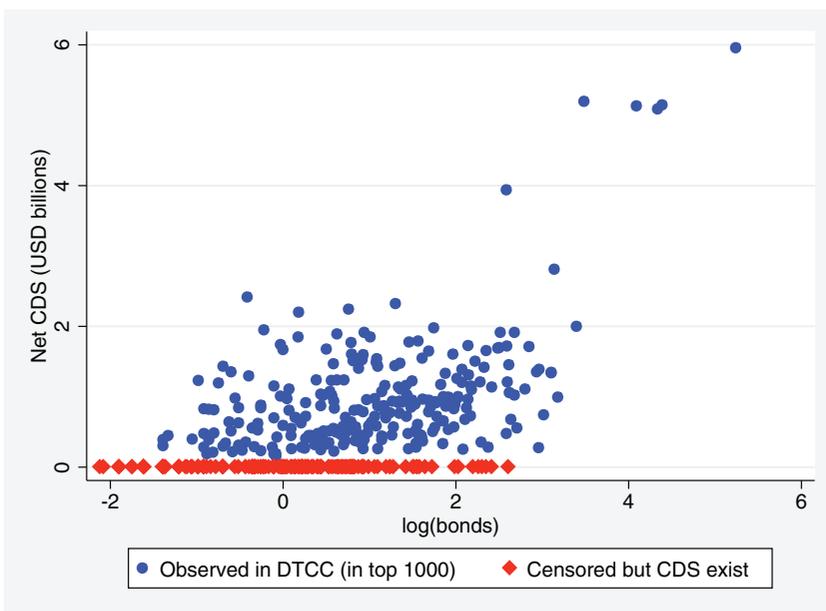


Figure 4
Censoring in net notional CDS amounts

This figure illustrates the censoring in our sample, based on one example month, December 2009. We plot *net CDS* as a function of $\log(\text{bonds})$ 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 three dealers. Circles denote firms in the DTCC data, and diamonds denote firms not in DTCC. 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).

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 outstanding bonds (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 could capture relevant hedging motives in the CDS market. Three observations emerge. First, when we include other types of debt in the regression, we find that bonds, not other types of debt, matter for CDS positions. In Column (3), we add total assets as an explanatory variable and find it is both economically and statistically insignificant at 0.093 cents per dollar of assets. More importantly, the coefficient on outstanding

¹² Given our relatively short time series and that, at the firm level, neither the amount of outstanding bonds nor net notional CDS positions vary much over time, it is not surprising that the effect is weaker when we include firm fixed effects. However, reassuringly even with firm fixed effects the result remains economically significant. In the trading volume regression below, where there is more time-series variation, outstanding bonds remain significant even with firm fixed effects. Finally, note that the sample size drops when we include firm fixed effects: 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.

bonds is almost unchanged compared with Column (1) and remains statistically and economically significant. Therefore, bonds are not simply a proxy for size. Column (4) includes bonds of subsidiaries and other nonbond 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 outstanding bonds remains of similar magnitude and significance. 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 subsidiaries.¹³ Second, the large positive and statistically significant coefficient on the dummy variable *credit enhancement* in Column (4) reflects a large amount of net notional CDS protection written on companies that provide credit enhancement (e.g., monoline insurers): firms that provide credit enhancement on average have an additional \$2 bn in net notional CDS positions.¹⁴ This suggests that investors who rely on insurance from monoline insurance companies and other providers of credit enhancement purchase CDSs to eliminate 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. We also find that net notional CDS amounts are 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

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. A separate market for loan credit default swaps (LCDSs) exists but is small, according to the DTCC data. For example, in December 2011, the net notional amount of LCDSs registered with the DTCC was \$7.2 billion for U.S. companies and \$1.1 billion for European companies, compared with a net notional of regular CDSs of \$1.1 trillion.

¹⁴ We categorized the following list of companies as providing credit enhancement: AMBAC, MBIA, Primus Guaranty, Triad Guaranty, Assured Guaranty, XL Group, Radian Group, ACE, Berkshire Hathaway, PMI Group, and 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.

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 larger net notional CDS positions, 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 \$146 m, which corresponds to 18% of the median net notional CDS amount. When controlling for firm fixed effects (Column (2)), the magnitude of the 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 uses 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 with above-median bond fragmentation on average have \$272 m more in net notional CDSs written on their debt. 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 \$110 m. Both of these effects are economically significant when compared with the median firm's net notional CDS amount of \$817 m.

While 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 in which the firm was already a traded CDS reference entity in January 2002 (when the CDS market was still in its infancy), we use the bond fragmentation at that point. This robustness

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 are essentially constant over time, we do not include firm fixed effects in these specifications.

check confirms our results by showing that 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 \$291 m. 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 slightly 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 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 with 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 (outstanding bonds), 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 effect of insurable interest (outstanding bonds) 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 outstanding bonds 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

Table 3
Bond and CDS trading volume

	(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	0.0283*** (8.94)	0.0862*** (29.72)	0.0156*** (2.79)	0.164*** (11.90)	0.0284*** (9.06)	0.0896*** (28.54)	0.0281*** (9.01)	0.0881*** (29.61)	0.0269*** (8.52)	0.0893*** (29.38)
Disagreement: analyst SD/price	4.594*** (3.29)	0.427 (1.14)	3.352*** (2.94)	0.208 (1.08)	4.831*** (3.42)	0.350 (0.90)	4.890*** (3.44)	0.391 (1.08)	4.825*** (3.55)	0.367 (1.04)
Bond fragmentation					0.0825** (2.05)	-0.0377*** (-3.88)				
High fragmentation (dummy)					0.0899*** (2.74)	-0.0201*** (-3.45)			0.0843** (2.52)	-0.0173*** (-2.97)
Contractual heterogeneity (dummy)										
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	8,041		8,029		8,041		8,041		8,041	
<i>p</i> -value: coefficients on bonds equal	0.000		0.000		0.000		0.000		0.000	
<i>p</i> -value: coefficients on disagreement equal	0.005		0.007		0.002		0.003		0.002	
<i>p</i> -value: coefficients on bond fragmentation equal					0.004		0.001			
<i>p</i> -value: coefficients on contr. heterogeneity equal									0.002	

Each pair of columns 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, and 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 heteroscedasticity of the error term in both regressions in the functional form of constant, plus a coefficient times *bonds*. The error terms in the two regressions are allowed to be correlated. *t*-statistics 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 *p*-values for the hypothesis that coefficients are equal across the CDS and the bond market.

market, an additional dollar of outstanding bonds 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 comparable. This dramatically changes 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 \$144 m in monthly trading volume in the CDS market, corresponding to 43.1% of the 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 \$13.3 m 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 Trading activity has much more time variation than CDS positions, such that the coefficients are much better identified than in the case of explaining net notional CDSs. Even after including firm fixed effects, the statistical and economic significance of the coefficients on outstanding bonds and disagreement are similar to those in Column (1), both for bond and CDS trading.

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 predominantly occurs 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, regardless 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 looking to offload credit risk could be institutional investors who 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

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

associated with \$20.1 m less in monthly bond trading volume, corresponding 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 \$89.9 m, 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 \$84 m more monthly trading volume in the CDS and a reduction of \$17.3 m 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. A one-standard-deviation increase in bond fragmentation is associated with a 6.2% increase in roundtrip trading costs (Column (1)) 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 is 21.9% lower (Column (5)) for firms with bonds that are contractually heterogeneous when compared with the median firm. When adding both bond fragmentation and contractual heterogeneity (Columns

¹⁸ Because bond trading costs and bond turnover are highly endogenous variables, we did not include them as regressors in our regressions above. However, 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 at most fifteen minutes and ten trades apart and then calculate the roundtrip trading cost, expressed as a spread. Half roundtrip spreads (customer to dealer) are multiplied by two to get the full implied roundtrip cost. We only consider trades with par value of at least \$1 million to capture institutional trades.

Table 4
Bond fragmentation and bond liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
	Roundtrip cost	Roundtrip cost	Roundtrip cost	Turnover	Turnover	Turnover
Bond fragmentation	0.0426*** (3.90)		0.0388*** (3.45)	-0.0199*** (-3.98)		-0.0186*** (-3.85)
Contractual heterogeneity (dummy)		0.0246** (2.46)	0.0121 (1.17)		-0.0101** (-2.54)	-0.00398 (-1.13)
log(bonds)	-0.00881* (-1.70)	-0.0124** (-2.25)	-0.0108** (-1.99)	0.0154*** (8.98)	0.0171*** (9.60)	0.0162*** (9.07)
Disagreement: analyst SD/price	2.145*** (7.26)	2.146*** (7.41)	2.146*** (7.28)	0.0948** (2.14)	0.0911** (1.99)	0.0933** (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	15,405	15,405	15,405	22,229	22,229	22,229
R-squared	0.240	0.238	0.240			

Columns (1)-(3) present the results of OLS regressions of *Implied bond roundtrip cost* on measures of bond market fragmentation, contractual heterogeneity, and controls. Columns (4)-(6) present the results of tobit regressions of *Bond turnover* on measures of bond market fragmentation, contractual heterogeneity, and controls. For variable definitions, see Table 1, and 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*-statistics are given in parentheses based on heteroscedasticity-consistent standard errors clustered by firms. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

(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 few bond issues, Table 12 in the [Online Appendix](#) shows 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 with more outstanding bonds 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 fragmented and contractually heterogeneous bonds, which are illiquid and costly to trade. This finding echoes the view, held among bond market practitioners, that the fragmented nature of the corporate bond market impedes its liquidity, thereby

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 outstanding bonds (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.

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

4. CDSs and Arbitrage

In this section, we examine the role of CDS markets in facilitating arbitrage between bond and CDS markets. The main idea is that such arbitrage activity should be reflected in CDS positions. Moreover, to the extent that 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

For arbitrageurs that connect the bond and CDS markets, the main object of interest is the CDS-bond basis. 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 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 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 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 to profit from a situation in which the CDS spread is higher than the associated bond

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, Mithal, and Neis \(2005\)](#) 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.

²² Absent limits-to-arbitrage frictions, the CDS-bond basis should be approximately zero ([Duffie 1999](#)). The CDS-bond basis historically has been slightly positive, due to imperfections in the repo market and the cheapest-to-deliver option ([JPMorgan 2006](#)).

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, that framework generates four main hypotheses on the relation between CDS positions and the negative basis. 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.

We investigate these predictions in Table 5, which 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 that 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 implementable 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

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.

²⁴ In a positive basis trade, the arbitrageur has to short sell the bond. We therefore use the bond's bid price, using transactions of more than \$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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS	Net CDS
Negative basis	0.0888*** (2.61)	0.0290*** (2.86)	0.203*** (4.16)	0.0923*** (2.88)	0.179*** (3.39)	0.127*** (3.11)	0.267*** (4.40)
TED spread * neg. basis			-0.104*** (-3.87)				-0.0840*** (-3.75)
Fragmentation * neg. basis				-0.104 (-1.34)			-0.158** (-2.08)
Roundrip cost * neg. basis					-0.123** (-2.48)		-0.0729** (-2.12)
Disagreement * neg. basis						-1.029*** (-2.90)	-0.721 (-1.29)
Positive basis	-0.0291 (-0.23)	0.00230 (0.09)	0.0523 (0.39)	-0.0700 (-0.49)	0.0280 (0.13)	-0.000358 (-0.00)	-0.0495 (-0.18)
TED spread * pos. basis			-0.0926 (-1.12)				0.103 (1.20)
Fragmentation * pos. basis				0.490* (1.70)			0.420 (1.23)
Roundrip cost * pos. basis					-0.0794 (-0.88)		-0.0473 (-0.54)
Disagreement * pos. basis						-0.238 (-0.34)	-0.270 (-0.36)
Bond fragmentation				0.258 (1.35)			0.275 (1.42)
Implied bond roundrip cost					0.329** (2.47)		0.204* (1.67)
Disagreement: analyst SD/price	7.656*** (4.95)	2.354*** (4.66)	7.767*** (5.29)	7.054*** (4.86)	7.902*** (3.15)	9.047*** (7.13)	8.825*** (2.63)
Bonds	0.0524*** (5.14)	0.0000943 (0.01)	0.0523*** (5.14)	0.0542*** (5.15)	0.0516*** (4.75)	0.0527*** (5.11)	0.0525*** (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	2,730	2,422	2,730	2,730	2,423	2,730	2,423

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, and for control definitions, see Table 2. We calculate the basis for firms with CDS quotes from at least three dealers in Market 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 \$1 million in face value. Second, we calculate the positive basis based on the bond bid price 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 heteroscedasticity of the error term in both regressions in the functional form of constant, plus a coefficient times *bonds*. *t*-statistics are given in parentheses based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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 for the given month. If, for a given issuer, no bond has an implementable negative basis, *Negative basis* takes a value of zero (and analogously for the positive basis). For robustness, Table 13 in the [Online Appendix](#) shows that all results continue to hold when we use the average basis instead of the largest negative or positive basis.

Table 5 confirms all four of the hypotheses laid out above. First, the estimated coefficient on the negative CDS-bond basis is significantly positive across all specifications, which means that a more 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 CDSs of \$133 m. For the median firm in the DTCC data, this 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 this apparent asymmetry could be partially 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 of an asymmetry in the effect of negative and positive CDS-bond bases on net notional CDS amounts: 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 ninety-seven 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

²⁵ Because the basis coefficient is lower when funding conditions are difficult, the relation between the negative CDS-bond basis and net CDS positions is unlikely to be driven by CDS dealer inventory concerns. If it were CDS dealer inventory management that drives the association between net notional CDS positions and the CDS-bond basis, then the effect should be larger, not smaller, when funding conditions for dealers are tough. For single name CDSs, dealers are typically short protection (i.e., they are protection sellers). Larger net notional positions therefore generally imply that dealers are short particularly large amounts of protection. From an inventory management perspective, this should induce them to charge higher CDS premia, which would translate into a less negative (or even positive) basis.

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 in 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.

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 outstanding bonds 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 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

²⁶ Bootstrapped standard errors are 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.

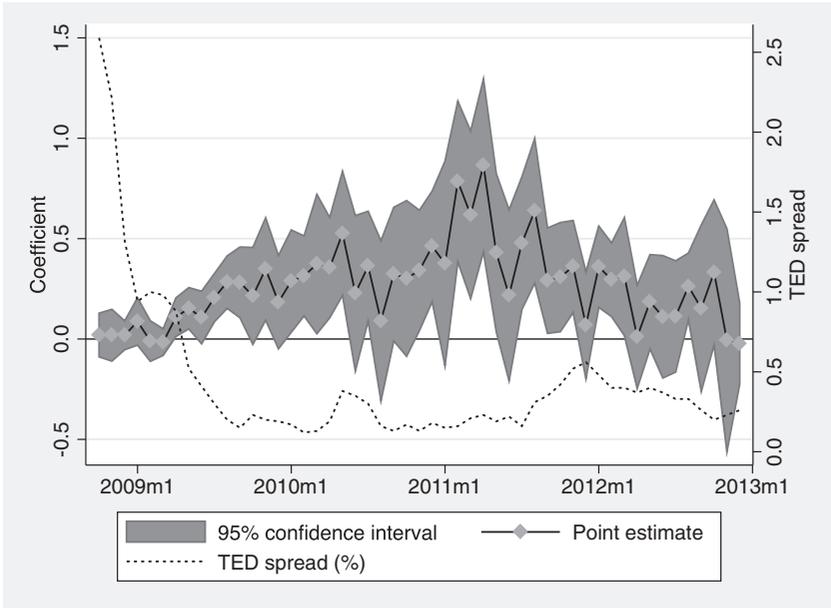


Figure 5
The strength of the basis trade

This figure plots the *Strength of the basis trade*, which is defined as the time-series of the cross-sectional regression coefficient of net notional CDS amounts on the *Negative 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 gray shaded region denotes the 95% confidence interval. The mean of the *Strength of the basis trade* is 0.265, and the standard deviation is 0.198. The dashed line plots funding conditions as measured by the *TED spread* (right axis).

in the sample, the basis coefficient becomes positive and statistically different from zero. Finally, toward the end 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, an errors-in-variables issue emerges 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

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.

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; and 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 outstanding bonds, which is insignificant in some specifications and significant in others, with changing sign.

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 (1) the basis was much more negative during the crisis, as shown by the significant positive coefficient on the crisis dummy, (2) 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, and (3) 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 strength of the basis trade with 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](#)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Neg. basis								
Strength of basis trade	-2.895*** (-4.75)	-2.624*** (-4.91)	-2.210*** (-5.09)	-0.282** (-2.51)	-0.291*** (-2.74)	-0.242* (-1.94)	-0.273** (-2.35)	-0.279*** (-2.58)	-0.229* (-1.80)
Strength of basis trade * crisis				-7.004*** (-4.27)	-7.128*** (-4.40)	-6.873*** (-4.60)	-6.128*** (-2.94)	-5.676*** (-2.91)	-5.096*** (-2.74)
TED spread					0.0594 (0.25)		0.0594 (0.25)	0.0759 (0.33)	0.0871 (0.38)
TED spread * crisis								0.238 (0.32)	0.310 (0.43)
Crisis (dummy)				2.478*** (7.00)	2.398*** (6.91)	2.376*** (6.76)	2.230*** (3.24)	1.979*** (3.08)	1.860*** (2.88)
log(bonds)		-0.0909 (-1.51)	-0.301* (-1.68)		0.0151 (0.34)	0.452** (2.32)		0.0173 (0.39)	0.461** (2.29)
Disagreement: analyst SD/price		15.34** (2.19)	20.43** (2.39)		7.737 (1.45)	10.87 (1.61)		7.930 (1.48)	11.35* (1.68)
Bond fragmentation		0.173 (1.56)			0.220** (2.26)			0.227 (1.43)	
Constant	2.046*** (8.08)	2.374*** (7.67)		0.828*** (18.81)	1.306*** (7.42)		0.809*** (9.09)	1.276*** (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	2,112	2,112	2,112	2,112	2,112	2,112	2,112	2,112	2,112
R-squared	0.116	0.239	0.439	0.303	0.397	0.561	0.304	0.400	0.565

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, and 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*-statistics, based on bootstrapped standard errors calculated from 1,000 bootstrapped samples drawn by first resampling dates and then resampling firms within each date, are given in parentheses. 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.

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 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, 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; and 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

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 interdealer 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Amihud price impact								
Strength of basis trade	-3.597*** (-3.70)	-2.954*** (-3.60)	-2.677*** (-3.95)	0.126 (0.33)	0.0753 (0.20)	-0.0214 (-0.20)	0.374 (1.04)	0.348 (1.02)	0.258 (0.77)
Strength of basis trade * crisis				-14.23*** (-4.46)	-12.67*** (-4.11)	-12.28*** (-4.17)	-5.221*** (-2.54)	-3.390* (-1.87)	-2.870 (-1.52)
TED spread							1.617*** (2.38)	1.792*** (2.79)	1.850*** (2.85)
TED spread * crisis							0.426 (0.44)	0.325 (0.37)	0.323 (0.38)
Crisis (dummy)				4.675*** (6.50)	4.060*** (5.77)	3.842*** (5.38)	2.369*** (3.39)	1.714*** (2.85)	1.462*** (2.37)
log(bonds)		-0.648*** (-9.97)	-1.615*** (-6.14)		-0.553*** (-10.63)	-0.624*** (-2.67)		-0.560*** (-10.98)	-0.581*** (-2.33)
Disagreement: analyst SD/price		35.05*** (8.07)	39.56*** (7.32)		25.61*** (6.56)	27.37*** (5.32)		25.43*** (6.72)	27.38*** (5.73)
Bond fragmentation		0.693*** (5.06)	-0.194 (-0.36)		0.735*** (5.83)	0.131 (0.26)		0.751*** (6.77)	0.108 (0.22)
Constant	4.112*** (9.91)	3.894*** (10.91)		2.373*** (18.25)	2.639*** (15.34)		1.848*** (8.36)	2.053*** (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	No	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	15,639	15,639	15,639	15,639	15,639	15,639	15,639	15,639	15,639
R-squared	0.0305	0.133	0.259	0.126	0.200	0.311	0.142	0.218	0.328

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 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, and for control definitions, see Table 2. The sample period is October 2008 to December 2012. t -statistics, based on bootstrapped standard errors calculated from 1,000 bootstrapped samples drawn by first resampling dates and then resampling firms within each date, are given in parentheses. 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.

finding that the effect is concentrated during the financial crisis lends 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 imprecisely estimated 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) and (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 outstanding bonds, 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 noninvestment 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 that have a more negative CDS-bond basis (i.e., the bond is undervalued relative to the CDS)

have larger outstanding net notional CDS amounts, suggesting that arbitrageurs use the CDS market to lean against price differences between the bond and the CDS. This has economic consequences. At times when 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.

A. Sample Construction

Matching between Compustat and the DTCC data was done by hand, only taking into account exact matches. CDSs written on subsidiaries were not matched to the parent company. We dropped Compustat firms with multiple matches in the DTCC data. We exclude companies once they enter bankruptcy and/or once a CDS settlement auction takes place. The CDS settlement auction data are available at www.creditfixings.com.

Given the complicated legal structure of many companies, we construct two different measures of outstanding bonds. The first measure, *bonds*, includes all bonds directly issued by the parent company, including all bonds issued by companies that have been acquired and fully dissolved (in 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 liable for the bonds of their subsidiaries unless they explicitly guarantee them. Note that Compustat looks at consolidated balance sheets and thus it treats the bond issuances of all subsidiaries as that of the parent or acquirer.

Outstanding bonds 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 (which, in our sample, have an average issue size of only \$7 million) and bonds with face value of less than \$1,000 are excluded because 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 99th percentile at the issue 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., an acquired company) to new CUSIPS (e.g., acquirer). In the case of a merger or acquisition, we use the same file to find the new parent company. We then hand-check all matches and verify whether the acquired companies (or subsidiaries) are limited liability entities (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 resources (Bloomberg BusinessWeek and Wikipedia). We then use the first six digits of the CUSIP (which identify 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 (nonoperating establishments) and companies with no assets. We also drop companies for which we do not have SIC codes. To avoid possibly erroneous matches with Mergent FISD that result in outliers, we filter our matches. We exclude all Mergent FISD observations for which the total amount of outstanding bonds as 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 (conglomerates) are hand-assigned to industries based on their dominant area

of business. In each month, we winsorize all unbounded variables at the 1% and 99% level. The CDS-bond basis, for which we typically have less than 100 observations per month, is winsorized at the 2% and 98% level. Finally, we drop (quasi) state-owned companies (Fannie Mae, Federal Home Loan Mortgage Corporation, and United States Postal Service).

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. This implies a censoring issue in the data: we do not observe CDS positions for firms that have outstanding gross notional amounts 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, that is, the amount traded shows no direct censoring.

The censoring issue in outstanding net notional CDS is illustrated in Figure 4. The figure plots the outstanding net notional CDS as a function of $\log(\text{assets})$. 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 outstanding gross notional amounts that lie below the cutoff to the 1,000 largest reference entities. Ignoring this censoring problem results 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 therefore 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 outstanding gross notional. Of course, the resultant censoring problem carries over to net notional values: reference entities that have low gross notional CDS amounts are also likely to have low net notional CDS amounts. Hence, because of the cutoff in terms of gross notional, our data are likely to leave out reference entities with small net notional CDS amounts. 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 outstanding CDS.

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 left out of our data because their outstanding gross notional amount is too small, the relation between gross notional and 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 CDS positions, 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 net CDS (denoted by $y_{i,t}$) for all firms for which $y_{i,t}$ exceeds the threshold $NetCutoff_t$. Given this censoring cutoff, we can write the likelihood function as:

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

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

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

X is a vector that contains our explanatory variables, controls, 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

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

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 some reference entities having zero trading volume. Zero trading volume can be inferred when 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 for 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 ,

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

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

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