Credit Default Swaps and Corporate Bond Trading*

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Abstract

Using regulatory data on CDS holdings and corporate bond transactions, I provide evidence for a liquidity spillover effect from CDS to bond markets. Bond trading volumes are larger for investors with CDS positions written on the debt issuer, in particular around rating downgrades. Moreover, an increase in CDS trading substantially improves the liquidity of the underlying bonds. I use a quasi-natural experiment to validate these findings. However, I also provide causal evidence that CDS mark-to-market losses lead to fire sales in the bond market. I instrument for mark-to-market losses with the fraction of non-centrally cleared CDS contracts. The monthly corporate bond sell volumes of investors exposed to large mark-to-market losses are three times higher than those of unexposed counterparties. Returns decrease by more than 100 bps for bonds sold by exposed investors, compared to same-issuer bonds sold by unexposed investors. My findings underline the risk of a liquidity spiral in the credit market.

Keywords: Corporate bonds, credit default swaps, trading volume, regulation, central clearing, liquidity spiral, financial stability

JEL Classification: G11, G12, G18, G20, G28

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1 Introduction

Since its inception two decades ago, the credit default swap (CDS) market has grown rapidly to become one of the most important venues for credit risk transfer. This raises the question of whether and how CDS trading affects related markets, particularly the market for corporate bonds. Do CDS markets attract liquidity away from corporate bond markets or are there positive spillover effects? And could a downturn in the CDS market have adverse effects on the prices and trading volumes of corporate bonds? These questions become even more pressing when examining post-crisis reforms of the CDS market, such as the shift to central clearing and higher margin requirements, and their effects on other credit markets.

The theoretical literature provides opposing views on this subject. From an asset pricing perspective, credit default swaps are redundant securities in that their payoffs can be replicated by generic credit sensitive assets (Garleanu and Pedersen, 2011). Therefore, the inception of CDS markets should not have an impact on corporate bond markets. However, various studies predict a crowding-out effect, i.e. a migration of long and short bond investors to the more liquid CDS market (see, e.g., Che and Sethi, 2014; Oehmke and Zawadowski, 2015). Sambalaibat (2018) challenges this view and shows that the presence of CDS markets leads to a liquidity spillover effect: a greater number of bond buyers and larger bond trading volumes.

Thus far, the empirical literature has not provided conclusive answers due to a lack of granular data on CDS and bond trading of individual investors.[1] Most studies (see, e.g., Ashcraft and Santos, 2009; Das et al., 2014; Shim and Zhu, 2014) focus on aggregated short-term effects of CDS introduction on the liquidity and pricing of corporate bonds. The aggregated data, however, do not account for the time-varying, unobservable heterogeneity in investor or issuer characteristics. By using regulatory data on single name CDS holdings and corporate bond transactions, I aim to fill this gap in the literature. This paper first explores how CDS positions affect corporate bond trading volumes of individual investors across different sectors. The main hypothesis I put forward is that the liquidity spillover effect dominates the crowding-out effect, leading to an increased number of

[1] In a recent paper, Boyarchenko et al. (2018) use regulatory US data to analyse the credit market participation decisions of institutional investors. Their results provide an excellent foundation for my analysis, which focuses on a narrower research question.

bond *buyers* and higher bond trading volumes. I show that investors with active CDS contracts on a particular issuer are associated with 60% higher buy volumes in the bonds of the reference entity, compared to non-CDS counterparties. The effect is particularly pronounced around rating downgrades.

However, it is possible that corporate bond transactions determine the CDS portfolio composition, and not vice versa. I rely on a quasi-natural experiment to address this endogeneity issue. In early 2015, several dealer banks unwound numerous CDS positions in response to higher margin requirements.[2] The termination of these CDS positions is associated with a 113% increase in sell volumes and a 54% drop in buy volumes in the bonds of the reference entities, indicating that dealer banks sharply reduced their bond holdings for these issuers. This finding is consistent with anecdotal evidence of a deterioration in bond market liquidity following the ban of naked CDS positions in the European Union in 2011 (Sambalaibat, 2018). Therefore, I provide further evidence for a positive relation between CDS positions and bond trading volumes, lending strong support to the liquidity spillover hypothesis.

Nevertheless, these findings raise the important question whether higher bond trading volumes of individual CDS investors ultimately translate into a significant improvement in the liquidity of the underlying bonds. One of my key results is the positive response of bond liquidity measures to the intensity of CDS trading, as measured by the total number of CDS contracts or the total gross notional amount written on the debt issuer. A 10% increase in the number of CDS contracts leads to a 5.9% increase in the bond's monthly trading volume and a 3.5% increase in the number of trades for this bond. An increase in the number of CDS contracts is also associated with significantly lower half spreads, higher bond turnover and fewer zero-trading days. I find similar effects when using the total gross notional amount as a proxy for CDS trading activity. Overall, my ability to observe the *intensity* of CDS trading on a particular debt issuer stands in stark contrast to prior studies that rely on aggregated before-after effects of CDS introduction (see, e.g., Das et al., 2014). This paper therefore makes an important contribution to the literature that studies the

[2] In March 2015, the Basel Committee and IOSCO published the final timeline for the implementation of higher margin requirements for bilateral over-the-counter (OTC) derivatives. This has led to several dealer banks either exiting the market or reducing their service offerings (Cognizant, 2016).

impact of CDS trading on bond market liquidity. Furthermore, my findings echo recent industry studies claiming that a more liquid single name CDS market would have positive implications for corporate bond market liquidity.[3]

In the second half of the paper, I explore a contagion channel between CDS and corporate bond markets. Brunnermeier and Pedersen (2009) and Brunnermeier et al. (2013) show that margin calls on derivatives can force distressed investors into fire sales to obtain liquidity. These fire sales can further depress prices and spread to bonds of correlated issuers, leading to new margin calls. I provide causal evidence for such a liquidity spiral. I use the fraction of non-centrally cleared CDS contracts of an individual investor as an instrument for the prevalence of mark-to-market losses.[4] Central clearing counterparties (CCPs) offer multilateral netting of derivatives contracts and more rigorous risk management practices. The typically higher netting efficiency of central clearing leads to a decrease in aggregate risk exposures and margin obligations, effectively reducing the occurrence of adverse funding liquidity shocks (International Capital Market Association, 2015).[5] Using this instrumental variable approach, I show that CDS mark-to-market losses cause a significant increase in sell volumes in the corporate bond market. The monthly sell volumes of investors exposed to large mark-to-market losses are three times higher than those of unexposed counterparties. The constrained investors are more likely to sell liquid and better rated bonds, hence reducing the liquidity of their bond portfolios. Their fire sales have a significant impact on bond prices. Returns decrease by more than 100 bps for bonds whose sellers are exposed to large mark-to-market losses, compared to same-issuer bonds sold by unexposed investors. The returns slowly recover over the following seven months, which confirms that the price drops are not driven by any changes in bond fundamentals.

My results have important financial stability implications. First, my findings emphasise that a well-functioning single name CDS market contributes to healthy trading volumes in the corporate

[3]For example, the International Capital Market Association (2016) notes that "it was pointed out by a number of dealers that if liquidity could be re-injected into the single-name CDS market, this would almost certainly have a positive knock-on effect for corporate bond market liquidity".

[4]Mark-to-market losses often translate into variation margin calls, increasing the liquidity needs of exposed investors.

[5]In the first stage regression, I find that a higher fraction of non-centrally cleared CDS contracts is indeed associated with higher mark-to-market losses.

bond market. CDS investors provide liquidity and help to stabilise the bond market, in particular around rating downgrades. Second, my results show that higher CDS margin requirements may have adverse effects on the corporate bond market. The increased cost of trading CDS has led to a bond sell-off by dealer banks, potentially limiting their ability to intermediate secondary corporate bond markets. Third, my results underline the importance and effectiveness of central clearing. The more rigorous risk management practices and higher netting efficiency of CCPs reduce the occurrence of mark-to-market shocks and the risk of subsequent bond fire sales. Central clearing can therefore help to prevent a liquidity spiral in the credit market.

2 Related literature and contribution

I identify four strands of the literature that are particularly relevant to my work. First, there is a growing theoretical literature on how the initiation of CDS has affected various characteristics of the corporate bond market.[6] Che and Sethi (2014) show that the introduction of CDS contracts enables lenders to provide funding without gaining credit risk exposure. As a result, more capital becomes available, bond yields decrease and terms for borrowers improve. However, the authors also predict that naked CDS positions can induce optimistic investors to divert their capital away from purchasing corporate bonds and towards selling CDS protection. Oehmke and Zawadowski (2015) also underline the ambiguous effect of CDS introduction on the underlying bond market. On the one hand, the migration of long and short bond investors to the CDS market reduces demand for corporate bonds (crowding-out effect). On the other hand, the availability of CDS contracts attracts negative basis traders, who hold a long position in the bond and buy CDS protection. The increased demand for bonds by negative basis traders pushes up prices, provided that basis traders can take leverage. In a similar spirit, Sambalaibat (2018) provides an explanation as to why the ban of naked CDS positions led to a reduction in bond market liquidity. She shows that introducing short positions through CDS contracts not only attracts investors who want to short the underlying credit risk, but also investors who want to take the opposite side. Overall, this leads to a greater

[6] For an excellent overview of the CDS literature, see Augustin et al. (2014) and Augustin et al. (2016).

number of bond buyers and to larger bond trading volumes. My paper provides direct empirical evidence for this liquidity spillover effect. With regard to the model of Oehmke and Zawadowski (2015), I show that the increased demand from basis traders dominates the crowding-out effect.

Second, my paper contributes to the empirical literature on the interconnectedness between CDS and bond markets. Thus far, the literature has been constrained by a lack of comprehensive CDS and corporate bond data on the investor-reference entity level. In one of the few empirical studies, Das et al. (2014) show that aggregated bond trading volumes and price impact measures remain unaffected or deteriorate following the introduction of CDS contracts. The authors conclude that CDS trading is largely detrimental to the secondary market for corporate bonds. Similarly, Ashcraft and Santos (2009) show that CDS introduction does not lower the cost of debt financing for the average borrower. Massa and Zhang (2013) and Oehmke and Zawadowski (2017) provide opposing views. Massa and Zhang (2013) show that availability of CDS contracts has a positive effect on bond market liquidity through a reduction of regulatory-induced fire sales by insurance companies. Oehmke and Zawadowski (2017) provide empirical evidence that negative basis traders act as absorbers of supply shocks, reducing the negative price impact of these shocks in the bond market.

However, due to the lack of counterparty information, the data used in all empirical papers thus far only allowed for a merge of CDS and bond data on the reference entity level. This means that the impact of CDS positions on the bond trading decisions of *individual* investors is still unexplored. Only recently, Boyarchenko et al. (2018) use regulatory US data to link flows across corporate bond and CDS markets at the investor-reference entity level. The authors analyse both the extensive and the intensive margins of credit market participation decisions. My main research question is narrower: are there spillover effects - both positive and negative - of CDS positions on bond market liquidity? By answering this question, I complement the results of Boyarchenko et al. (2018) and provide novel insights into the interconnectedness of CDS and bond markets. More precisely, I show that CDS investors have larger trading volumes in the bonds of the reference entities compared to non-CDS counterparties. Importantly, CDS investors also provide liquidity around rating downgrades and therefore help to stabilise the market.

Third, my paper also underlines the risk of a liquidity spiral in the credit market in the spirit of

Brunnermeier and Pedersen (2009). Margin calls on CDS positions can force distressed investors into fire-selling corporate bonds. It can be difficult and costly to sell these bonds due to the illiquidity of the corporate bond market, in particular during times of stress (Garleanu and Pedersen, 2011). The resulting price pressure leads to new margin calls and can also affect bond prices of correlated issuers (Brunnermeier et al., 2013). I contribute to this stream of the literature by providing novel, causal evidence for such a spiral in the credit market using an instrumental variable approach. More precisely, I show that a funding liquidity shock due to CDS mark-to-market losses causes corporate bond fire sales and a subsequent drop in bond returns.

Fourth, my work also contributes to the large literature on the financial stability implications of central clearing of derivatives contracts (see, e.g., Duffie and Zhu, 2011; Duffie et al., 2015; Ghamami and Glasserman, 2017; Heller and Vause, 2012; Loon and Zhong, 2014; Slive et al., 2012). The impact of CCPs on collateral demand and market liquidity has received particular attention in the literature.[7] The seminal paper of Duffie and Zhu (2011) emphasises that central clearing lowers system-wide collateral demand and improves netting efficiency, as long as there is a sufficiently large number of participants and a small number of CCPs.

In the context of CDS contracts, Loon and Zhong (2014) and Slive et al. (2012) show that the introduction of central clearing leads to lower counterparty credit risk and an improvement in market liquidity. Duffie et al. (2015) provide empirical evidence that the new initial margin requirements for dealer-to-dealer contracts significantly increase the system-wide collateral demand. Given these higher initial margins for bilateral OTC contracts, the authors reiterate that central clearing can substantially lower the collateral demand due to netting and diversification benefits. My contribution to this literature is twofold. I show that a higher fraction of centrally cleared CDS contracts is associated with lower mark-to-market losses and therefore reduces funding liquidity risks. Building on this result, I also provide novel evidence that central clearing of CDS contracts can lower the risk of fire sales by capital-constrained investors in the corporate bond market.

[7]'Variation margin' and 'collateral' both refer to the compensating payment that directly reflects the mark-to-market process in a CDS contract, and hence the two terms mean the same thing in this context (McDonald and Paulson, 2015).

3 Data and summary statistics

3.1 Data sources

I collect data from several sources. First, I obtain monthly single name CDS positions from the Depository Trust & Clearing Corporation's (DTCC) trade repository dataset, covering the period from November 2014 to December 2016. This regulatory dataset provides information on counterparties, notional amounts, mark-to-market values and initiation and maturity dates.[8] The DTCC trade repository data capture the vast majority of CDS positions and have previously been used in numerous academic studies.[9] Within the DTCC's trade repository data, I observe positions meeting one of two conditions: (i) the underlying reference entity is a UK firm or (ii) at least one of the counterparties in the CDS is registered in the UK.

Following the guidelines in Abad et al. (2016), I eliminate duplicates, intragroup transactions, compression trades, CDS positions with implausible notional amounts (greater than £10bn and lower than £1,000) and positions for which the mark-to-market value of the contract is missing. Finally, I delete all observations with inconsistent values for the reported notional, the identities of the counterparties, the counterparty side, the maturity date or the underlying reference entity. After cleaning the data, I aggregate CDS buy and sell volumes on the investor-reference entity level and calculate the net and gross notional amounts.

Second, I use regulatory data on corporate bond transactions from the Financial Conduct Authority's Zen database, which covers all trades in sterling corporate bonds of UK-regulated firms, or branches of UK firms regulated in the EEA.[10] Each transaction report includes counterparties, date, time, quantity, price, International Securities Identification Number (ISIN), a buyer/seller flag and trading capacity information. I aggregate the transactions on the investor-reference entity level to match the level of aggregation of CDS positions in the trade repository data. Moreover, I

[8] I convert all notional amounts and mark-to-market values to pound sterling.

[9] See, e.g., Abad et al. (2016), Boyarchenko et al. (2018), Choi et al. (2018), Oehmke and Zawadowski (2017) or Siriwardane (2018).

[10] The Zen data capture who executes the trade, but not necessarily who the beneficial owner is. See Czech and Roberts-Sklar (2017) for a more detailed description of the Zen data.

use a hand-collected dataset to attribute an investor type to each firm identity.[11]

Finally, I complement my unique dataset with publicly-available data. I obtain information on corporate bond characteristics from Bloomberg, issuer ratings from Standard & Poor's, exchange rates from Thomson Reuters and yield curve data from the Bank of England.

I focus on single name CDS contracts in my analysis to achieve a clean match of CDS positions and corporate bond transactions. Therefore, I delete all observations with indices and baskets as underlying. Furthermore, I drop all swap positions written on issuers for which I do not observe any corporate bond transactions in the Zen database. My final sample consists of 404,087 observations on the investor-reference entity-month level. I observe 722 different bond issuers and 1,825 counterparty families. The subsample for which I obtain CDS position data includes 51,640 observations, 232 issuers and 140 counterparty families.

3.2 CDS summary statistics and institutional background

Single name CDS contracts play an important role in the financial system, allowing investors to extend or hedge their exposure to a particular reference entity (Boyarchenko et al., 2018). Despite a recent decline in single name CDS activity,[12] CDS contracts are usually more liquid than corporate bonds. They allow banks and insurance companies to hedge their credit risk and free up regulatory capital. Negative basis traders, who purchase CDS protection and the underlying bond, are another important source of demand. Furthermore, CDS contracts allow leverage-constrained investors to take levered risk and enhance the yields of their fixed income portfolios (Jiang and Zhu, 2016).

The CDS gross notional amount - defined as the total par amount of credit protection bought (or sold) - has been continuously decreasing from £650bn to £400bn in my sample period (Figure 1).[13] At the same time, the net notional amount has remained relatively stable around £75bn (Figure 2). The net notional amount is defined as the sum of net protection bought (sold) by counterparties

[11]The investor type allocation is imperfect since some investors could be allocated to different types (e.g. insurance companies with asset manager arms).

[12]See, e.g., Culp et al. (2016).

[13]This compares with global gross notional amounts of $9.1tn in December 2014 and $5.6tn in December 2016 (Aldasoro and Ehlers, 2018). My sample therefore covers around 7% of the global single name CDS market.

that are net buyers (sellers) of protection for a particular reference entity (Depository Trust & Clearing Corporation, 2011). Therefore, the net notional amount gives a "better estimate of the net exposure because it represents the aggregate payments that would be made in the event of the default of a reference entity" (International Organization of Securities Commissions, 2012). The stable net notional amount and the simultaneous decline in the gross notional amount reflect portfolio compression trades and the increasing use of central clearing. Portfolio compression trades reduce the gross notional amount without affecting the counterparties' net positions by eliminating offsetting CDS contracts (D'Errico et al., 2018). Central clearing, in turn, facilitates the multilateral netting of exposures and contributes to a reduction in inter-dealer positions (Aldasoro and Ehlers, 2018).

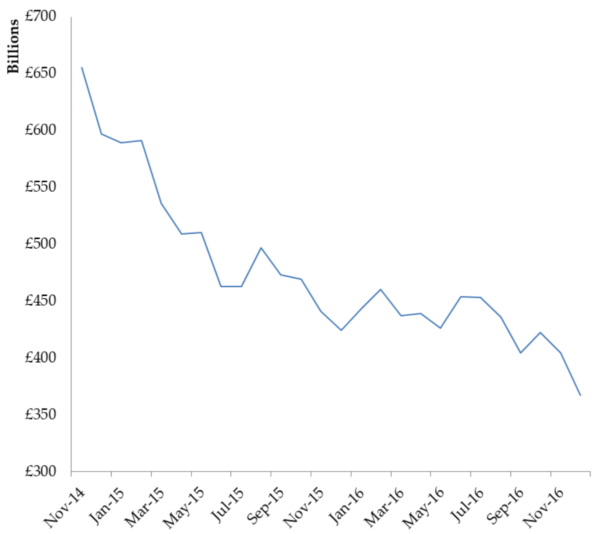

Figure 1: *CDS gross notional amount*

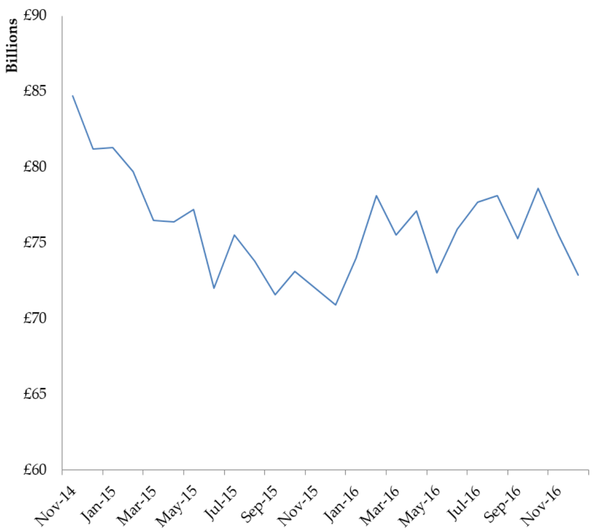

Figure 2: *CDS net notional amount*

Table 1 provides descriptive statistics for my CDS sample. Most CDS contracts in my sample have an initial maturity of five years and a gross notional below £3m.[14] The vast majority of contracts are denominated in EUR or USD, while less than 1% of contracts are denominated in GBP. CDS contracts that are cleared with a central clearing counterparty account for around 15% of the gross notional in my sample. This share is relatively small compared to multi name contracts

[14]The dominance of contracts written with a five-year maturity reflects the standardisation of CDS contracts following ISDA's 'Big Bang' and 'Small Bang' protocols.

due to the lower degree of standardisation in single name CDS contracts.[15]

[Insert Table 1 here.]

More than half of the CDS contracts in my sample are referenced on banks or other financial institutions. This is consistent with the fact that around 45% of the corporate bonds in my sample are issued by these institutions. Furthermore, many investors use CDS contracts to hedge their financial counterparty exposure (Oehmke and Zawadowski, 2017). Around two thirds of the CDS contracts in my sample are written against medium grade issuers, i.e. issuers with a rating between A+ and BBB-. These issuers carry a greater degree of long-term investment risk compared to prime & high grade issuers (AA- or higher), and downgrades could drop the credit rating of medium grade issuers to below investment grade. Overall, these statistics are in line with other CDS studies such as Abad et al. (2016) and Aldasoro and Ehlers (2018).

Figure 3 shows the evolution of CDS net positions by investor type.[16] The main net protection buyers in my sample are dealer banks and hedge funds. The persistent, positive CDS net positions of hedge funds are likely to be attributable to negative basis trades, in which the funds exploit differences between bond and CDS spreads. Dealer banks switched from being net protection sellers to being net protection buyers. This development coincides with the publication of the final revised timelines for new margin requirements for non-centrally cleared derivatives by the Basel Committee on Banking Supervision and IOSCO in March 2015 (Bank for International Settlements, 2015). More precisely, the report provides new, higher standards for the initial margin that the CDS buyer can demand from the CDS seller as some minimum protection should the seller default. The margin requirements are linked to the aggregate notional amount on the group level.[17] The new regulation has therefore increased trading costs in bilateral OTC derivatives, particularly for large investors. This has led to several dealer banks either exiting the market or reducing their service

[15] Aldasoro and Ehlers (2018) report that at the end of 2016, the adjusted share of all multi name contracts cleared with CCPs stood at around 40%.

[16] The net positions are calculated by adding up all CDS net protection bought minus all CDS net protection sold by institutions of a certain investor type. This allows me to determine which investor types are net protection buyers or net protection sellers in a given month.

[17] The first phase-in of the new margin requirements applies to entities with group notional amount of non-centrally cleared OTC derivatives above EUR 3 trillion. Furthermore, entities with group notional amount below EUR 8 billion are exempted from the new margin requirements (Financial Conduct Authority, 2017).

offerings (Cognizant, 2016).

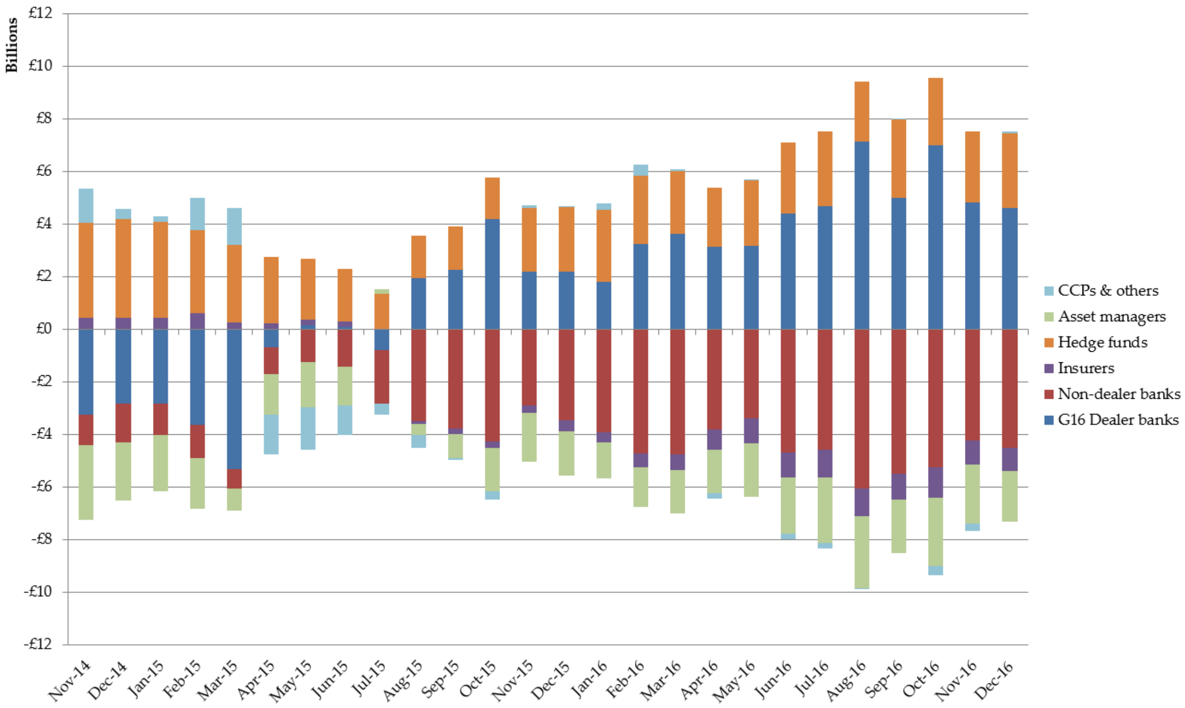

Figure 3: *CDS net positions of different investor types*

The main CDS protection sellers are asset managers and non-dealer banks, specifically smaller-sized regional banks.[18] Many of these small banks are not affected by the more stringent margin requirements, allowing them to sell over-the-counter credit protection at lower trading costs than dealer banks. This competitive advantage has led to considerably larger CDS positions of non-dealer banks in 2016 compared to early 2015. Figure 3 also shows that asset managers are persistent net protection sellers. This finding is in line with Jiang and Zhu (2016), who find that CDS contracts serve as an important vehicle for asset managers to enhance yields on their bond portfolio by doubling-up on credit risk.

[18]This finding is in line with Acharya et al. (2018), who show that smaller-sized banks use CDS to extend rather than hedge their exposure to credit risk.

3.3 Corporate bond summary statistics

Corporate bond markets play a crucial role in the financial system by providing funding to the real economy. Corporate bonds are traded over-the-counter, with dealer banks intermediating the vast majority of trades (Czech and Roberts-Sklar, 2017). In the Zen data, I can observe all trades in sterling corporate bonds for UK-regulated firms, or branches of UK firms regulated in the EEA. The sterling corporate bonds in my sample are issued by both domestic as well as foreign companies.

Table 2 presents the summary statistics for my corporate bond sample. I observe 4,660 bonds and 722 unique issuers. The monthly trading volume is around £30bn. The spreads over UK government bonds have gradually increased for all rating categories since 2014.[19] The yields of high yield bonds and unrated bonds slightly increased over the same period, while the yields of investment grade bonds have fallen. Around one quarter of the bonds in my sample have a prime & high grade rating, around 50% have a medium grade rating, 9% are high yield bonds and 15% of the bonds are unrated. Furthermore, almost half of the bonds in my sample are issued by banks or other financial institutions.

[Insert Table 2 here.]

Panel C of Table 2 shows the overlap between the corporate bond and the CDS market. All major dealer banks are active in both the corporate bond and the CDS market. This fraction is much smaller for all other investor types, potentially reflecting the fact that I observe many smaller-sized investors in my sample. Regulatory challenges and the opaqueness of the CDS market could prevent these investors from entering. The bond investors that are also active in the CDS market buy or sell credit protection on a large fraction of their bond portfolio. Dealer banks and non-dealer banks have active CDS positions on almost 50% of their bond portfolio. This fraction is lower for hedge funds and asset managers with 35% and 22%, respectively.

[19] See Czech and Roberts-Sklar (2017) for a more detailed overview of the spread and yield development in the sterling corporate bond market.

4 CDS positions and bond market liquidity

4.1 Micro-level link between CDS positions and bond trading volumes

CDS markets provide an alternative trading venue through which investors can trade credit risk (Oehmke and Zawadowski, 2017). There are several reasons why one would expect a positive impact of CDS positions on corporate bond trading volumes. Oehmke and Zawadowski (2015) predict that CDS introduction allows buy-and-hold investors to absorb more of the bond supply because they can lay off unwanted credit risk in the CDS market. Furthermore, hedging via CDS enables dealer banks to free up regulatory capital, which means they can better warehouse risk and hold more long and short positions in the bond market. Sambalaibat (2018) predicts a positive spillover effect of CDS introduction on bond market liquidity: larger trading volumes, higher turnover, and a greater number of bond buyers.

Conversely, CDS introduction could have a detrimental effect on the bond market. Das et al. (2014) hypothesise that large institutional traders shift from trading in the bond market to trading in the CDS market, thereby reducing bond market liquidity. Jiang and Zhu (2016) find that investment funds with more frequent liquidity needs are more likely to substitute long bond positions with short positions in the CDS market.

Due to a lack of comprehensive trade data for both markets, previous empirical research has mostly focused on aggregated pricing and liquidity implications of CDS introduction for the corporate bond market. My regulatory data allow me to provide novel evidence for the impact of CDS positions on bond trading decisions of individual investors across different sectors. Furthermore, I provide a direct empirical test for the theories of Oehmke and Zawadowski (2015) and Sambalaibat (2018).

I estimate the following specification:

$$\ln(Volume^{Buy/Sell})_{i,z,t} = \beta \, CDS \; counterparty_{i,z,t} + \alpha_{i,t} + \alpha_{z,t} + \xi_{i,z,t}, \tag{1}$$

where i is the issuer, z is the investor, and t is at the monthly level. The dependent variable $\ln(Volume^{Buy/Sell})_{i,z,t}$ refers to the natural logarithm of the amount bought (Buy volume) or sold

(Sell volume) across bonds of issuer i by investor z in month t.[20] $CDS\ counterparty_{i,z,t}$ is an indicator variable equal to one if investor z is long or short in a CDS contract written on issuer i during month t. This specification therefore measures the overall impact of CDS positions on bond trading volumes, regardless of whether an investor is long or short in a CDS contract. I also estimate a second specification to account for these different directional views:

$$\ln(Volume^{Buy/Sell})_{i,z,t} = \beta_1\ CDS\ buyer_{i,z,t} + \beta_2\ CDS\ seller_{i,z,t} + \alpha_{i,t} + \alpha_{z,t} + \xi_{i,z,t}, \qquad (2)$$

where $CDS\ buyer_{i,z,t}$ ($CDS\ seller_{i,z,t}$) is an indicator variable equal to one if investor z is net short (long) in a CDS contract written on issuer i during month t. Standard errors are clustered on the year-month, issuer and investor level in both specifications. I control for all unobserved, time-variant and time-invariant investor characteristics by including *investor∗month* fixed effects ($\alpha_{z,t}$). By controlling for *investor∗month* fixed effects, I can confirm that my results hold if I control for the amount bought or sold by a specific investor across all issuers at a given time. The additional inclusion of *issuer∗month* fixed effects ($\alpha_{i,t}$) controls for all unobserved issuer characteristics, such as the borrower risk or amounts outstanding. Therefore, I am able to isolate the effect of CDS positions on bond trading volumes.

Panel A of Table 3 shows the results for the first specification. I find that investors with active CDS contracts written on a specific issuer have larger buy volumes in the bonds of this reference entity compared to non-CDS counterparties. The effect is statistically highly significant. The economic magnitude is also large: investors that use CDS contracts are associated with almost three times higher buy volumes in the bonds of the reference entity (Column 1).[21]

[Insert Table 3 here.]

A possible concern with this result is that CDS investors are generally large institutions with higher buy volumes in the corporate bond market. The inclusion of *investor∗month* fixed effects addresses this concern by controlling for the aggregated bond trading volumes of a specific investor

[20] The dependent variable is explained in more detail in the appendix.

[21] As the dependent variable is the natural logarithm of buy or sell volume, the percentage change coming from a change in the binary variable *CDS counterparty* is $100(\exp(\beta) - 1)$, where β is the estimated coefficient.

at a given time. Another concern is that CDSs are often written on reference entities with a large number of outstanding bonds. The inclusion of *issuer∗month* fixed effects controls for these unobserved issuer characteristics. My results remain statistically and economically significant in the most conservative specification with both interacted fixed effects (Column 4). CDS investors are associated with 60% higher buy volumes in the bonds of the reference entity in this specification.

The coefficients in the specification with *Sell volume* as the dependent variable are not statistically significant after the inclusion of *investor∗month* fixed effects. This indicates that the significant results in Columns 5 and 6 are driven by large investors with inherently high sell volumes. Overall, CDS investors are therefore not associated with higher sell volumes in the bonds of the reference entity compared to investors that are not active in the CDS market. The results lend direct support to the theoretical predictions of Sambalaibat (2018) that CDS contracts increase the number of *buyers* in the bond market. With respect to the model of Oehmke and Zawadowski (2015), the results also indicate that the positive spillover effect dominates the negative crowding-out effect in terms of trading volumes.

Panel B of Table 3 shows the results for the second specification, which includes distinct indicator variables for net long and short CDS investors. The effect is statistically significant for both variables and the magnitudes of both effects are similar to the coefficient of interest in the previous specification. Importantly, investors that are net protection sellers are associated with even higher buy volumes compared to net protection buyers (68% versus 52% higher buy volumes (Column 4)). This finding underlines that many CDS investors double-up on credit risk by buying bonds and selling credit protection. Again, this in line with the prediction of Sambalaibat (2018): long credit risk investors search in the markets for both instruments, thereby increasing the trading opportunities for bond investors and alleviating their search frictions.

The relationship between CDS positions and bond buy volumes may also vary by investment strategy. For instance, the increased buy volumes of net protection buyers could reflect negative basis trades or hedging of credit risk by market makers and buy-and-hold investors. Therefore, I am interested in the relative differences between investor types with distinct trading motivations and investment horizons.[22] I estimate the following specification:

$$\begin{aligned} ln(Buy\ volume)_{i,z,t} =& \beta_1\ CDS\ buyer_{i,z,t} + \sum_{j=1}^{4} \beta_{2,j}\ CDS\ buyer_{i,z,t} * Type_z^j \\ & + \beta_3\ CDS\ seller_{i,z,t} + \sum_{j=1}^{4} \beta_{4,j}\ CDS\ seller_{i,z,t} * Type_z^j + \alpha_{i,t} + \alpha_{z,t} + \xi_{i,z,t}, \end{aligned} \tag{3}$$

where $Type_z^j$ are indicator variables that equal one if investor z belongs to investor type j. I use insurance companies as the benchmark in this specification. I compare these typical buy-and-hold investors to dealer banks, non-dealer banks, hedge funds and asset managers. Standard errors are again clustered on the year-month, issuer and investor level. I also include *investor∗month* fixed effects ($\alpha_{z,t}$) and *issuer∗month* fixed effects ($\alpha_{i,t}$) to control for all time-variant and time-invariant investor and issuer characteristics.

Table 4 shows the results. Surprisingly, insurance companies that are net protection buyers for a specific issuer reduce their buy volumes in the bonds of the reference entity, relative to investors without CDS contracts written on this issuer. This result therefore challenges the prediction of Oehmke and Zawadowski (2015) that CDS contracts allow buy-and-hold investors to absorb more of the bond supply. Regarding the other investor types, I find positive and large magnitudes for hedge funds, followed by dealer banks and asset managers. Hedge funds often combine a short CDS position with a long position in the underlying bond to capitalise on the spread difference between the bond market and the CDS market (negative basis trade). The large economic magnitude of the coefficient indicates that the positive effects on bond buy volumes in Table 3 are, to a large extent, driven by negative basis traders (as predicted by Oehmke and Zawadowski, 2015). Dealer banks, on the other hand, typically use the CDS market to hedge their credit and counterparty risk. The hedge enables dealers to hold more (long and short) positions in the bond market and to keep bonds on their balance sheet until a buyer is found - which can often take several months due to the illiquidity of the corporate bond market.

[22] Using a hand-collected dataset, I can distinguish between dealer banks, non-dealer banks, insurance companies, hedge funds, asset managers, and CCPs & others.

[Insert Table 4 here.]

There are no statistically significant results for relative differences across investor types for net protection sellers. However, the estimates indicate that the positive effect on bond buy volumes is largely driven by asset managers, dealer banks, and insurance companies. This finding echoes the results of Jiang and Zhu (2016), who show that CDS contracts allow mutual funds (and also insurance companies) to take levered risk and double-up on credit risk, thereby enhancing the yields of their bond portfolio.

4.2 Responses to higher margin requirements

The results in the previous section are somewhat difficult to interpret because of endogeneity concerns. Intuitively, it is possible that transactions in the corporate bond market determine the composition of an investor's CDS portfolio, and not vice versa.

Hence, I rely on a quasi-natural experiment to mitigate this reverse causality issue. I use the publication of the final revised timelines for the phase-in of new margin requirements for non-centrally cleared derivatives in March 2015 as my experiment. The new margin requirements are linked to the aggregate notional amount at group level. The vast majority of investors were not immediately affected due to a fairly high threshold for this aggregate notional amount. However, the new regulation increased trading costs in non-centrally cleared OTC derivatives for large investors, particularly dealer banks. Several dealer banks therefore reduced their service offerings or completely left the market (Cognizant, 2016). As a result, the number of reference entities covered by CDS portfolios of dealer banks dropped as numerous CDS positions were terminated.[23] The question then is whether there is also an economically significant impact on corporate bond trading volumes. I expect a drop in bond buy volumes for these terminated investor-reference entity combinations, i.e. a reversal of the effect that I presented in the previous section.

In my experiment, I first focus on CDS positions that were terminated by dealer banks in this period to measure the immediate impact of the new margin requirements. I create the indicator

[23]It is possible to unwind an active CDS contract in three ways: by entering into an offsetting transaction, by assigning the contract to a different counterparty or by agreeing on an unwind payment to terminate the transaction.

variable $CDS\ exit_{i,z,t}$ that equals one if a dealer bank unwound a CDS position written on a specific reference entity to zero in March or April 2015.[24] I add this indicator variable to the regression model in equation (2).

Panel A of Table 5 shows the results. Dealer banks that terminate their CDS contracts written on a specific reference entity dramatically reduce their buy volumes in the bonds of this issuer. This confirms the premise of my quasi-natural experiment. Importantly, dealer banks also increase their sell volumes in the bonds of the affected issuers. Both effects are statistically highly significant and economically meaningful. The termination of a CDS position is associated with a 54% drop in bond buy volumes and a 113% increase in bond sell volumes. The effects are also robust to the inclusion of *investor∗month* and *issuer∗month* fixed effects. I can therefore exclude the possibility that my results are driven by different aggregated trading patterns in these months, or by any unobserved characteristics of the affected issuers.

[Insert Table 5 here.]

Second, I am also interested in the more permanent impact of higher margin requirements on bond trading volumes. Therefore, I estimate a difference-in-difference specification:

$$\ln(Volume^{Buy/Sell})_{i,z,t} = \beta\ Dealer_z * after_t + \alpha_z + \alpha_{i,t} + \xi_{i,z,t}, \tag{4}$$

where $Dealer_z{*}after_t$ indicates whether investor z is a dealer bank in month t after the new regulation (March 2015 or later). In contrast to dealer banks, smaller-sized non-dealer banks were not immediately affected by the more stringent margin requirements due to the high notional amount threshold at group level. Therefore, non-dealer banks serve as the control group. Furthermore, I control for all time-varying issuer ($\alpha_{i,t}$) and time-invariant investor (α_z) characteristics.

I present the results in Panel B of Table 5. The difference-in-difference estimators confirm that higher margin requirements lead to lower buy volumes and higher sell volumes in the corporate bond market. More precisely, the change in buy volumes is 36% lower for dealer banks compared to

[24] The new margin requirements were published on 18 March 2015. To capture all relevant trades, I also add April 2015 to my period of interest. Furthermore, my results are robust to adding May 2015 to my period of interest.

non-dealer banks (Column 2). Moreover, the change in sell volumes is 46% higher for dealer banks (Column 4). Hence, the treatment effect is statistically significant and economically meaningful for both buy and sell volumes.

Overall, the results suggest that dealer banks terminated numerous CDS positions *and* sold off bonds of the underlying reference entities in response to the new margin requirements. Therefore, the results lend strong support to my previous findings and allow me to draw a more nuanced picture of the interconnectedness between CDS positions and bond trading volumes. Investors with active CDS positions have higher buy volumes in the bonds of the reference entity, suggesting that they extend their credit exposure to this issuer. Accordingly, the termination of a CDS position is associated with lower buy volumes and higher sell volumes in the bonds of the reference entity, indicating that investors may sharply reduce their bond holdings for this issuer.

4.3 CDS positions and issuer downgrades

The main function of a CDS contract is to insure the protection buyer against adverse credit events. Credit events are usually a failure of the reference entity to make a payment on its debt, but can also include restructuring, bankruptcy, or rating downgrades (International Capital Market Association, 2018). I am going to focus on the latter in this section. Regulatory constraints force some investors (in particular insurance companies, see Ellul et al., 2011) to fire-sell the bonds of a downgraded issuer. These fire sales can cause significant downward pressure on the prices and liquidity of the downgraded issuer's bonds. However, investors can reduce the credit risk of their bond portfolio by buying CDS protection, allowing them to defer the sales of downgraded bonds (Massa and Zhang, 2013).

Therefore, the question is whether CDS contracts can reduce the procyclical bond selling of regulatory-constrained investors around rating downgrades. Furthermore, the availability of CDS contracts also attracts arbitrageurs, who capitalise on the widening negative basis in the downgrade period. In a similar study, Massa and Zhang (2013) find that the presence of CDS contracts lowers the yield spreads and increases the liquidity of downgraded bonds. However, the authors only analyse how the *availability* of CDS contracts alters the impact of downgrades on bond institutional ownership. My regulatory data allow me to go further because I can analyse whether investors with active CDS protection behave differently around rating downgrades compared to investors without such protection.

To answer this question, I estimate the following specification:

$$\begin{aligned}\ln(Volume^{Buy/Sell})_{i,z,t} =& \beta_1\, CDS\ buyer_{i,z,t} + \beta_2\, CDS\ seller_{i,z,t} \\ &+\beta_3\, CDS\ buyer_{i,z,t} * upgrade_{i,t} + \beta_4\, CDS\ seller_{i,z,t} * upgrade_{i,t} \\ &+\beta_5\, CDS\ buyer_{i,z,t} * downgrade_{i,t} + \beta_6\, CDS\ seller_{i,z,t} * downgrade_{i,t} \\ &+\alpha_{i,t} + \alpha_{z,t} + \xi_{i,z,t}, \qquad (5)\end{aligned}$$

where $upgrade_{i,t}$ and $downgrade_{i,t}$ are indicator variables that equal one if issuer i is upgraded or downgraded in month t, based on long-term issuer ratings from Standard & Poor's. I also include *investor*month* fixed effects ($\alpha_{z,t}$) and *issuer*month* fixed effects ($\alpha_{i,t}$) to control for all time-variant and time-invariant investor and issuer characteristics.

I present the results in Table 6. CDS net protection buyers have higher buy volumes and lower sell volumes in the bonds of the downgraded issuer. The effect is statistically significant and economically large. The buy volumes of CDS net protection buyers are more than five times higher compared to investors without CDS contracts written on the reference entity (Column 2). Furthermore, the sell volumes of protection buyers are 64% lower. These results suggest that net protection buyers extend their bond holdings and therefore act in a countercyclical fashion around issuer downgrades.

[Insert Table 6 here.]

Surprisingly, I find an effect of similar significance for net protection sellers. The economic magnitude, albeit smaller compared to net protection buyers, is still large. The buy volumes of CDS net protection sellers are almost four times higher, and the sell volumes are 51% lower compared to investors without CDS contracts written on the reference entity (Column 4). Therefore, net protection sellers also behave countercyclically around rating downgrades by increasing their buy volumes and lowering their sell volumes.

The results confirm my hypothesis that CDS contracts can reduce bond fire sales around rating downgrades. This finding is in line with the results of Massa and Zhang (2013). For net protection buyers, the countercyclical behaviour around downgrades can be attributed to the regulatory relief for constrained investors or, alternatively, the increased bond buying of negative basis traders. The results for net protection sellers are somewhat puzzling. One possible explanation is that net protection sellers have an informational advantage over investors that are not active in the CDS market with regard to the credit quality of the underlying reference entity.

My results show that CDS contracts can effectively insure investors against adverse credit events. The use of CDS contracts can lead to a reduction in regulatory-induced fire sales and an improvement in bond market liquidity around rating downgrades.

4.4 Impact on bond-level liquidity measures

Sambalaibat (2018) predicts that the presence of CDS markets reduces search frictions and increases the trading opportunities for bond investors. In the previous sections, I provide supporting evidence that individual investors increase their bond buy volumes if they hold CDS positions written on the debt issuer. However, it is not clear whether this ultimately leads to a significant improvement in the liquidity of the underlying bonds.

To answer this question, I regress a range of bond-level liquidity measures on i) the total number of CDS contracts or ii) the total CDS gross notional amount written on bond issuer i in a given month. I estimate the following specification:

$$Bond\ liquidity_{b,t} = \beta\ \ln(CDS\ trading)_{i,t} + \alpha_t + \alpha_b + \lambda'\ Z_{b,t} + \xi_{b,t}, \tag{6}$$

where $Bond\ liquidity_{b,t}$ refers to six different measures of liquidity of bond b in month t: the Amihud price impact measure, the effective half spread, bond turnover, zero-trading days, the natural logarithm of total trading volume and the natural logarithm of the total number of trades.[25] $\ln(CDS\ trading)_{i,t}$ refers to the natural logarithm of either the total number of active CDS contracts or the total CDS gross notional amount written on bond issuer i in month t. $Z_{b,t}$ is a vector that includes three time-varying, bond-specific controls: the bond rating, time-to-maturity and age. I include *month* fixed effects (α_t) and *bond* fixed effects (α_b) to control for changes in aggregate economic conditions and all unobserved time-invariant issuer or bond characteristics, respectively.

Panel A of Table 7 shows that the liquidity of corporate bonds increases with the number of CDS contracts written on the bond issuer. The effect is statistically significant for all liquidity measures except for the Amihud ratio. The economic magnitude is also large: a 10% increase in the number of CDS contracts, for example, leads to a 5.9% increase in the bond's monthly trading volume and a 3.5% increase in the number of trades for this bond. An increase in the number of CDS contracts is also associated with significantly lower half spreads, higher bond turnover and fewer zero-trading days, underlining the consistently positive impact of CDS trading on bond liquidity. However, a possible concern is that CDS contracts are generally written on big firms with larger and more liquid bond issues. The inclusion of bond fixed effects (α_b) addresses this concern by controlling for such unobserved issuer or bond characteristics.

[Insert Table 7 here.]

I obtain results of similar statistical and economic significance for the CDS gross notional specification, as shown in Panel B of Table 7. A 10% increase in the CDS gross notional amount written on the debt issuer leads to a 2% increase in the bond's monthly trading volume and a 1.3% increase in the number of trades. Furthermore, a higher CDS gross notional amount is associated with a significant increase in the bond's turnover, significantly lower half spreads and fewer zero-trading days.

Importantly, the results emphasise that the positive liquidity spillovers are not limited to trading

[25]The Amihud illiquidity measure estimates the price impact of trades within each month, and is defined as the ratio of the bond's absolute return scaled by trading volume. The effective half spread is the difference between the trade price and the bid/ask midpoint, which is viewed as a proxy for the fundamental value of the asset. Turnover is defined as the bond's monthly trading volume as a percentage of its total amount outstanding. Zero-trading days measure the percentage of days within a month where a bond does not trade. See, e.g., Dick-Nielsen et al. (2012) for more details on these liquidity measures.

volumes of individual investors. A higher intensity of CDS trading - i.e. a higher number of active contracts or a larger gross notional amount written on the debt issuer - significantly improves the liquidity of the underlying corporate bonds. The improved bond liquidity ultimately reduces risks for investors by allowing them to trade on demand, which in turn reduces borrowing costs for firms in the real economy.

5 Fire sales caused by CDS mark-to-market losses

5.1 The instrument

The summary statistics emphasise that many financial institutions hold large amounts of corporate bonds and credit default swaps. A potential contagion channel between these two markets is described in Brunnermeier et al. (2013): margin calls on derivatives can force distressed institutions into fire sales to obtain liquidity, which further depresses asset prices. These price drops can lead to new margin calls and also affect bond prices of correlated issuers.

To my knowledge, my paper is the first to provide empirical evidence for a liquidity spiral in the context of credit default swaps and corporate bonds. My regulatory data allow me to analyse the impact of CDS mark-to-market losses on corporate bond sell volumes, both measured on the investor-month level. The mark-to-market process is directly reflected in the variation margin for CDS counterparties, which is used to settle current price changes. Significant mark-to-market losses inevitably lead to variation margin calls and increase the investors' demand for liquidity. Therefore, I use mark-to-market losses as a proxy for margin calls.

However, there are serious endogeneity concerns when regressing bond sell volumes on CDS mark-to-market losses. Of particular concern is reverse causality, because significant corporate bond sales could also cause a shift in CDS spreads and lead to subsequent mark-to-market losses. To establish causality, I use the fraction of non-centrally cleared CDS contracts - also measured on the investor-month level - as an instrument for mark-to-market losses.[26]

Large investors, who are the predominant players in both markets, usually have separate derivatives and fixed income desks (see, e.g., Bank for International Settlements, 2014). Therefore, it is plausible to assume that an investor's decision whether to clear CDS contracts or not has no direct impact on the behaviour of her fixed income traders. The exclusion restriction is hence not violated.

Regarding the relevance condition, the fraction of non-centrally cleared contracts should have a significant impact on the level and volatility of variation margin calls. The reasons for this are twofold. First, CCPs offer multilateral netting of derivatives positions, typically leading to a higher netting efficiency and reduced risk exposures (Duffie and Zhu, 2011). The multilateral netting of exposures, if effective, should therefore lead to lower variation margin payments. Second, the jump-to-default risk complicates the risk management of CDS contracts. Importantly, CCPs explicitly consider 'jump-to-default' as a main component in their variation margin calculations (Capponi et al., 2017). By contrast, bilateral collateral requirements often fail to cover the 'jump-to-default' risk (Cont and Kokholm, 2014). This may lead to an under-collateralisation of bilateral OTC contracts, and potentially large variation margin calls when the creditworthiness of the reference entity suddenly deteriorates (International Organization of Securities Commissions, 2012).

The first stage equation estimates the impact of the fraction of non-centrally cleared CDS contracts on mark-to-market losses:

$$\ln(MtM\ losses)_{z,t} = \pi\ fraction\ noncleared_{z,t} + \alpha_{j,t} + \epsilon_{z,t}, \tag{7}$$

where z is the investor, t is at the monthly level, and j is the investor type of z. *MtM losses* measures the losses in the aggregated mark-to-market values across all single name CDS positions of investor z from month $t-1$ to month t.[27] *fraction noncleared* is the fraction of non-centrally

[26] I use the term 'fraction of non-centrally cleared contracts' to emphasise the differences to CDS contracts with a central clearing counterparty. One could also call this instrument 'fraction of bilateral OTC-contracts'. I use this fraction as an instrumental variable for the natural logarithm of the mark-to-market losses variable, which is defined in the appendix.

[27] The endogenous variable *MtM losses* is explained in more detail in the appendix.

cleared CDS contracts for investor z in month t. Standard errors are clustered on the year-month and investor level. I control for all unobserved, time-variant and time-invariant investor type characteristics by including *type∗month* fixed effects ($\alpha_{j,t}$).

Panel A of Table 8 shows the results for the first stage regression. As expected, my instrument is highly correlated with CDS mark-to-market losses, with a first stage F-statistic of 284.63.[28] A higher fraction of non-centrally cleared CDS contracts is therefore associated with higher mark-to-market losses. This result is robust to the inclusion of *type∗month* fixed effects, confirming that my instrument is valid and relevant.

[Insert Table 8 here.]

5.2 Impact on bond sell volumes

The second stage equation estimates the impact of CDS mark-to-market losses on corporate bond sell volumes:

$$\ln(Sell\ volume)_{z,t} = \beta \ln(\widehat{MtM\ losses})_{z,t} + \alpha_{j,t} + \xi_{z,t}, \tag{8}$$

where $\ln(Sell\ volume)_{z,t}$ is the natural logarithm of the aggregated corporate bond sell volumes of investor z in month t. Standard errors are clustered on the year-month and investor level. I control for the average sell volume of a specific investor type in a given month by including *type∗month* fixed effects ($\alpha_{j,t}$).

Panel B of Table 8 provides both the 2SLS estimates and conventional OLS estimates. The results show that investors sell corporate bonds in response to a mark-to-market loss on their CDS positions. The effect is statistically and economically significant. A 10% increase in CDS mark-to-market losses causes a 2.7% increase in the corporate bond sell volumes of investor z (Column 1). One possible concern with the result is that dealer banks are active market makers for corporate bonds with inherently higher sell volumes. To address this concern, I include *type∗month*

[28]The Stock and Yogo (2005) critical value at the 10% maximal IV size is 16.38.

fixed effects to control for any unobserved investor type characteristics. In the most conservative specification with these fixed effects, a 10% increase in mark-to-market losses causes a 2.2% increase in the aggregated corporate bond sell volumes of investor z (Column 3).

The IV estimates are around two to three times higher than the OLS estimates. This is not surprising given the measurement error in the mark-to-market losses variable: not every mark-to-market loss translates into a variation margin call and increases the need for liquidity. Therefore, the OLS estimates are likely to underestimate the impact of severe mark-to-market losses on corporate bond sell volumes.

Following this line of thought, the fire sale risk should be higher for very large mark-to-market losses. I use *MtM Shock* to proxy for these large losses. *MtM Shock* is an indicator variable equal to one if an investor is facing a mark-to-market loss in the highest 10th percentile of the sample. These large mark-to-market losses can lead to significant variation margin calls and exhaust available funding, potentially leading to subsequent corporate bond fire sales.

Panel C of Table 8 shows the regression results for a specification with *MtM Shock* as the independent variable. Investors that experience a mark-to-market shock have three times higher sell volumes in the corporate bond market compared to investors that are not exposed to such substantial losses. The results are statistically significant and also robust to the inclusion of *type∗month* fixed effects. To get a better idea of the economic magnitude, I also report the results for specifications with the non-log-transformed sell volume as the dependent variable (Columns 4-6). Investors exposed to large mark-to-market losses have on average £16m higher monthly sell volumes compared to unexposed counterparties. This difference is economically highly significant, given that the monthly sell volume of the average investor in my sample is £31m.

In summary, I provide causal evidence for a potential contagion channel between CDS and corporate bond markets. Large market swings lead to mark-to-market losses and variation margin calls. These margin calls force some market participants into corporate bond fire sales to obtain liquidity (as predicted by Brunnermeier et al., 2013).

5.3 Choice of fire sale bonds

Which bonds are more likely to be sold following large mark-to-market losses? Jiang et al. (2017) show that investors generally follow either a 'horizontal cut' or a 'vertical cut' strategy to obtain liquidity. When following a horizontal approach, investors typically sell their most liquid assets first to reduce upfront transaction costs. The vertical strategy, on the other hand, implies proportionate selling across asset classes to preserve the current portfolio liquidity.

I follow the approach in Ellul et al. (2011) to determine which characteristics increase the fire sale probability of a bond after a mark-to-market shock. I estimate the following probit function:

$$\Pr(distressed_{b,z,t} = 1) = \Phi(\beta_0 + \delta' \, X_{b,t} + \gamma' \, Y_{b,t-1} + \alpha_t + \alpha_i + \xi_{b,z,t}), \tag{9}$$

where $distressed_{b,z,t}$ is an indicator variable equal to one if an investor, who is exposed to a mark-to-market shock on her CDS positions, sells bond b in month t (the month of the shock).[29] $X_{b,t}$ is a vector of bond-specific characteristics that includes the time-to-maturity, age, and an indicator variable for investment grade bonds. $Y_{b,t-1}$ is a vector that includes lagged liquidity measures ($Amihud_{b,t-1}$ and $turnover_{b,t-1}$) and the lagged yield change ($\Delta yield_{b,t-1}$) of bond b. Standard errors are clustered on the issuer level. I include time fixed effects to control for any differences in aggregate economic conditions that could drive the fire sale behaviour. I also use issuer fixed effects to account for all unobserved, time-invariant issuer characteristics.

I present the results in Table 9. Investors exposed to a mark-to-market shock on their CDS positions are more likely to sell liquid and better rated bonds. The coefficient on the lagged Amihud price impact measure is negative and statistically significant in all specifications, suggesting that lower bond liquidity reduces the fire sale probability of a bond. The positive (albeit less significant) coefficient on the bond turnover ratio strengthens this interpretation. The fire sale probability also decreases with bond age and increases with the remaining time-to-maturity. Younger bonds with longer remaining maturities are typically relatively liquid, which again suggests that investors avoid selling illiquid bonds. These results are in line with other fire sale studies such as Chaderina et al.

[29] As in the previous section, *MtM Shock* is an indicator variable equal to one if an investor is facing a mark-to-market loss in the highest 10th percentile of the sample.

(2018) or Ellul et al. (2011). I also find that investment grade bonds are more likely to be sold compared to high yield or unrated bonds. This effect is statistically highly significant.

[Insert Table 9 here.]

Overall, my results provide further evidence that investors try to minimise the price impact of their fire sales by selling relatively liquid bonds. This indicates that they follow a 'horizontal cut' liquidation strategy, echoing the findings of Jiang et al. (2017). Ironically, the price impact may actually be larger for more liquid bonds if multiple investors follow this strategy at the same time (Ellul et al., 2011). Moreover, these investors are potentially more vulnerable to future funding shocks due to the increased illiquidity of their bond portfolios.

5.4 Impact of fire sales on bond returns

The IV regressions show that investors sell large quantities in the corporate bond market when they are exposed to mark-to-market shocks on their CDS positions. To reduce the transaction costs of these fire sales, the investors follow a 'pecking order' by selling relatively liquid bonds first. The question then is whether the fire sales still have a significant impact on bond returns. Therefore, I analyse the return differences between bonds whose sellers are exposed to large mark-to-market losses, compared to bonds of the same issuer sold by unexposed investors.

I estimate the following model:

$$return_{b,t} = \sum_{\tau=-2}^{10} \beta_\tau \; distressed_{b,t-\tau} + \alpha_{i,t} + \lambda' \; Z_{b,t} + \xi_{b,t}, \tag{10}$$

where $return_{b,t}$ is the trade-weighted return on bond b for month t.[30] $distressed_{b,t-\tau}$ is an indicator variable equal to one if bond b is sold by investors facing CDS mark-to-market shocks in month $t-\tau$. As in the previous section, these shocks are defined as mark-to-market losses in the highest 10th percentile of the sample. $Z_{b,t}$ is a vector of bond-specific controls that includes the

[30] I follow Bai et al. (2018) in the calculation of bond returns. The dependent variable is explained in more detail in the appendix.

rating, time-to-maturity, age, and the UK gilt yield of comparable maturity. Hence, I control for the major factors that drive bond returns, which enables me to better isolate the price effects of the fire sales. Standard errors are clustered on the issuer level in this specification.

One possible concern is that investors with large CDS mark-to-market losses might choose corporate bonds issued by riskier firms, along other unobserved dimensions. The inclusion of *issuer*month* fixed effects ($\alpha_{i,t}$) mitigates these endogeneity concerns by accounting for any unobserved time-variant and time-invariant issuer characteristics. The use of *issuer*month* fixed effects allows me to compare the return of bond b issued by firm i and sold by *distressed* investors to the return of another bond c of the same issuer but sold by *non-distressed* investors (Manconi et al., 2012).

I report the results in Table 10 and Figure 4. Bond returns significantly decrease in the first three months after a mark-to-market shock, compared to same-issuer bonds sold by unexposed investors. The effect is statistically significant and economically meaningful: bond returns decrease by more than 100 bps in the three months after the shock. The returns then exhibit a typical reversal pattern and recover over the following seven months. Importantly, the returns of bonds sold by distressed investors are not significantly different from those of same-issuer bonds sold by unexposed investors in the two months prior to the shock and the month of the shock. The results are robust to the inclusion of bond-specific control variables. Furthermore, the magnitude of the effect is relatively consistent across various specifications.

[Insert Table 10 here.]

The results lend strong support to the liquidity spiral hypothesis. The fire sales of distressed investors exposed to large CDS mark-to-market losses lead to a significant drop in bond returns, holding any issuer-specific characteristics constant. The subsequent reversal confirms that the price drop is not driven by any changes in bond fundamentals, but rather by the increased selling of capital-constrained investors. The price drops are likely to cause further variation margin calls on CDS positions, which, in turn, may lead to new fire sales in the corporate bond market. The resulting liquidity spiral in the credit market can lead to a reduction in the provision of immediacy, particularly for high margin assets such as corporate bonds (Brunnermeier and Pedersen, 2009).

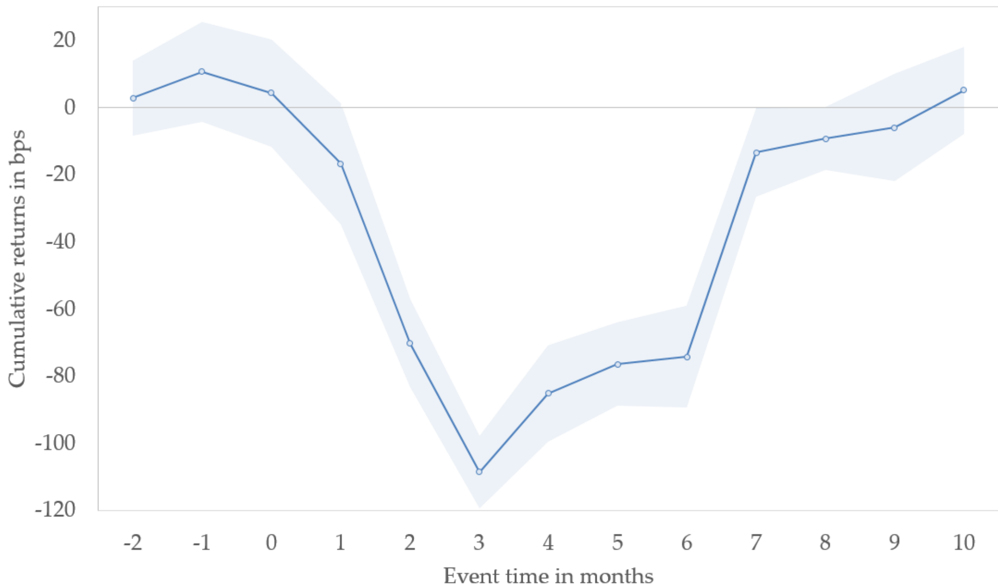

Figure 4: *Cumulative returns of bonds held by distressed investors*

This figure shows the cumulative monthly returns for bonds sold by investors exposed to CDS mark-to-market shocks (where 0 is the month of the fire sale). These shocks are defined as mark-to-market losses in the highest 10th percentile of the sample. The graph is based on the cumulated coefficient estimates of the $distressed_{b,t-\tau}$ indicator variables shown in Column 4 of Table 10. *issuer∗month* fixed effects and bond-specific control variables are included in this specification. The blue band around the cumulative returns represents the 95% confidence interval.

6 Concluding remarks

I provide novel empirical evidence for a positive spillover effect from CDS positions to corporate bond market liquidity. Using regulatory data on single name CDS holdings and corporate bond transactions, I show that institutions increase their bond trading volumes if they hold CDS positions written on the debt issuer. Consequently, CDS counterparties can provide liquidity and help to stabilise the corporate bond market, particularly around rating downgrades. However, these positive spillovers need to be balanced against potential risks for the corporate bond market that can originate from investors' losses on their CDS positions. My findings highlight the risk of a liquidity spiral: severe CDS mark-to-market losses cause fire sales in the corporate bond market, which subsequently lead to a significant drop in bond returns.

From a financial stability perspective, a well-functioning and accessible CDS market can enhance liquidity and market-making in the secondary corporate bond market. Therefore, regulations that increase CDS transaction costs are likely to have a negative impact on bond market liquidity. On the contrary, the shift to central clearing improves the efficiency and transparency of the single name CDS market, with positive implications for the liquidity of the corporate bond market. Furthermore, the move to central clearing also reduces the risk of a liquidity spiral in the credit market.

Appendix

Variable construction

I want to explore how CDS positions affect corporate bond trading volumes. In the spirit of Abassi et al. (2016) and Czech and Roberts-Sklar (2017), I separately examine buying and selling behaviour. The main dependent variable in my analysis is the natural logarithm of corporate bond buy or sell volumes, $\ln(Volume^{Buy/Sell})$.[31] *Buy volume* and *Sell volume* refer to the monthly amount bought or sold by investor z. For each investor-reference entity combination, I calculate the measure by aggregating the individual transaction volumes in month t:

$$Buy\ volume_{i,z,t} = \max(Net\ volume_{i,z,t}, 0),$$

$$Sell\ volume_{i,z,t} = \max(-Net\ volume_{i,z,t}, 0).$$

One of the main goals of this paper is to analyse how corporate bond sell volumes are affected by mark-to-market losses. Therefore, I define *MtM losses* as the losses in the aggregated mark-to-market values across all single name CDS positions of investor z from month $t-1$ to month t:

$$MtM\ losses_{z,t} = \max(-\Delta MtM_{z,t}, 0).$$

The mark-to-market process is directly reflected in the variation margin for CDS counterparties, which is used to settle current price changes. Therefore, mark-to-market losses can lead to margin calls and dry up available funding, potentially leading to a liquidity spiral in the spirit of Brunnermeier and Pedersen (2009). Intuitively, this fire sale risk should be higher for very large mark-to-market losses. I use *MtM Shock* to proxy for these large losses. *MtM Shock* is an indicator variable equal to one if an investor is facing a mark-to-market loss in the highest 10th percentile of the sample.

Next, I analyse how fire sales of investors exposed to mark-to-market shocks affect bond returns.

[31] By construction, I only include non-zero issuer-investor-month combinations in my sample.

I follow Bai et al. (2018) in the calculation of bond returns:

$$r_{b,t} = \frac{P_{b,t} + AI_{b,t} + C_{b,t}}{P_{b,t-1} + AI_{b,t-1}} - 1,$$

where $AI_{b,t}$ is the accrued interest and $C_{b,t}$ is the coupon payment, if any, of bond b in month t. $P_{b,t}$ is the trade-weighted price of bond b in month t. I construct this monthly price by weighting each trade by its size, thereby putting more weight on institutional trades at lower transaction costs (Bessembinder et al., 2009).

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Table 1: *CDS summary statistics*

This table provides descriptive statistics for my CDS sample. My dataset covers the period from November 2014 to December 2016. 'Notional amount' measures the notional amount of a CDS contract in £m. 'Initial time-to-maturity' measures the time in years at initiation until a CDS contract reaches its maturity date. 'Currency' refers to the currency of the CDS contract. 'Cleared' is the gross notional-weighted share of contracts cleared with a central clearing counterparty (CCP). 'Industry' refers to a broad industrial classification of the issuing firm. 'Prime & high grade' refers to issuers with a credit rating of AA- or higher. 'Medium grade' refers to issuers with a credit rating between A+ and BBB-. 'High yield' refers to issuers with a credit rating of BB+ or lower. 'Unrated' refers to issuers that do not have a credit rating. Note that the percentages do not always add up to 100% due to rounding.

# unique issuers	232
# unique counterparties	140
Notional amount	
$\leq$ £1m	31.0%
>£1m & $\leq$ £3m	27.4%
>£3m & $\leq$ £5m	19.3%
>£5m	22.4%
Initial time-to-maturity	
<3 years	25.4%
$\geq$ 3 years & <5 years	27.1%
= 5 years	28.6%
>5 years	18.9%
Currency	
EUR	60.3%
USD	38.2%
GBP	0.7%
Other	0.8%
Clearing status	
Cleared	14.6%
Not cleared	85.4%
Industry	
Bank	35.0%
Financial	21.6%
Industrial	22.1%
Other	21.3%
Credit quality	
Prime & high grade	11.4%
Medium grade	66.1%
High yield	7.4%
Not rated	15.1%

Table 2: *Corporate bond summary statistics*

This table provides descriptive statistics for my corporate bond sample. My dataset covers the period from November 2014 to December 2016. 'Market volume' refers to the average gross trading volume in the sterling corporate bond market per month in £bn. '# unique bonds', '# unique issuers' and '# unique counterparties' measure the number of distinct bonds, issuers and counterparties in the sample. 'Yield' and 'Spread' refer to the average yield-to-maturity and spread over UK government bonds in percentage points; measured separately for four credit quality categories. 'Prime & high grade' refers to issuers with a credit rating of AA- or higher. 'Medium grade' refers to issuers with a credit rating between A+ and BBB-. 'High yield' refers to issuers with a credit rating of BB+ or lower. 'Unrated' refers to issuers that do not have a credit rating. In Panel B, all figures are trade-weighted percentages. 'Industry' refers to a broad industrial classification of the issuing firm. In Panel C, 'Active in bond & CDS market' measures the fraction of counterparties per investor type that are trading in both the corporate bond as well as the CDS market. 'CDS on % of reference entities' measures the fraction of reference entities in an investor's bond portfolio for which the investor holds a CDS position, provided that the investor is active in the CDS market. The fractions are separately aggregated for each investor type. Note that the percentages do not always add up to 100% due to rounding.

Panel A: Trade characteristics

Market volume (per month in £bn)	29.2
# unique bonds	4,660
# unique issuers	722
# unique counterparties	1,825
Yield-to-maturity (in ppts)	
Prime & high grade	2.4
Medium grade	2.9
High yield	6.6
Unrated	4.1
Spread (in ppts)	
Prime & high grade	1.0
Medium grade	1.6
High yield	5.6
Unrated	2.7

Panel B: Bond characteristics

Industry	
Bank	23.1%
Financial	20.3%
Industry	15.6%
Other	41.1%
Rating	
Prime & high grade	23.3%
Medium grade	53.0%
High yield	8.8%
Unrated	14.8%

Panel C: Overlap with CDS market

Active in bond & CDS market	
Dealer banks	100.0%
Non-dealer banks	5.9%
Insurers	13.9%
Hedge funds	7.9%
Asset managers	5.6%
CDS on % of reference entities	
Dealer banks	49.6%
Non-dealer banks	42.2%
Insurers	15.1%
Hedge funds	35.4%
Asset managers	22.3%

Table 3: *Micro-level impact of CDS positions on bond trading volumes*

The dependent variable in Columns (1)-(4) is the natural logarithm of the amount bought by investor z across all bonds of issuer i during month t in the period from November 2014 to December 2016, if investor z is a net buyer of issuer i's bonds during this period. In Columns (5)-(8), the dependent variable is the natural logarithm of the amount sold by investor z across all bonds of each issuer i during month t, if investor z is a net seller of issuer i's bonds during this period. In Panel A, '$CDS\ counterparty_{i,z,t}$' is an indicator variable equal to one if investor z is long or short in a CDS contract written on issuer i during month t. In Panel B, '$CDS\ buyer_{i,z,t}$' ('$CDS\ seller_{i,z,t}$') is an indicator variable equal to one if investor z is net short (long) in a CDS contract written on issuer i during month t. All regressions are at the monthly level and estimated using ordinary least squares. I include issuer*time and investor*time fixed effects at the monthly level. Robust standard errors clustered at issuer, investor and year-month level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: CDS counterparty

Dependent variable:	*ln(Buy volume)*				*ln(Sell volume)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CDS\ counterparty_{i,z,t}$	1.007***	0.977***	0.514***	0.470***	0.646***	0.618***	0.052	-0.020
	(0.140)	(0.164)	(0.098)	(0.108)	(0.129)	(0.147)	(0.068)	(0.087)
Issuer*time fixed effects	N	Y	N	Y	N	Y	N	Y
Investor*time fixed effects	N	N	Y	Y	N	N	Y	Y
Observations	404,087	404,083	403,825	403,821	404,087	404,083	403,825	403,821
R-squared	0.003	0.015	0.083	0.090	0.001	0.010	0.063	0.069

Panel B: CDS buyers vis-à-vis CDS sellers

Dependent variable:	*ln(Buy volume)*				*ln(Sell volume)*			
	(1)	(2)	(3)	(4)				
$CDS\ buyer_{i,z,t}$	0.952***	0.913***	0.473***	0.423***	0.771***	0.749***	0.138*	0.066
	(0.149)	(0.169)	(0.119)	(0.126)	(0.144)	(0.164)	(0.072)	(0.092)
$CDS\ seller_{i,z,t}$	1.061***	1.039***	0.554***	0.512***	0.524***	0.490***	-0.032	-0.104
	(0.146)	(0.171)	(0.098)	(0.109)	(0.133)	(0.150)	(0.078)	(0.094)
Issuer*time fixed effects	N	Y	N	Y	N	Y	N	Y
Investor*time fixed effects	N	N	Y	Y	N	N	Y	Y
Observations	404,087	404,083	403,825	403,821	404,087	404,083	403,825	403,821
R-squared	0.003	0.015	0.083	0.090	0.001	0.010	0.063	0.069

Table 4: *Relative differences between investor types*

The dependent variable in this table is the natural logarithm of the amount bought by investor z across all bonds of issuer i during month t in the period from November 2014 to December 2016, if investor z is a net buyer of issuer i's bonds during this period. '$CDS\ buyer_{i,z,t}$' ('$CDS\ seller_{i,z,t}$') is an indicator variable equal to one if investor z is net short (long) in a CDS contract written on issuer i during month t. '$Dealer_z$', '$Non\ dealer\ bank_z$', '$Hedge\ fund_z$', '$Asset\ manager_z$' are indicator variables that equal one if investor z belongs to the specific investor type. I use insurance companies as the benchmark in this specification. All regressions are at the monthly level and estimated using ordinary least squares. I include issuer*time and investor*time fixed effects at the monthly level. Robust standard errors clustered at issuer, investor and year-month level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Dependent variable:	$ln(Buy\ volume)$	
	(1)	(2)
$CDS\ buyer_{i,z,t}$	-0.049	-1.135***
	(0.338)	(0.321)
$CDS\ seller_{i,z,t}$	1.975***	0.239
	(0.687)	(0.199)
$CDS\ buyer_{i,z,t} * Dealer_z$	1.077***	1.641***
	(0.344)	(0.343)
$CDS\ seller_{i,z,t} * Dealer_z$	-0.847	0.355
	(0.688)	(0.209)
$CDS\ buyer_{i,z,t} * Non\ dealer\ bank_z$	0.401	1.383***
	(0.430)	(0.351)
$CDS\ seller_{i,z,t} * Non\ dealer\ bank_z$	-1.877**	-0.144
	(0.756)	(0.280))
$CDS\ buyer_{i,z,t} * Hedge\ fund_z$	1.879***	2.446**
	(0.517)	(0.991)
$CDS\ seller_{i,z,t} * Hedge\ fund_z$	-1.614	-0.951
	(1.332)	(1.207)
$CDS\ buyer_{i,z,t} * Asset\ manager_z$	1.064***	1.418***
	(0.271)	(0.288)
$CDS\ seller_{i,z,t} * Asset\ manager_z$	-0.624	0.396
	(0.742)	(0.281)
Issuer*time fixed effects	N	Y
Investor*time fixed effects	N	Y
Observations	386,769	386,591
R-squared	0.003	0.086

Table 5: *Impact of new margin requirements*

The dependent variable in Columns (1)-(2) is the natural logarithm of the amount bought by investor z across all bonds of issuer i during month t in the period from November 2014 to December 2016, if investor z is a net buyer of issuer i's bonds during this period. In Columns (3)-(4), the dependent variable is the logarithm of the amount sold by investor z across all bonds of each issuer i during month t, if investor z is a net seller of issuer i's bonds during this period. In Panel A, '$CDS\ buyer_{i,z,t}$' ('$CDS\ seller_{i,z,t}$') is an indicator variable equal to one if investor z is net short (long) in a CDS contract written on issuer i during month t. $CDS\ exit_{i,z,t}$ is an indicator variable equal to one if a dealer bank unwound an existing CDS position written on a specific issuer to zero in March or April 2015. I include investor*time and issuer*time fixed effects at the monthly level and robust standard errors (reported in parentheses) clustered at issuer, investor and year-month level. In Panel B, '$Dealer_z * after_t$' indicates whether investor z is a dealer bank at month t after the new margin regulation (March 2015 or later). I include time, investor and issuer*time fixed effects at the monthly level and robust standard errors (reported in parentheses) clustered at issuer level. All regressions are at the monthly level and estimated using ordinary least squares. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: CDS exit indicator variable

Dependent variable:	$ln(Buy\ volume)$		$ln(Sell\ volume)$	
	(1)	(2)	(3)	(4)
$CDS\ buyer_{i,z,t}$	0.953***	0.424***	0.770***	0.065
	(0.150)	(0.128)	(0.144)	(0.092)
$CDS\ seller_{i,z,t}$	1.062***	0.518***	0.522***	-0.105
	(0.146)	(0.109)	(0.133)	(0.094)
$CDS\ exit_{i,z,t}$	-0.764***	-0.779***	0.833***	0.757***
	(0.006)	(0.007)	(0.297)	(0.215)
Issuer*time fixed effects	N	Y	N	Y
Investor*time fixed effects	N	Y	N	Y
Observations	404,087	403,821	404,087	403,821
R-squared	0.003	0.090	0.001	0.069

Panel B: Difference-in-difference

Dependent variable:	$ln(Buy\ volume)$		$ln(Sell\ volume)$	
	(1)	(2)	(3)	(4)
$Dealer_z * after_t$	-0.252***	-0.458***	0.238**	0.377***
	(0.097)	(0.098)	(0.094)	(0.096)
Time fixed effects	Y	-	Y	-
Investor fixed effects	Y	Y	Y	Y
Issuer*time fixed effects	N	Y	N	Y
Observations	208,635	207,608	208,635	207,608
R-squared	0.051	0.118	0.029	0.094

Table 6: *Responses to issuer downgrades*

The dependent variable in Columns (1)-(2) is the natural logarithm of the amount bought by investor z across all bonds of issuer i during month t in the period from November 2014 to December 2016, if investor z is a net buyer of issuer i's bonds during this period. In Columns (3)-(4), the dependent variable is the logarithm of the amount sold by investor z across all bonds of each issuer i during month t, if investor z is a net seller of issuer i's bonds during this period. '$CDS\ buyer_{i,z,t}$' ('$CDS\ seller_{i,z,t}$') is an indicator variable equal to one if investor z is net short (long) in a CDS contract written on issuer i during month t. '$upgrade_{i,t}$' ('$downgrade_{i,t}$') is an indicator variable equal to one if issuer i is upgraded (downgraded) in month t. All regressions are at the monthly level and estimated using ordinary least squares. I include issuer*time and investor*time fixed effects at the monthly level. Robust standard errors clustered at issuer, investor and year-month level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Dependent variable:	$ln(Buy\ volume)$		$ln(Sell\ volume)$	
	(1)	(2)	(3)	(4)
$CDS\ buyer_{i,z,t}$	0.929***	0.399***	0.791***	0.086
	(0.150)	(0.127)	(0.145)	(0.103)
$CDS\ seller_{i,z,t}$	1.044***	0.500***	0.535***	-0.093
	(0.151)	(0.112)	(0.136)	(0.100)
$CDS\ buyer_{i,z,t} * upgrade_{i,t}$	0.856	0.816	-0.789	-0.635
	(0.924)	(0.938)	(0.843)	(0.875)
$CDS\ seller_{i,z,t} * upgrade_{i,t}$	0.876**	0.851**	-0.464	-0.430
	(0.398)	(0.383)	(0.273)	(0.262)
$CDS\ buyer_{i,z,t} * downgrade_{i,t}$	1.321***	1.272***	-1.060***	-1.110***
	(0.225)	(0.212)	(0.146)	(0.183)
$CDS\ seller_{i,z,t} * downgrade_{i,t}$	0.815**	0.812**	-0.619*	-0.616*
	(0.334)	(0.109)	(0.357)	(0.328)
Issuer*time fixed effects	N	Y	N	Y
Investor*time fixed effects	N	Y	N	Y
Observations	404,087	403,821	404,087	403,821
R-squared	0.003	0.090	0.001	0.069

Table 7: *Impact of CDS trading on bond-level liquidity measures*

The dependent variables in Columns (1) and (2) are the natural logarithm of the total trading volume and the natural logarithm of the total number of trades for bond b in month t, respectively. In Column (3), turnover is defined as bond b's trading volume as a percentage of its total amount outstanding in month t. In Column (4), zero-trading days measure the percentage of days in month t where bond b does not trade. In Column (5), the effective half spread of bond b is the median in month t of the daily average difference between the trade price and the bid/ask midpoint for each bond b, divided by the bid/ask midpoint. The dependent variable in Column (6) is the monthly median of the Amihud illiquidity measure, which is defined as bond b's daily absolute return divided by its trading volume on that day. In Panel A, $\ln(CDS\ number)_{i,t}$ refers to the natural logarithm of the total number of active CDS contracts written on bond issuer i in month t. In Panel B, $\ln(CDS\ gross\ notional)_{i,t}$ refers to the natural logarithm of the total CDS gross notional written on bond issuer i in month t. I include three time-varying control variables for each bond b: the bond rating, time-to-maturity and age. All regressions are at the monthly level and estimated using ordinary least squares. I include bond fixed effects and month fixed effects. Robust standard errors clustered at issuer level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: Number of CDS contracts

Dependent variable:	*ln(Volume)*	*ln(# trades)*	*Turnover*	*Zero trading*	*Half spread*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(CDS\ number)_{i,t}$	0.601***	0.357***	0.024***	-0.062***	-0.000***	0.007
	(0.078)	(0.048)	(0.004)	(0.009)	(0.000)	(0.009)
Bond fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	33,364	33,364	32,048	32,986	15,584	25,774
R-squared	0.858	0.800	0.857	0.846	0.286	0.408

Panel B: CDS gross notional amount

Dependent variable:	*ln(Volume)*	*ln(# trades)*	*Turnover*	*Zero trading*	*Half spread*	*Amihud*
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(CDS\ gross\ notional)_{i,t}$	0.209***	0.133***	0.008***	-0.025***	-0.000***	0.007
	(0.039)	(0.021)	(0.002)	(0.004)	(0.000)	(0.006)
Bond fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	33,410	33,410	32,094	33,033	15,562	25,811
R-squared	0.858	0.798	0.857	0.845	0.286	0.407

Table 8: *Fire sales caused by CDS mark-to-market losses*

Panel A shows the results from the first stage regressions. The endogenous variable '$ln(MtM\ losses)_{z,t}$' is the natural logarithm of the CDS mark-to-market losses of investor z during month t in the period November 2014 to December 2016. The instrument '$fraction\ noncleared_{z,t}$' is the fraction of non-centrally cleared CDS contracts of investor z during month t. In Panel B, the dependent variable '$ln(Sell\ volume)$' is the natural logarithm of the corporate bond sell volume of investor z during month t. Columns (1)-(3) of Panel B show the results of the two-stage least squares (2SLS) regressions. Columns (3)-(6) of Panel B report the results for ordinary OLS regressions. Panel C shows OLS regression results for a specification with '$MtM\ shock_{z,t}$' as independent variable. '$MtM\ shock_{z,t}$' is an indicator variable equal to one if investor z is facing a mark-to-market loss in the highest 10th percentile of the sample during month t. The dependent variable in columns (1)-(3) of Panel C is '$ln(Sell\ volume)$'. In Columns (3)-(6), the dependent variable is '*Sell volume*', the non log-transformed corporate bond sell volume of investor z during month t (in £m). I include investor type, time and investor type*time fixed effects at the monthly level in all three panels. Standard errors clustered at investor and year-month level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: First stage

Dependent variable:	$ln(MtM\ losses)$		
	(1)	(2)	(3)
$fraction\ noncleared_{z,t}$	6.257***	5.980***	5.978***
	(0.313)	(0.354)	(0.354)
Time fixed effects	N	Y	-
Investor type fixed effects	N	Y	-
Investor type*time fixed effects	N	N	Y
Observations	24,696	24,696	24,696
F-statistic	400.21	286.05	284.63

Panel B: 2SLS and OLS

Dependent variable:	$ln(Sell\ volume)$					
	2SLS			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(MtM\ losses)_{z,t}$	0.274***	0.223***	0.224***	0.116***	0.075**	0.074**
	(0.053)	(0.058)	(0.058)	(0.031)	(0.029)	(0.029)
Time fixed effects	N	Y	-	N	Y	-
Investor type fixed effects	N	Y	-	N	Y	-
Investor type*time fixed effects	N	N	Y	N	N	Y
Observations	24,696	24,696	24,696	24,696	24,696	24,696
R-squared				0.002	0.013	0.011

Panel C: Mark-to-market shocks

Dependent variable:	$ln(Sell\ volume)$			*Sell volume*		
	(1)	(2)	(3)	(4)	(5)	(6)
$MtM\ shock_{z,t}$	1.698***	1.145***	1.165***	23.869***	15.997**	15.878**
	(0.441)	(0.400)	(0.396)	(6.255)	(5.943)	(5.868)
Time fixed effects	N	Y	-	N	Y	-
Investor type fixed effects	N	Y	-	N	Y	-
Investor type*time fixed effects	N	N	Y	N	N	Y
Observations	24,696	24,696	24,696	24,696	24,696	24,696
R-squared	0.002	0.013	0.011	0.021	0.054	0.054

Table 9: *Choice of fire sale bonds*

This table reports probit estimates for the effects of different bond characteristics on the probability that an investor fire-sells a corporate bond following large mark-to-market losses on her CDS positions. The dependent variable '$distressed_{b,z,t}$' is an indicator variable equal to one if an investor facing a mark-to-market shock sells bond b in month t (the month of the shock). Mark-to-market shocks are defined as mark-to-market losses in the highest 10th percentile of the sample. '$Time\ to\ maturity_{b,t}$' is the remaining time-to-maturity of bond b in month t. '$Age_{b,t}$' is the time since issuance of bond b in month t. '$Investment\ grade_{b,t}$' is an indicator variable that equals one if bond b has an investment grade rating in month t, and zero otherwise. '$Turnover_{b,t-1}$' is the turnover of bond b during month $t-1$. '$Amihud_{b,t-1}$' is the Amihud price impact measure of bond b during month $t-1$. '$\Delta yield_{b,t-1}$' is the change in the monthly trade-weighted yield of bond b from month *t-2* to month *t-1*. I include time and issuer fixed effects at the monthly level. Robust standard errors clustered at issuer level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Dependent variable:	*Fire sale probability*			
	(1)	(2)	(3)	(4)
$Time\ to\ maturity_{b,t}$	0.007***	0.007***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
$Age_{b,t}$	-0.002	-0.002	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
$Investment\ grade_{b,t}$	0.209***	0.212***	0.261***	0.264***
	(0.031)	(0.031)	(0.045)	(0.046)
$Turnover_{b,t-1}$	0.192*	0.207**	0.024	0.042
	(0.101)	(0.104)	(0.056)	(0.058)
$Amihud_{b,t-1}$	-0.371***	-0.375***	-0.127***	-0.127***
	(0.104)	(0.106)	(0.045)	(0.046)
$\Delta yield_{b,t-1}$	0.008	0.022**	0.002	0.012
	(0.010)	(0.009)	(0.010)	(0.009)
Constant	-0.846***	-0.951***	-0.572***	-0.678***
	(0.036)	(0.039)	(0.012)	(0.016)
Time fixed effects	N	Y	N	Y
Issuer fixed effects	N	N	Y	Y
Observations	287,842	287,842	287,728	287,728
Pseudo R-squared	0.014	0.029	0.031	0.046

Table 10: *Impact of fire sales on bond returns*

The dependent variable '$return_{b,t}$' is the trade-weighted return on bond b for month t in the period from November 2014 to December 2016 (in percentage points). '$distressed_{b,t-\tau}$' is an indicator variable equal to one if bond b is held by investors with CDS mark-to-market shocks in month $t-\tau$. Mark-to-market shocks are defined as mark-to-market losses in the highest 10th percentile of the sample. In columns (3)-(4), I control for bond-specific characteristics including the rating, time-to-maturity, age, and the UK gilt yield of comparable maturity. All regressions are at the monthly level and estimated using ordinary least squares. I include issuer or issuer*time fixed effects at the monthly level. Robust standard errors clustered at issuer level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Dependent variable:	$return_{b,t}$			
	(1)	(2)	(3)	(4)
$distressed_{b,t+2}$	0.027	0.001	0.050	0.029
	(0.064)	(0.063)	(0.056)	(0.057)
$distressed_{b,t+1}$	0.025	0.019	0.111	0.079
	(0.066)	(0.068)	(0.075)	(0.075)
$distressed_{b,t+0}$	-0.064	-0.056	-0.087	-0.063
	(0.075)	(0.070)	(0.083)	(0.082)
$distressed_{b,t-1}$	-0.200**	-0.214**	-0.268***	-0.210**
	(0.080)	(0.088)	(0.088)	(0.092)
$distressed_{b,t-2}$	-0.475***	-0.498***	-0.580***	-0.536***
	(0.069)	(0.071)	(0.068)	(0.067)
$distressed_{b,t-3}$	-0.395***	-0.396***	-0.438***	-0.386***
	(0.064)	(0.067)	(0.058)	(0.056)
$distressed_{b,t-4}$	0.146**	0.148**	0.198***	0.237***
	(0.070)	(0.071)	(0.073)	(0.074)
$distressed_{b,t-5}$	0.057	0.069	0.048	0.087
	(0.059)	(0.061)	(0.065)	(0.064)
$distressed_{b,t-6}$	-0.027	-0.013	-0.002	0.022
	(0.070)	(0.070)	(0.075)	(0.078)
$distressed_{b,t-7}$	0.544***	0.563***	0.600***	0.613***
	(0.064)	(0.063)	(0.065)	(0.067)
$distressed_{b,t-8}$	0.123***	0.142***	0.043	0.041
	(0.043)	(0.043)	(0.047)	(0.048)
$distressed_{b,t-9}$	0.095	0.116	0.028	0.033
	(0.074)	(0.075)	(0.081)	(0.081)
$distressed_{b,t-10}$	0.057	0.091	0.119	0.111*
	(0.061)	(0.058)	(0.066)	(0.066)
Issuer fixed effects	Y	-	Y	-
Issuer*time fixed effects	N	Y	N	Y
Bond-specific controls	N	N	Y	Y
Observations	47,051	47,051	36,907	36,907
R-squared	0.051	0.111	0.050	0.074