Clear(ed) decision: The effect of central clearing on firms' financing decision

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Abstract

Does credit derivative market regulation affect real economic outcomes? We investigate this question in the setting of the central counterparty (CCP) clearing reform on the corporate credit default swap (CDS) market. Exploiting the staggered introduction of CCP clearing to CDS contracts – an insurance against firm default – we uncover adverse real economic consequences. Firms whose CDS contracts are eligible for clearing with the monopolist CCP lose debt market funding, shrink their balance sheet, cut investment and become less profitable. As a response to the funding short-fall on debt markets, firms increase demand for bank loans. We theoretically motivate two channels through which the CCP environment can adversely affect firms' debt funding situation: the hedging channel – higher trading costs on the centrally cleared derivative market push hedged investors away from affected firms; and the arbitrage channel – lower counterparty risk on the centrally cleared derivative market attracts investors from the bond market to the CDS market. Our results indicate that the arbitrage channel dominates the hedging channel.

JEL classification: G12, G14, G18, G32

Keywords: central clearing, real effects, financial regulation, firm capital structure

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1 Introduction

As a response to the Great Financial Crisis (GFC), regulatory authorities around the globe have passed an array of new laws with the aim of improving the resilience of the global financial system. One major incision to derivative markets was the promotion of central clearing (CC) through central counterparties (CCPs). That is, derivative trades are not only cleared through a clearing house by settling payments, but the clearing house actively takes on the counterparty risk against both trading partners. As a consequence of this regulatory push, the share of centrally cleared derivatives has substantially increased over the last decade (see Figures A2 and A3).[1] Clearly, a regulatory change of this magnitude has implications beyond its narrowly defined intended target – financial stability. In particular, it seems likely that there are (unintended) consequences for the real economy as the reform affects financial intermediaries and their capital allocation decisions with implications for efficiency and growth. In this paper, we ask what are the consequences for a firm if its CDS contract – an insurance contract against its default – is available for central clearing? Broad changes to the market environment (risk structure, collateral requirements, etc.) of such an insurance product, provoked by the CCP reforms, could significantly affect investors' demand for CDS and corporate bonds and thus the firm's capital structure and performance.

To tackle this question empirically we use a staggered difference-in-differences setup. Our setting is the CDS market for US firms in the years 2012 – 2019. To identify the impact of CC, we exploit the fact that clearing is not mandatory for single name corporate CDS contracts. Instead, the monopolistic clearing entity decides on the eligibility of firms[2] in a time-staggered fashion.[3] We exploit this temporal variation to estimate the effect of CC eligibility on firm-level variables. One possible threat to our identification strategy is the potential endogeneity in the eligibility decision by the monopolist CCP. A for-profit CCP should make firms whose CDS contract is in high demand eligible for clearing to maximize profits. This demand could correlate with, e.g., higher risk of default because more investors want to buy insurance, biasing our results. Using a propensity-score matching approach controlling for firm-level balance-sheet and financial soundness factors, we address this issue

[1] These reforms and their efficacy are evaluated in Financial Stability Board (2018).

[2] Throughout this paper we will speak of the "eligibility of a firm" when we refer to the eligibility of the CDS contract which specifies the firms as the reference entity.

[3] Due to regulatory incentives for banks who act as market makers this decision immediately leads to a strong shift of the trading activities for the eligible firms' CDS to the centrally cleared market segment.

to come closer to identifying the average causal effect on treated firms.

We find that in the three trading weeks following the announcement of clearing eligibility, the CDS spreads of affected firms rise significantly by more than 2.5%. Since this effect could be market-specific, as the reform directly targets CDS contracts, we further investigate the stock market reaction around the announcement. Our results show that stock valuations drop significantly and persistently by 1.5% in the event window. That is, markets perceive clearing eligibility as a meaningful and adverse event for the real economic outlook of affected firms.

We back this assertion of the market by showing that corporates whose CDS contracts become eligible for clearing through a CCP lose debt financing compared to firms who are not (yet) eligible. These reductions are economically sizeable with an average total debt reduction of 2.7%. Long-term debt (with a maturity of more than 1 year) is the main driver with a reduction of 2.9%, whereas short-term debt is not affected. The debt decrease is accompanied by a reduction in firm size (measured as total assets) of 1.6%, while equity is not significantly affected. Consistent with this finding, firms reduce their leverage by around 0.4 percentage points. Thus, firms shrink as a response to clearing eligibility relative to uncleared firms and seem unable to compensate the loss in debt financing.[4]

How can the derivative market structure changes brought upon by CC lead to a reduction in firms' debt and assets? *A priori*, the pass-through from credit derivative markets to firms' balance sheet is unclear. We rationalize our empirical findings in a parsimonious model which incorporates both bond and CDS markets and use a calibrated version of the model to assess the relative strength of the economic channels we propose.

Central counterparties are complex entities particularly designed to be the center piece of a large trading network. Their main mechanism is to split contracts between investor A and B into two, one between investor A and the CCP and one between investor B and the CCP – the so-called novation of contracts. This allows the CCP to take on the counterparty risk for all players in the market, thereby minimizing contagion risks. To fulfil this task and absorb potential losses, the CCP is equipped with several lines of defense: initial and

[4] The estimation horizon of these effects varies from three to five years due to the staggered structure of our data set. To better understand the dynamics of the effects, Section 4.3 contains event studies where we look at the impact at quarterly frequency. We find that the balance sheet responses take two to three years to build up.

variation margins, default fund contribution (all of which can be subsumed under collateral), and its own equity capital built up by making profits and collecting fees. For a more elaborate treatment of CCPs and their history, please see Appendix A.

Notwithstanding their complex nature and the heterogeneity between various entities acting as CCPs in different derivative markets, our model will focus on the two most salient features for investors brought upon by the introduction of CC in the CDS market: i) the decrease in counterparty default risk, and ii) the increase in trading costs (collateral, fees).[5] This allows us to identify two channels through which firms' debt funding is affected.

We start from the model put forward by Oehmke and Zawadowski (2015). In this framework, there exists a corporate bond of a single firm that stochastically defaults. Additionally, there is a CDS contract available that pays out the bond's face value in case of the firm's default. The model is populated by a continuum of investors that differ along two dimensions: their belief about the default risk of the firm and the risk of liquidity shock occurrence forcing them to liquidate their position before maturity. The differential beliefs generate a trading motive, while the differential liquidity risk ensures that some investors prefer the CDS market over the bond market since the former is assumed to incur smaller trading costs.

On top of the Oehmke and Zawadowski (2015) framework, we introduce counterparty default risk on the derivative market. That is, if the firm defaults, there is a non-zero probability that investors holding the CDS contract will not be paid out the insurance. The main regulatory aim of the introduction of central clearing was to mitigate this counterparty default risk.[6] Such a risk mitigation does not come for free, however. Investors incur higher trading costs on a centrally cleared market by the means of collateral requirements or trading fees[7], potentially deterring them. We investigate the equilibrium effects of lower counterparty risk and higher trading costs both separately and jointly.

We propose two channels of effect. First, the decrease in counterparty risk raises the attractiveness of CDS contracts because a payout becomes more likely. This mechanically increases the price. Due to the higher price, it becomes more attractive for investors to sell CDS

[5] Our analysis is not restricted to a decrease in counterparty default risk and an increase in trading costs. Our calibration exercise shows, however, that the data is only consistent with these directions of change. Since they are both the intuitive *and* the empirically documented directions, we favor this language, despite our results being general.

[6] See, e.g., Loon and Zhong (2014).

[7] See, e.g., Duffie, Scheicher, and Vuillemey (2015).

contracts instead of buying corporate bonds – two alternatives that otherwise exhibit similar cash flows. As a result, the demand for CDS increases and the demand for bonds decreases. For bond market clearing, the amount of outstanding bonds and/or the price of bonds need to adjust downward. The relative strength of these effects depends on firms' bond supply function. We term the changes induced by lower counterparty risk the *arbitrage channel*, as the no-arbitrage condition between the two markets gets shifted inducing traders to leave the bond, and enter the CDS market.

Second, higher CDS trading costs induce investors to leave the CDS market and to switch to either buying bonds or holding cash. Since former CDS sellers have two alternatives (holding cash and buying bonds), but former CDS buyers only have one (holding cash), there are more sellers than buyers leaving the CDS market. This creates an upward pressure on the CDS price. As some CDS sellers become bond buyers, there is upward pressure on the bond price as well. The rise in both bond and CDS prices leads fewer people to conduct the hedged trade of jointly buying the bond and the CDS contract. In sum, CDS prices go up while CDS demand goes down. The effect on bond demand is ambiguous due to fewer people conducting the hedged trade. We term this effect the *hedging channel* as its relevance depends on the existence of investors with a hedged position.

Taken together, both channels imply a rise in the CDS price. However, the predictions with respect to the outstanding CDS volume and with respect to bond outcomes differ.

As a natural next step, we test whether we can detect the arbitrage and hedging channel in our data set. To link the theoretically described channels to empirical estimates, we need concepts that represent the quantities and prices for bonds, and the quantities and prices for CDS contracts. The quantity of bonds is measured by total outstanding bond debt of the firms such that the demand can be inferred from jointly analyzing quantities and prices which we measure with yields. The quantity of CDS contracts is measured by the outstanding notional (i.e., the total insurance sum) for a firm, while the price of CDS contracts is measured by the CDS spread.

Our diff-in-diff results show that CDS spreads are, on average, 20 basis points higher for eligible firms, confirming the unambiguous model prediction of higher prices. Bond supply is significantly reduced, with the volume of outstanding bond debt dropping by 2.2%. At the same time, yields rise slightly albeit not being statistically significant. This suggests that demand had to be substantially lower to allow for market clearing at lower quantities and

stable prices. Thus, firms in our sample strongly adjust their corporate debt supply instead of letting market prices move too heavily.
Furthermore, our results indicate that the outstanding notional for eligible firms is not moving significantly. The demand for CDS contracts is therefore higher to achieve market clearing and higher prices and stable quantities. These results are consistent with the move from investors from the bond to the CDS market – the arbitrage channel. That is, the arbitrage channel dominates the hedging channel.

To understand the relative strengths of the two channels in more detail, we link the empirical findings back to our model. We calibrate our model to the pre-event time window of our sample in terms of CDS and bond market characteristics. We then jointly simulate a reduction in the counterparty risk (driving the arbitrage channel) and an increase in the trading costs (driving the hedging channel). The changes in outcomes observed in the data prove to be consistent with a strong decrease in the counterparty risk (30-50%) and a small increase in trading costs (5-10%). That is, we find the *arbitrage channel* to outweigh the *hedging channel* by a significant margin. This is an important contribution to the understanding of the CCP reform. From a financial stability point of view, the reform seems to have provoked a large decrease in the (perceived) counterparty risk on the market for only a small increase in the trading costs (cf. Duffie et al. (2015)). These changes, however, imply non-trivial consequences for the funding situation of non-financial firms. In a world where the Modigliani-Miller theorem does not apply this has adverse real consequences for firms.

To shed light on the real economic effects of the CCP reforms in a normative sense, we investigate the impact of CC – and the resulting reduction of debt financing – on the performance of affected firms. We document that they have a return on assets that is 0.23 percentage points lower and that they suffer from a decrease in their stock price of around 3%. Moreover, affected firms reduce their capital stock, measured as plants, property and equipment by roughly 1.5 percentage points. These estimates are statistically and economically significant.[8] Firms seem to be forced to reduce their production inputs to balance operating expenses and cash-flows from debt financing. This is not a healthy shrinkage as profitability drops and the stock market reacts accordingly. Thus, we document a trade-off between financial stability and real economic activity to be inherent to the CCP reform.

[8]Estimates for the number of employees are negative and economically meaningful, but not statistically significant.

Given these negative outcomes, one would expect firms to search for other forms of funding to mitigate some of the adverse effects. A natural candidate would be loans from banks, as these are less closely related to CDS markets and can be accessed on relatively short notice. We test this hypothesis using syndicated loan[9] data from Dealscan.

Using the same identification strategy as before we show that, indeed, bank credit increases after CC eligibility. Outstanding exposure increases by 3.4% of previous quarter total assets, relative to uncleared firms. Although supportive of our hypothesis, this result does not tell us whether firms actually increased their demand for bank loans. To distinguish between credit supply and demand we make use of the fact that, in our data set, banks lend to multiple firms. Following a variant of the approach of Khwaja and Mian (2008), we then employ a regression model with $bank \times time$ fixed effects which control for bank credit supply. We find that after CC eligibility, firms increase their demand for bank loans by around 4.3% of total assets. We interpret the larger coefficient of the second specification such that the increase in credit demand was larger than the amount of credit extended to firms. That is, firms could not fully compensate their loss in debt funding. Lastly, we split the sample into term loans and credit lines. We show that the demand increase is mainly driven by credit lines, funding which can be accessed on short notice.

Literature. Despite its importance, surprisingly, no one has explored the implications of CC's structural shift in the market structure of derivatives for the real economy, to the best of our knowledge.[10] We fill this gap.

There has been extensive research on the design of CC as well as the asset pricing and, in particular, the market microstructure impact of CC of derivative contracts. Du, Gadgil, Gordy, and Vega (2019) examine trade repository data for the over-the-counter CDS market and detect counterparty risk associated inefficiencies that a CCP should be able to resolve. As in our empirical setup, Loon and Zhong (2014) use the staggered eligibility for CC of CDS contracts to causally identify its effects on the CDS market in the US. The authors find that CDS spreads increase around the introduction of CC and that trading activity as well as liquidity improve for eligible contracts.

In terms of optimal design, Biais, Heider, and Hoerova (2012) and Biais, Heider, and Hoerova

[9] Syndicated loans are extended by a consortium of banks to a firm.

[10] Vuillemey (2020) takes a historical perspective on the real economic implications of central clearing by examining the coffee futures market in Le Havre in the 1880s.

(2016) establish that a well-designed CCP can mitigate aggregate financial risk. Not properly accounting for potential moral hazard problems could lead to an increase in aggregate risk, however. Huang (2019) re-iterates the relevance of mis-incentive concerns for for-profit CCPs, a finding that is also echoed in Kessler (2021) who shows that insurance buyers are strictly worse off in a mandatory CC setting.

Regarding the efficiency properties of exposure netting and collateral requirements, Duffie and Zhu (2011) and Duffie et al. (2015) have highlighted ambiguous effects. CCPs might be unable to reduce outstanding (risk) exposures by netting, but might also not increase system-wide collateral demand, although inducing a reallocation of the collateral across market participants.

Despite its broad implementation after the GFC, the literature thus advises caution in praising CC as the solution to financial stability and market efficiency concerns. We add empirical evidence to this literature that effects of central clearing are not only ambiguous from a financial stability point of view, but also from a real economic perspective.

Additionally, we tie into the strand of literature concerned with the impact of CDS contracts on the quantity and composition of corporate debt. Duffee and Zhou (2001) theoretically motivates the positive externalities of hedging instruments for credit supply. Ashcraft and Santos (2009) show that the introduction of the CDS market itself did not significantly affect the cost of corporate debt on average. Saretto and Tookes (2013), however, show that a traded CDS contract allows firms to increase leverage and debt maturities.[11]

A set of theoretical papers connecting the CDS and corporate debt markets also shows the relevance of market design and instrument properties for corporate finance. Oehmke and Zawadowski (2015) show that in the presence of liquidity advantages in the CDS market, investors might switch from buying bonds to selling CDS contracts (the essence of the 'arbitrage channel' in this paper). Che and Sethi (2014) also highlight that in the presence of an attractive CDS market, the cost of borrowing for underlying firms can both shrink and increase depending on the nature of the investors buying the excess supply of contracts. Speculators drive the cost of borrowing up, while investors with insurable interest drive it down.[12]

Our paper adds a further piece of evidence that the structure of the CDS market does indeed

[11] Hirtle (2009) provides mixed evidence on the quantity of debt funding.

[12] For an excellent overview of the literature related to the asset pricing and corporate finance perspective of CDS markets, see Augustin, Subrahmanyam, Tang, and Wang (2014).

affect corporate capital structure.

Lastly, our paper is related to the literature concerned with the impact of financial regulation, respectively policy intervention, on real economic outcomes. Fraisse, Lé, and Thesmar (2020) show in a cleanly identified empirical setting that bank capital regulation has real economic effects for firms – an assertion that the academic and policy communities have shared for decades. A higher bank capital requirement on its loans leads to less credit, lower investment and employment for the affected firm.[13] Buss, Dumas, Uppal, and Vilkov (2016) build regulatory constraints into a production economy with speculative financial markets, highlighting the differential welfare impact of a set of financial market regulation policies targeting financial stability. Kaldorf and Wicknig (2021) show in a structural model that the eligibility of corporate bonds as central bank collateral increases debt issuance, but also default risk of firms in the relevant rating categories. These effects of collateral eligibility on credit supply are also empirically backed by Pelizzon, Riedel, Simon, and Subrahmanyam (2020) and, for mortgages, Van Bekkum, Gabarro, and Irani (2018). Related, Grosse-Rueschkamp, Steffen, and Streitz (2019) show that eligibility for the corporate sector purchase program of the ECB enabled firms to attain more corporate debt funding.[14]

We extend this set of papers by showing that the eligibility of CDS contracts for central clearing creates sizeable negative externalities for non-financial firms.

Roadmap. The remainder of the paper is structured as follows: Section 2 presents our data and the empirical setup, Section 3 discusses our identification strategy, and Section 4 presents our results on the relevance of central clearing eligibility for firms. Section 5 then describes our model and economic channels before Section 6 empirically discusses the channels. Section 7 studies the real effects of the reform, before Section 8 concludes.

[13] Based on the Modigliani-Miller theorem, such an effect was famously questioned by Admati, DeMarzo, Hellwig, Pfleiderer et al. (2010). Earlier empirical evidence (e.g., Peek and Rosengren (1995)), had been less well-identified.

[14] This short paragraph cannot do justice to the extensive literature relating financial regulation and the real economy over the last decades. Our aim is to highlight recent, well-identified empirical or structural settings measuring the impact of financial regulation on non-financial firms directly.

2 Empirical strategy

This section presents the data used as well as our regression setup which we employ to estimate the effects of central clearing.

2.1 Data

Firms do not become eligible for clearing all at once. Instead, the monopolistic (100% market share in the relevant submarket) CCP in the CDS market decides on the eligiblity of treatment: IntercontinentalExchange Clear Credit (ICECC). The dates for clearing eligibility are retrieved from the ICECC website directly. We identify 98 firms which become eligible in our sample period (see Table E1 for a list of firms and Figure E6 for the distribution of clearing dates over time). We restrict our sample to firms cleared after the 1st of January of 2013. There are three main reasons for that: 1) we want to avoid any lingering remains from the financial crisis such as deleveraging which would affect the comparability of the pre- and post-treatment windows; 2) the CDS market was reformed by the so-called "big bang" and the "small bang" initiatives in the direct aftermath of the GFC.[15] We want to prevent any pollution of our estimates due to these structural changes; 3) the Dodd-Frank act gave market making banks preferential regulatory treatment of cleared derivatives as of 1st of January 2013. Hence, the incentive for market makers to move the firm to the cleared market segment after eligibility is much stronger in this time period than it was before.[16]

Our control sample consists of all firms in the S&P 1500 which have an actively traded 5-year CDS contract written on their debt[17] and for which there is sufficient data. For our selected firms we obtain quarterly balance sheet information from Compustat. Additionally, we use CDS pricing data from Markit. From DTCC, we get publicly available information on the total and average number of clearing dealers, average daily notional and average trades per day by reference entity for a subset of firms.[18] For all available firms we get corporate bond trading data from the WRDS Bond return database.[19] This data is merged via the bonds'

[15] For further information on the "big bang" and the "small bang", see, e.g., Augustin et al. (2014).

[16] ICECC started its business in 2009. However, clearing was not yet incentivized by the regulator in any way back then. In a robustness exercise we use all firms becoming eligible starting in January 2011. Almost all of our results uphold in this sample, while the point estimates are a bit smaller (see Tables F5 to F7).

[17] We crosscheck this list with the list of firms that are listed on the DTCC website with their CDS trading volumes.

[18] http://www.dtcc.com/repository-otc-data

[19] https://wrds-www.wharton.upenn.edu/pages/grid-items/wrds-bond-returns/

CUSIP with the Mergent FISD bond issue data. This corporate bond data set contains information on corporate bond yields, return, trading volumes, and other characteristics. To match corporate bonds to CDS we only include corporate bonds which are senior debt, dollar-denominated, and have a fixed interest coupon.

Lastly, we obtain information on syndicated loans extended to the firms in our sample from Thomson Reuters Dealscan for the same period.

An overview of all the variables used in this paper, their definition and sources can be found in Table E2.

2.2 Estimation

To gauge the impact of eligibility for central clearing on various balance sheet and market outcomes, we estimate two types of panel models. The first is a staggered difference-in-differences (DiD) model:

$$y_{it} = \theta \mathbf{1}(t \geq \mathit{Eligibility}_i) + \beta \mathbf{x}_{i,t-1} + \delta y_{i,t-1} + \alpha_i + \alpha_t + u_t, \quad (1)$$

where $\mathbf{1}(t \geq \mathit{Eligibility}_i)$ is an indicator function recording a one for a treated firm starting at the quarter of treatment, $\mathbf{x}_{i,t-1}$ contains lagged control variables at the firm-level, α_i is a firm-fixed effect, and α_t is a time-fixed effect. This regression compares the level of the outcome variable y before treatment with the level after treatment and therefore allows us to estimate an average treatment effect on the treated. The difference to a classic DiD setup is that firms receive the treatment at varying points in time whereas in the classic set up all firms would be treated at the same time.

The estimate obtained for θ in Equation 1 will only consistently measure the average treatment effect on the treated (ATT) under two conditions. First, there may be no heterogeneity in the size of treatment effects, in general. Second, there may be no difference in the treatment effects of a firm which is eligible for five years (treatment at the beginning of the sample) compared to a firm which is eligible for only two years (treatment at the end of the sample). Our results show that most effects level off after two years, and we have no economic rationale for a mitigation of our effects over time.

To more formally refute concerns about treatment heterogeneity, we apply the methodology laid out in De Chaisemartin and d'Haultfoeuille (2020). The authors show that θ is equivalent to a weighted sum of all individual treatment effects. These weights can be negative, potentially biasing the estimate up to the point where the estimated sign differs from the actual treatment effect. We find that more than 99.9% of the weights in our setting are positive. In addition, the method of the authors shows that the standard deviation of ATTs must be implausibly high to be consistent with a data generating process (DGP) where all ATTs are actually of opposite sign compared to θ (e.g. in the case of debt, positive). A DGP where the average of ATTs is zero also requires an implausible high standard deviation in ATTs. This together alleviates concerns about treatment heterogeneity. Hence, we can carefully interpret our results as the causal effect of becoming eligible for clearing.

We employ a second approach to better understand the dynamics of the effects. We estimate an event-study type regressions – an extension of the staggered DiD model:

$$\begin{aligned} y_{i,t} = &\sum_{j=-k}^{l} \theta_j \mathbf{1}(t + j = Eligibility_i) \\ &+ \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_t + before_t + after_t + u_{i,t}, \end{aligned} \tag{2}$$

where $\mathbf{1}(t + j = Eligibility_i)$ is an indicator which equals one if firm i becomes eligible for clearing in period $t + j$. The set $\{\theta_j\}_{j=-k}^{l}$ is our main object of interest. It contains the impact coefficients of clearing eligibility from k quarters before until l quarters after the date of clearing eligibility. We normalize $\theta_t = 0$. $\mathbf{x}_{i,t-1}$ is a set of lagged firm specific controls. $before_t$ and $after_t$ are dummies for the time period before, respectively after, our event window. The fixed effects structure is as before. With this approach we exploit the temporal variation of the treatment to identify the impact coefficients, while controlling for all factors that could drive a wedge between the average observation of the LHS variable for two different points in time. In all our estimations we cluster standard errors at the firm level.

3 Identification

Our identification strategy builds three key institutional details. First, under the Dodd-Frank act only index CDS have a mandatory clearing requirement. For all other CDS, such as sovereign and corporate single-name contracts, central clearing is encouraged (e.g. through more lenient capital requirements) but not mandatory. For this reason, CCPs can determine which reference entities (such as countries or corporates) to clear. Second, the CCPs did not make reference entities eligible for clearing at the same point in time. Instead, there was a staggered introduction to central clearing across time. This allows us to control for potentially confounding events at the time of treatment which cannot be controlled for in a setting in which all units get treated at the same time. Lastly, central clearing of corporate CDS contracts in the US is concentrated at only one CCP, namely ICECC . This monopolistic market structure allows us to estimate effects which are general to the whole market and not particular to a subset of cleared CDS contracts.

In our regressions, we use the temporal variation in clearing eligibility across firms to identify the effect of central clearing. A typical concern would be that the timing of treatment (becoming eligible for clearing) coincides with some other event that is driving the results and therefore produces spurious estimates. Since firms in our sample are treated at various points in time, and we can therefore control for time fixed effects, this is very unlikely. Hence, an omitted factor would have to highly correlate with the timing of clearing eligibility across firms and time. Second, we use propensity score matching to select firms for the control sample (see below). Since control firms are therefore very similar to the treated firms, any factor which has an effect on the treated firms would most likely also affect the control firms (except for clearing eligibility). For these two reasons we are highly confident that our results are only attributable to the eligibility for central clearing. We will inspect parallel trends both in terms of quarterly balance sheet data and daily market prices around the announcement dates later in the paper. There are no signs that the matched control group deviates from the treatment group in any measurable way in the pre-treatment period.

Are there firm characteristics that predict eligibility? From direct communication with ICECC we know that potential candidate firms for clearing eligibility can neither suggest themselves as candidates nor can they directly influence the selection process in any way. ICECC does not inform selected firms about its decision. Instead, reference entities become eligible for clearing when it is commercially viable for ICECC to do so. It therefore appears reasonable to assume that firm characteristics play a role. For example, CDS demand for more risky firms could be higher, making it more attractive to clear these derivatives. For causal identification, we need the decision to make a firm eligible for clearing (and therefore the underlying determinants at the time of the decisions) to be uncorrelated with the future development of our variables of interest on the firm level (e.g. outstanding (long- and short-term) debt, leverage, assets and equity), conditional on observables.

We formally test this by analyzing whether any firm-level balance sheet variable can predict clearing eligibility. For this purpose we run a logistic regression with the following latent variable form:

$$\mathbf{1}(Eligibility_i) = \begin{cases} 1, & \text{if } \beta \mathbf{x}_{i,\overline{2011-2012}} + u_i > 0, \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where the latent variable of our logit model $\mathbf{1}(Eligibility_i)$ takes the value one if firm i gets treated during our sample and zero otherwise. The vector of predictive variables $\mathbf{x}_{i,\overline{2011-2012}}$ contains the following variables: cash, capital expenditures, revenues, return on assets, leverage, total assets, total debt. All those variables are measured as the average over the eight quarters from 2011Q1 until 2012Q4. This specification is the result of several iterations maximizing both the fit of the regression (statistical accuracy) and the robustness of parallel pre-treatment trends (economic accuracy). Variables that are not part of the final specification, but have been tried without improving the accuracy are, for example, the z-score, the standard deviation of stock returns, or the average bond yield.

Column (1) of Table 1 shows the results of this regression.[20] It is evident that firms which become eligible for clearing between 2013 and 2017 are different than the average firm in our control sample. Cleared firms have more cash and revenues but are less profitable. Furthermore, they are smaller (measured by total assets) but have higher leverage.

To address concerns of selection into treatment arising from those results, we use a matching approach to select the sample for our analyses. For this purpose, we pair firms using the predicted propensity score of becoming eligible for CC from Equation 3. This allows us to only compare firms which were ex-ante similar in their balance sheet characteristics and likelihood of being made eligible for clearing. Table 2 shows descriptive statistics for the unmatched and the matched sample.[21] The table highlights statistically significant differences of leverage, debt and profitability between treated and control firms in the unmatched sample using bivariate t-tests. After matching, as Panel B demonstrates, there are almost no statistically significant differences between those (or other) variables anymore. Only the differences in leverage remain significant for which we will control in all our regressions.

[20] At this stage we are purely concerned with maximizing fit. Hence, we went for a kitchen sink approach and tried several models. The reported model had the highest goodness of fit and produced the best balance of matched sample characteristics.

[21] Table E3 shows descriptive statistics for all used variables during the estimation sample period.

Table 1: Eligibility prediction regression

The table presents the results of logit regressions for clearing eligibility. The eligibility dummy takes the value of one for firms that become eligible for clearing between 2013 and 2017, and zero for firms that do not become eligible before 2018 (or at all). Explanatory variables are averages over the eight quarters from 2011Q1 and 2012Q4 in column (1). Explanatory variables are averages over the eight quarters from 2009Q1 and 2010Q4 in column (2). Explanatory variables are values from the quarter directly before the eligibility decision in column (3). N refers to the number of firms in the regression. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)
	Benchmark matching	Matching from 2011	Pre-quarter matching
Cash	0.624***	0.585***	0.213**
	(0.218)	(0.165)	(0.089)
Capex	0.353	-0.058	-0.066
	(0.257)	(0.149)	(0.096)
Revenues	0.589**	0.407*	0.340*
	(0.268)	(0.239)	(0.181)
ROA	-59.52***	-30.29***	-15.54***
	(18.04)	(11.32)	(3.382)
Leverage	3.922*	5.267**	1.084
	(2.333)	(2.287)	(1.645)
Total Assets	-1.851**	-0.460	-1.157
	(0.831)	(0.621)	(0.748)
Total Debt	0.780	0.301	0.966
	(0.668)	(0.578)	(0.737)
N	195	250	210

Aside from assuring that there is no selection into treatment by firms they must also exhibit a common trend pre-treatment for our results to have a causal interpretation. We examine this assumption for our setting of staggered treatment in Figure 1. We plot the difference between the treated and control group of our main variables of interest – total assets and total debt. One can see that there are no significant differences in the 10 quarters pre-treatment plotted in the graphs.[22] Significant differences only seem to arise after the eligibility. We have produced corresponding graphs for all variables of our prediction model above, and do not identify any significant pre-treatment deviations.

the series develop in a very parallel fashion in the earlier years of our sample were none or only few of the firms composing the treated group (blue line) were already treated. The more

[22] A joint F-test strongly rejects significance of the sum of those coefficients.

Table 2: Descriptive statistics – full vs. matched

The table presents descriptive statistics for the full sample (Panel A) and the matched sample (Panel B). The columns contain the means of the respective variables calculated from 2011Q1 to 2012Q4 both for treated and control firms, the difference between treated and control firms in absolute values, and the p-value of a t-test for equality of the means with unequal variances.

Variable	Mean treated firms	Mean control firms	Absolute difference	P-value t-test
		Panel A – full sample		
Cash	6.6088	6.2816	0.3272	0.23
Capex	5.5466	5.2552	0.2914	0.29
Revenues	7.7211	7.4724	0.2487	0.18
ROA	0.0068	0.0138	0.0070	0.00
Leverage	0.4208	0.2698	0.1510	0.00
Total Assets	9.4099	9.2539	0.1560	0.45
Total Debt	8.4003	7.7633	0.6370	0.00
		Panel B – matched sample		
Cash	6.6088	6.3489	0.2599	0.40
Capex	5.5466	5.326	0.2206	0.48
Revenues	7.7211	7.6242	0.0969	0.63
ROA	0.0068	0.0103	0.0035	0.17
Leverage	0.4208	0.3557	0.0651	0.09
Total Assets	9.4099	9.2538	0.1561	0.50
Total Debt	8.4003	8.1102	0.2901	0.23

firms become eligible for clearing, the more the dynamics of the lines diverge with the lines for the treated group becoming flatter. This development accelerates towards the end of our treatment sample when the blue line consists (almost) exclusively of firms that have already been treated. In Section 4.3, we further show event study graphs which corroborate that there are no significant differences between treated and control firms before treatment.

Taken together, the firms that we use for estimation purposes are statistically non-distinguishable in their relevant balance sheet characteristics pre-treatment. As we are going to show, statistically significant differences in their balance sheet composition will arise after treatment which we will thus interpret causally as treatment effects.[23] Our final matched sample consists of

[23] All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters (see Tables F9 to F11).

(a) Total debt

(b) Total assets

Figure 1: Total debt and total assets – parallel trends

These figures show difference in the mean of total debt (Panel a) and total assets (Panel b) between control firms and treated firms. The dark red are is the 10/90% confidence interval, the light red area is the 5/95% confidence interval.

50 treated and 50 control firms.

A final concern is that our estimates are confounded by the mandatory clearing mandate for index CDS products. This mandate was introduced by the Commodity Futures Trading Commission in the beginning of 2013.[24] It seems plausible that mandatory central clearing for CDS indices containing almost all our treated firms already had an impact before the single-name contract of the firm gets eligible. Our estimated coefficients would therefore be a lower bound for the true effect.

4 The Relevance of Central Clearing for Firms

This section examines the relevance of central clearing eligibility for non-financial firms. We divide the results into three parts. The first set of results looks at announcement effects in the equity prices and CDS spreads of affected firms to assess short-term effects. The second set of results then documents effects on balance sheet items, in particular assets, debt and equity to assess long-term effects. The last set of results then investigates the dynamics of the build-up of the long-term effects.

[24]For details see https://www.cftc.gov/PressRoom/PressReleases/6429-12.

4.1 Announcement Effects

If central clearing constitutes a meaningful structural change for firms, markets should react to the announcement of firms being made eligible for clearing by adjusting asset prices. To measure whether this is the case, we set up a standard announcement effect event study. That is, we normalize the time axis for all affected firms around their individual announcement date and track how the stock prices and CDS spreads develop in a short time window before and after the event.[25]

We can confidently argue that the timing of clearing eligibility is surprising for most market participants because announcements are made very briefly (i.e. a few days) before the implementation date.[26] We choose a window of 5 trading days before and 15 trading days after the event, to capture four trading weeks in total. In order for the stock prices and CDS spreads to be comparable across firms, we normalize the value at the day before the announcement to 100. Asset prices are adjusted using the Capital Asset Pricing Model (CAPM), by filtering out co-movement of the firm-level prices with the corresponding market index (CDX, respectively SP 500) during the event window. We then run a daily regression of the form:

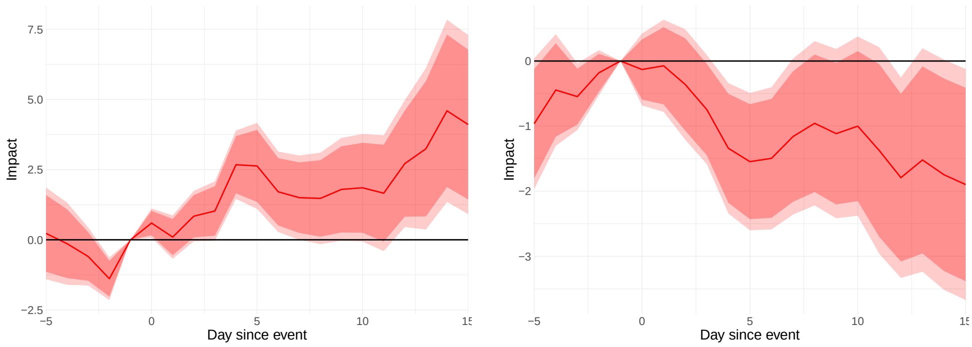
$$y_{i,t} = \sum_{j=-5}^{15} \theta_j \mathbf{1}(t + j = Eligibility_i) + \alpha_i + u_{i,t}, \tag{4}$$

where $\mathbf{1}(t + j = Eligibility_i)$ is an indicator which equals one if firm i becomes eligible for clearing in period $t+j$. The set $\{\theta_j\}_{-15}^{5}$ contains the impact coefficients of clearing eligibility from 5 quarters before until 15 quarters after the date of clearing eligibility. We normalize $\theta_{t-1} = 0$. We add firm fixed effects to control for firm-specific sensitivities of asset prices and other time-invariant firm-level characteristics.

In Figure 2a we plot the results for CDS spreads. In the two to three days leading up to the announcement there is a small statistically significant downtick potentially hinting at some information leakage. However, this small decrease of approximately 0.5% is eclipsed by an increase in the CDS spreads of 2.5% in the first five days after the announcement. While this effect first seems to weaken a bit over time (days 7 - 11), it stays statistically significant and of the same magnitude even 15 days after eligibility. Thus, the announcement of clearing

[25] To be precise, we use the actual eligibility date and not the announcement date. As discussed above in Section 3 these two events almost coincide.

[26] See https://www.theice.com/publicdocs/clear_credit/circulars/Circular_2019_047.pdf for an example of such an announcement. The time between announcement and clearing eligibility is just 3 days.



(a) CDS spreads

(b) Equity prices

Figure 2: Equity prices and CDS spreads around announcement day
The figures show the impact of the announcement of clearing eligibility. Asset prices are normalized to 100 on the day before the announcement. The estimation is based on a matched sample of 50 treated and 50. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is five days pre-announcement until fifteen days post-announcement.

eligibility clearly drives up CDS spreads of affected firms. We will elaborate more on the reasons for this upward price pressure in Section 5, but since the announcement directly concerns CDS markets, a market reaction is not surprising.[27]

Therefore, we also investigate the stock market reaction to the same announcement. If clearing eligibility is a CDS market phenomenon only, with no implications for firms and their performance, the stock market should not react in any meaningful way to the announcement. In Figure 2b we plot the corresponding event study for equity prices. There is no statistically significant pre-announcement trend, and if anything, prices were on an upward trajectory. After the announcement, prices sharply drop, however, such that on the third day after announcement the equity value of affected firms already decreased by 1.5% relative to ineligible firms. Just as with the CDS results, this effects weakens temporarily (days 7 and 11), to then pick up speed again and leave equity prices at almost 2% below their pre-announcement value after 15 trading days. Thus, stock markets clearly perceive clearing eligibility as an adverse economic event for affected firms.[28]

[27] This result is also consistent with Loon and Zhong (2014) who find an increase in CDS spreads after CC eligibility.

[28] In untabulated results, we have repeated this exercise using the canonical CAR event study methodology. The dynamics look very similar. We prefer our methodology for a better comparison of CDS and stock prices.

4.2 Balance Sheet Effects

Is this negative reaction by stock markets justified? To shed light on this question, we investigate the balance sheet effects of central clearing eligibility for affected firms. Any relevant and persistent change to the economic environment of a firm, and particularly the debt funding situation, is eventually captured on the balance sheet. Therefore, major balance sheet items such as total debt, total assets or leverage should tell us more about the direction and magnitude of central clearing effects.

Table 3 shows the results from estimating Equation 1. Unless otherwise stated, the set of controls include the (lagged) log of total assets, leverage, revenue, cash, capital expenditures, total debt as well as the return on assets. The most direct link between a reform of the CDS market and firms' balance sheet is corporate debt. Hence, column (1) of Table 3 shows the impact of central clearing eligibility on the total debt levels of firms. The point estimate is highly statistically significant and indicates that firms reduced their debt level by 2.7% as a response to their CDS becoming eligible for clearing. The most liquid CDS contracts have a maturity of five to ten years and many investors want to hedge against corporate bonds which they are holding. Since most corporate bonds also have maturity of more than one year, long-term debt (defined as maturity > one year) should be more strongly affected by the CDS market reform. Column (2) of Table 3 confirms this assertion with a highly significant coefficient of −2.9%. The corresponding coefficient for short-term debt is not significant (not tabulated).[29]

If firms lose part of their funding, the natural question is whether this affects their overall firm size (measured as total assets) or whether they are able to compensate for the loss in debt funding. Column (3) of Table 3 shows that firms in fact shrink by 1.6%, on average. Column (4) then shows that affected firms do significantly reduce their leverage by 0.4 percentage points. That is, they reduce their debt slightly more than assets and adjust their capital structure. Column (5) confirms that firms do not increase equity to compensate the loss in debt funding on the liability side of the balance sheet. The coefficient suggests that equity even decreases by 0.9%. However, the coefficient is imprecisely estimated.[30]

[29] In column (2), total debt is not among the control variables to avoid multi-colinearity issues with long-term debt.

[30] In the appendix, we show an unmatched sample version of Table 3 in Table F4. One can see that ignoring the endogeneity in the eligibility selection would bias the results downwards with an even stronger effect on debt.

Table 3: Balance sheet impact of clearing eligibility

The table presents results of running regression specification 1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

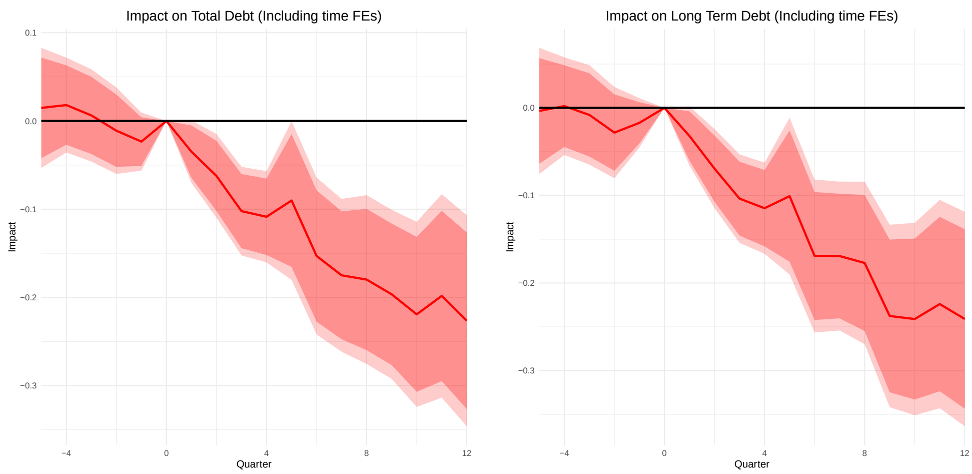
	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.027***	-0.029***	-0.016**	-0.004*	-0.009
	(0.009)	(0.01)	(0.007)	(0.002)	(0.016)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	3000	3000	3000	3000	2756
adj. R^2 (within)	0.81	0.81	0.88	0.80	0.81

Summing up, a firm that becomes eligible for clearing loses a significant portion of its (long-term) debt funding which results in a balance sheet size reduction. In the following we want to analyze the dynamics of these effects. Do firms reduce debt and assets immediately or is this a slow but steady process?

4.3 Timing of Long-term Effects

To present our event study results we plot the impact coefficients $\{\theta_j\}_{-k}^{l}$ from estimating Equation 2. We use the following set of lagged controls: leverage, revenue, cash, and capital expenditures. The impact window starts 4 quarters before the time of clearing eligibility and ends 12 quarters afterwards. The plotted confidence intervals are at the 90 and 95-percent level, respectively. Coefficients are normalized such that $\theta_0 = 0$.

The corresponding results to columns (1) and (2) of Table 3 are plotted in Figure 3. We plot the impact of central clearing on total debt (Panel 3a) and long-term debt (Panel 3b). First, consider the left panel. Total debt declines very rapidly and persistently. The effect seems to level-off roughly eight quarters after the treatment. Just as in the raw examination in Figure 1, there is no significant pre-trend in this regression framework which strengthens our conjecture of causal effects. The dynamics are very similar for long-term debt.



(a) Total debt

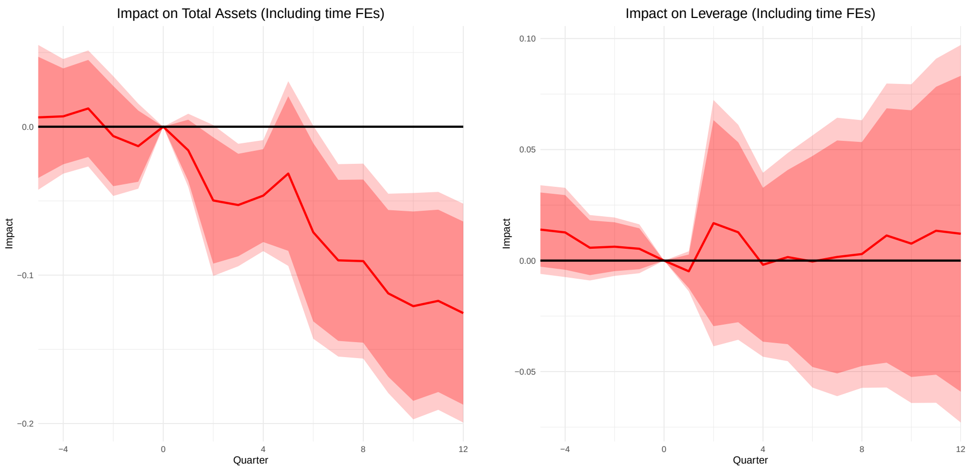
(b) Long-term debt

Figure 3: Debt and assets after clearing eligibility

These figures show the eligibility impact coefficients and confidence intervals from running regression specification 2. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is four quarters pre-treatment until twelve quarters post-treatment.

The counterparts to columns (3) and (4) from Table 3 in Figure 4 are Panel 4a, displaying the impact on total assets, and Panel 4b, displaying the impact on leverage. Total assets in the left-hand panel appear to be considerably more sticky than debt. The
first four to five quarters after eligibility total assets barely react significantly. Only in the sixth quarter they start dropping to significantly lower levels representing a substantial shrinkage of those firms. When looking at the results in the right hand panel, one can see that the reaction of leverage is very imprecisely estimated, but does not suggest that leverage is moving in any direction in the long-term.

In this section we documented a very immediate and economically sizeable impact of CDS clearing eligibility on underlying firms' debt levels which translates into considerably smaller balance sheet size in the two to three years following the treatment. Eligibility therefore *affects* firms' balance sheets. However, it is *a priori* unclear why CC eligibility would cause a decline in firms' debt and total assets. In the next section we build a parsimonious model based on Oehmke and Zawadowski (2015) which captures the relevant features of the corporate debt and CDS market. In this framework, we propose two economic channels to explain the pass-



(a) Total assets (b) Leverage

Figure 4: Debt and assets after clearing eligibility

These figures show the eligibility impact coefficients and confidence intervals from running regression specification 2. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is four quarters pre-treatment until twelve quarters post-treatment.

through from the derivative market structure reform to firms' funding situation and thereby rationalize our empirical findings. The model further allows us to assess the relative size of the two channels by means of a calibration.

5 A model of Credit Default Swaps and corporate debt

In this section, we present a model environment of the corporate bond and CDS market. The model allows us to capture the main features of CC and to rationalize our findings from Section 4.

We first adapt the basic model presented in Oehmke and Zawadowski (2015) to include counterparty default risk for investors trading CDS contracts. That is, the counterparty of the derivative trade, i.e. the protection seller, might not fulfil its payment obligations. We then introduce CC in a reduced form by assuming that centrally cleared markets have a lower probability of a seller's default. We present closed form solutions for this model that allow us to make predictions about the effects of central clearing on prices of CDS and bonds. Moreover, we introduce non-zero trading costs for CDS contracts. We assume that tradings costs rise when central clearing is introduced, due to higher collateral demand, default fund contributions or trading fees. Our results are general, though, and we do not restrict the trading cost dynamics in any way. We provide a numerical solution for this model, further extending our set of predictions to the CDS trading volume. We thus obtain a full set of hypotheses about the effects of central clearing on the CDS and the bond market in terms of prices and quantities. Lastly, we relate these findings back to firm outcomes such as debt and assets.

5.1 Basic model – setup

We start from the model presented in Oehmke and Zawadowski (2015). There is a financial market with two types of assets, a risky corporate bond and a CDS contract. Bonds are in positive net supply $S > 0$[31] while CDS contracts are in zero net supply. Bonds can be purchased at equilibrium price p. At maturity, the bond repays its face value of 1 with probability $1-\pi$ and zero otherwise, i.e. the firm that issues the bond defaults with probability π. Maturity occurs randomly with Poisson arrival rate λ. Trading the bond incurs trading costs c_b. In particular, the ask price of the bond (i.e. the price when buying the bond) is $p + \frac{c_b}{2}$, while the bid price (i.e. the price when selling the bond) is $p - \frac{c_b}{2}$. Hence, c_b can be interpreted as the bid-ask-spread while p is the midquote price.
Aside from the bond, investors can buy or sell CDS contracts which reference the firm issuing bonds. The CDS contract insures against the default of the firm. It matures jointly with the bond, i.e. at Poisson rate λ. The contract is traded at equilibrium price q. It pays out 1 if the firm defaults and zero otherwise. The CDS contract incurs costs c_{CDS} which we interpret as the costs associated with trading such as posting collateral.[32] We extend the basic model and assume that investors on the CDS markets default on their payment obligations with probability $d > 0$ (which is independent of the firm's default event). In case of a default by the CDS seller, the contract pays out zero regardless of the firm's performance. Similarly, as a CDS seller, one does not have to pay out the insurance amount if the buyer defaults.
Following Oehmke and Zawadowski (2015) our main assumption is

$$c_b \geq c_{CDS} \geq 0.$$

i.e. bonds have higher trading costs than CDS contracts. This is consistent with evidence that CDS markets are more active and that dealer inventory management is more expensive for bonds relative to CDS (see Oehmke and Zawadowski, 2015, for a more detailed discussion).

[31] This assumption is loosened below.

[32] Since CDS are much more liquid than bonds, we will not interpret the c_{CDS} as the bid-ask spread even though a small part of the costs might be bid-ask spread driven.

For most of our analysis we further assume that $c_{CDS} = 0$ which allows us to derive closed form solutions. In the last part of our analysis, we ease this assumption.

Assets are traded by a continuum of risk-neutral, competitive investors with discount factor 1. To generate trading motives in the model, investors vary along two dimensions. First, investor i believes that the bond defaults with probability $\pi_i \in \left[\overline{\pi} - \frac{\Delta}{2}, \overline{\pi} + \frac{\Delta}{2}\right]$. Variation in beliefs about the default probability generates a motive for trade. More optimistic investors take a long position w.r.t. the firm whereas more pessimistic investors take a short position. Additionally, investors have different liquidity needs. In particular, investor i receives a liquidity shock with Poisson intensity $\mu_i \in [0, \infty)$. The arrival of this shock forces an investor to liquidate her position. The investor then exits and is replaced by a new investor with the same beliefs and liquidity needs (to keep the model stationary). For investors with stronger liquidity needs (high μ_i) trading costs play a larger role such that they prefer trading CDS rather than bonds. This is because they stand a higher chance of liquidating their position early such that they would incur trading costs twice.

Investors are uniformly distributed across beliefs about the default probability. There is a mass one of investors at each $\mu_i \in [0, \infty)$ such that the conditional density function is given by $f(\pi|\mu) = \frac{1}{\Delta}$. Lastly, to prevent investors from taking infinitely large positions (due to risk neutrality), investors are allowed to only hold one unit of risky assets (i.e. buy one bond, sell one bond, buy one CDS or sell one CDS). Alternatively, investors can buy a hedged position (buy one bond and one CDS, or sell one bond and one CDS). As an outside option, investors can buy a risk-free asset – cash – with zero return.

5.2 Basic model – solution

To solve the model we need to derive the value of each asset for all types of investors. The value of buying a bond is given by

$$V_{buyBond,i} = -\left(p + \frac{c_b}{2}\right) + \frac{\mu_i}{\lambda + \mu_i}\left(p - \frac{c_b}{2}\right) + \frac{\lambda}{\lambda + \mu_i}(1 - \pi_i).$$

Investor i purchase the bond at ask price $p + \frac{c_b}{2}$. With probability $\frac{\mu_i}{\lambda+\mu_i}$, arising from the Poisson processes governing bond maturity and liquidity shock arrival, investors incur a liquidity shock before the bond matures. In that case the investor sells the bond at bid price $p - \frac{c_b}{2}$. With probability $\frac{\lambda}{\lambda+\mu_i}$ the bond matures before a liquidity shock occurs. Investor i believes that the bond defaults with probability π_i. The value of short selling a bond is given by

$$V_{sellBond,i} = \left(p - \frac{c_b}{2}\right) - \frac{\mu_i}{\lambda + \mu_i}\left(p + \frac{c_b}{2}\right) - \frac{\lambda}{\lambda + \mu_i}(1 - \pi_i),$$

where the interpretation is symmetric to before. In a similar spirit, the value of buying a CDS contract is given by

$$V_{buyCDS,i} = -\left(q + \frac{c_{CDS}}{2}\right) + \frac{\mu_i}{\lambda + \mu_i}\left(q - \frac{c_{CDS}}{2}\right) + \frac{\lambda}{\lambda + \mu_i}(1 - d)\pi_i.$$

Initially, the contract is bought at price $q + \frac{c_{CDS}}{2}$ and liquidated early with probability $\frac{\mu_i}{\lambda+\mu_i}$ at price $q - \frac{c_{CDS}}{2}$. If the bond matures before any liquidity shock (with probability $\frac{\lambda}{\lambda+\mu_i}$) the contract pays out the face value if the firm defaults (with probability π_i) and the CDS seller does not default (with probability $1 - d$). The value of selling a CDS contract is then

$$V_{sellCDS,i} = \left(q - \frac{c_{CDS}}{2}\right) - \frac{\mu_i}{\lambda + \mu_i}\left(q + \frac{c_{CDS}}{2}\right) - \frac{\lambda}{\lambda + \mu_i}(1 - d)\pi_i,$$

where the interpretation is symmetric to before.

To solve for equilibrium prices we need to determine what type of investors choose which asset (combination). We first determine what type of investor is indifferent between buying the CDS and the risk-free asset. Solving $V_{buyCDS,i} = 0$ with $c_{CDS} = 0$ yields $q_i = \pi_i(1 - d)$. At price q_i investor i is indifferent between buying the CDS and the risk-free asset. All investors j with $\pi_j > \pi_i$ get a positive value from buying the CDS. Similarly, all investors j with $\pi_j < \pi_i$ prefer to sell the CDS contract at price q_i. Following Oehmke and Zawadowski (2015), due to the infinite support of μ_i we can employ a limit argument to show that the CDS market clears at price $q = (1 - d)\overline{\pi}$ where all investors with $\pi_i > \overline{\pi}$ ($\pi_i < \overline{\pi}$) buy (sell) the CDS contract respectively. Hence, the CDS market is infinitely large and the relative size of the bond market vanishes. This feature allows us to clear markets sequentially, rather than simultaneously.

Given the equilibrium CDS price of q we can then determine bond demand. The optimal decision of all agents is shown in Figure 5. The x-axis shows the range of believes regarding the bond's probability of default while on the y-axis shows the size of the μ_i which governs the probability of a liquidity shock. Relatively optimistic investors (with low π_i) and smaller probability of liquidity shocks (low μ_i) prefer to buy bonds over all alternatives as shown in the dark grey trapezoid. In addition, there is a set of more pessimistic investors, that still buy the bond but also buy a CDS to hedge their portfolio (light grey triangle). Total bond demand is given by the area of the trapezoid plus the area of the triangle multiplied by the conditional density function $f(\pi|\mu) = \frac{1}{\Delta}$. Setting demand equal bond supply S gives:

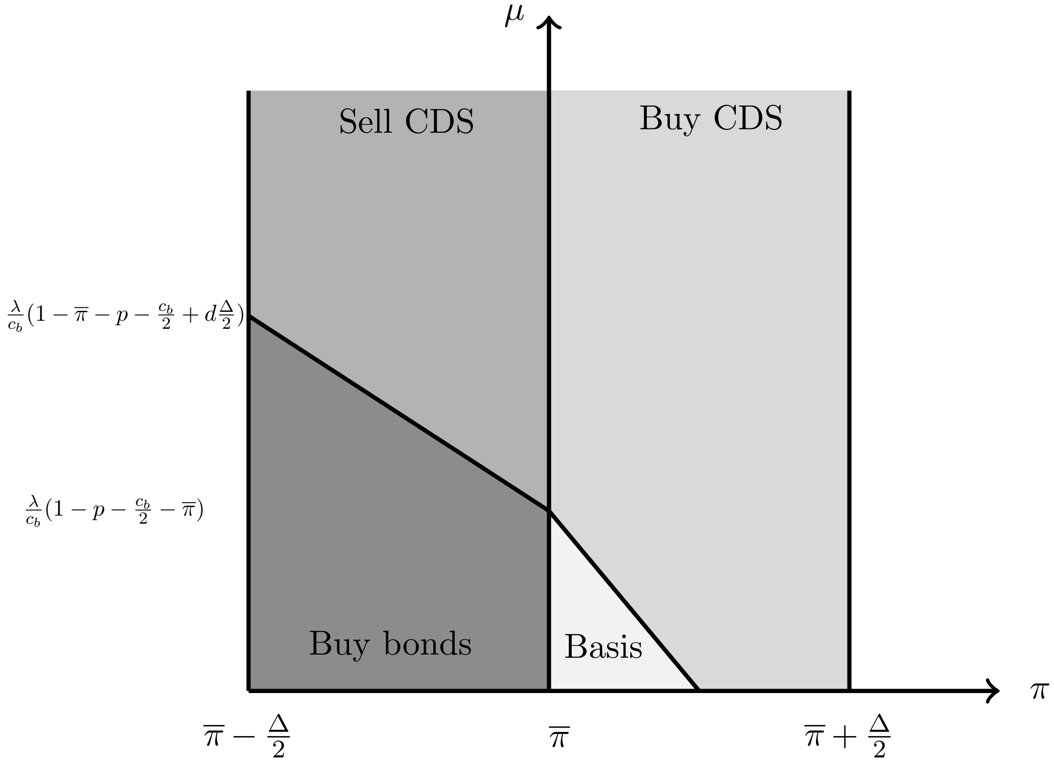


Figure 5: Bond and CDS trading

$$\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\left(1-\overline{\pi}-p-\frac{c_b}{2}+d\frac{\Delta}{2}\right)+\frac{\lambda}{c_b}\left(1-p-\frac{c_b}{2}-\overline{\pi}\right)\right)\frac{\Delta}{2}+\frac{1}{2}\frac{\lambda}{c_b}\left(1-\overline{\pi}--p\frac{c_b}{2}\right)^2\right)=S$$

Solving for p yields the equilibrium bond price.

Proposition 1. *With $c_{CDS}=0$, the equilibrium CDS price is $q^*=(1-d)\overline{\pi}$ and the equilibrium bond price is*

$$p^*=1-\overline{\pi}-\frac{c_b}{2}+\frac{\Delta}{2}-\sqrt{\frac{\Delta^2}{4}(1-d)+2\frac{c_b}{\lambda}\Delta S}$$

Proof: *See Appendix C.*

Note that setting $d=0$ yields the same equilibrium bond price as in Oehmke and Zawadowski (2015). With this model we want to study the effect of CC on bond and CDS prices. As argued, e.g. by Loon and Zhong (2014), CC lowers the counterparty risk. Hence, we want to know how prices change when d decreases. Proposition 2 shows the results.

Proposition 2. *A lower counterparty default probability d increases the CDS price q^* and lowers the bond price p^*.*

Proof:

$$\frac{\partial q^*}{\partial d} = -\overline{\pi} < 0$$
$$\frac{\partial p^*}{\partial d} = \frac{\Delta^2}{8\sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}} > 0 \quad \square$$

q^* increases when d decreases. The lower counterparty default probability increases the expected payout of the CDS when the firm defaults, mechanically raising the price for this insurance. A lower d therefore shifts the upper side of the "Buy bond" trapezoid downwards by increasing the set of investors willing to sell CDS contracts. This is illustrated in Figure 6. We label the shift of investors from buying bonds to selling CDS contracts as the "arbitrage channel". The arbitrage channel puts downward pressure on the bond price given the fixed supply S. This incentivizes more investors to enter a hedged position of jointly buying the bond and the CDS contract instead of only buying CDS contracts, as can be seen from the outward shift of the "basis" triangle. This mitigates the bond price impact of the "arbitrage channel" effect without ever fully compensating for it.

In this section we discussed an equilibrium with fixed bond supply. In the empirical setting, bond supply is not fixed, however. Including bond supply as a function of bond prices allows us to talk about both price and quantity effects. Assuming that the supply function is upward sloping (the firm wants to issue more debt with higher bond prices), we can show that there will always be a split of the adjustment between the price and the supply, the relative size of which depends on the functional form of bond supply. We document this in Appendix B, where we also provide closed form solutions for the special case where bond supply is a linear function.

5.3 Costly trading of CDS contracts

The reduction in counterparty default risk stimulated through the central clearing reform does not come for free. While the market restructuring helps in achieving this goal, there are costs for traders associated with it: higher collateral requirements (initial and variation margins), contributions to CCP default funds and fees to access the CCP. To capture this, we allow for $c_{CDS} > 0$ in this section. This enables us to consider the comparative static of the model solution with respect to d (as before) and c_{CDS}.

In terms of modelling, introducing $c_{CDS} > 0$ implies that we can no longer solve the model

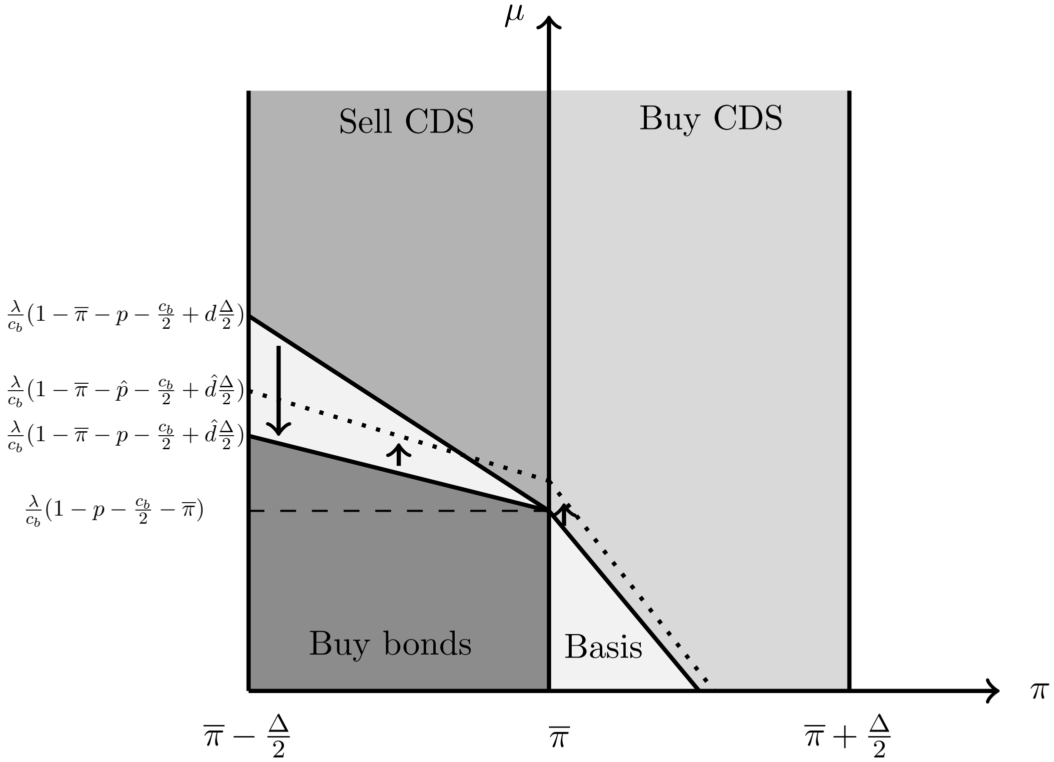


Figure 6: Bond and CDS trading – decrease in d

in closed form but have to rely on numerical solutions. The reason for this is that the CDS market is not infinitely large anymore, hindering us from solving for market clearing on the CDS and the bond market sequentially. On the upside, this allows us to explicitly measure the impact of central clearing not only on CDS pricing (as before) but also on the volume of CDS traded.

For the purpose of solving the model, we have to define two market clearing conditions, both dependent on p and q, which we solve jointly. The regions defining the supply and demand of bonds and CDS that are used as the inputs for the market clearing conditions can be seen in Figure 7. It becomes apparent that the regions of selling and buying CDS are no longer unbounded at the top. Since there are costs of trading CDS contracts now, investors facing a risk of liquidity shocks which is too high, no longer want to trade anything else but the risk-free asset. The market clearing condition for the CDS market therefore implies equating the "Sell CDS" triangle (supply) and the sum of the "Buy CDS" triangle and the "basis" triangle (demand). Similarly, the market clearing condition for the bond market implies equating the "Buy bond" trapezoid and triangle and the "basis" triangle (demand) with the supply S. We then jointly solve these two equations for the two market prices $\tilde{p}$ and $\tilde{q}$.

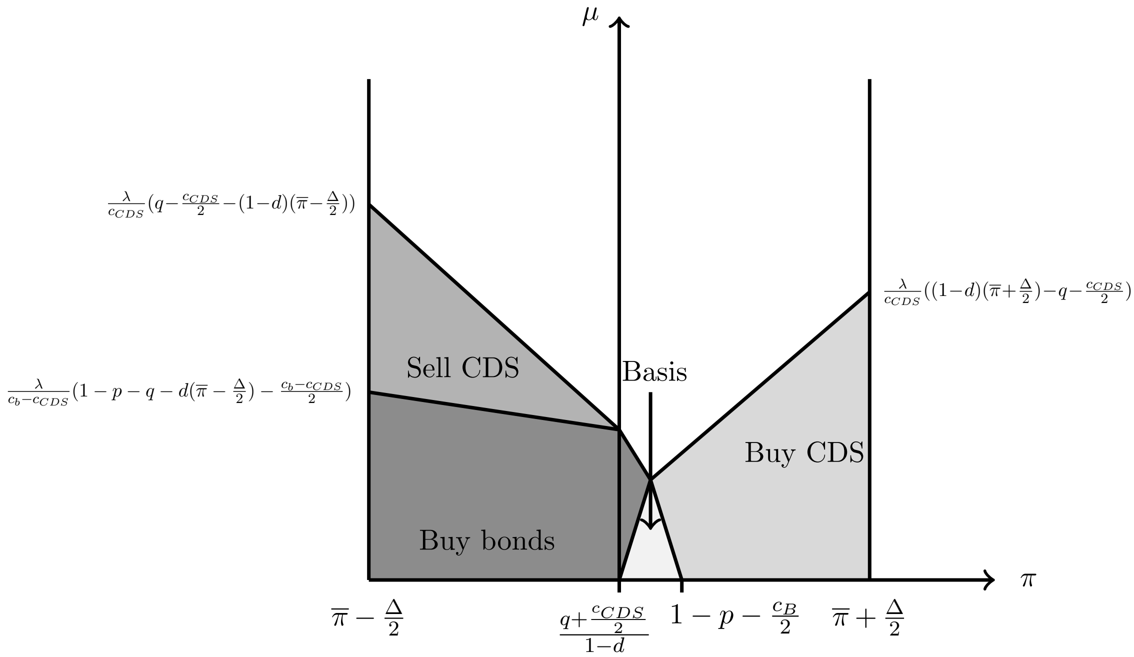


Figure 7: Bond and CDS trading - $c_{CDS} > 0$

Even without an analytical solution, the effects of a decrease in d and increase in c_{CDS} can be easily observed in Figure 7. As before, a decrease in d leads to an increase in the attractiveness of the CDS market thereby increasing the equilibrium price and now also the trading volume. As this implies that some investors switch from buying bonds to selling CDS contracts (the arbitrage channel), the bond price and demand shrink. This induces more investors to conduct the hedged trade. An increase in c_{CDS} has the opposite effects as it makes the CDS market less attractive. An equal amount of investors leaves the CDS market on the buying and selling side by switching to the risk-free asset. However, there is an additional set of investors switching from selling CDS to buying bonds thereby creating an excess demand for CDS contracts. Thus, the equilibrium price of CDS contracts has to rise to achieve market clearing. Compared to a decrease in d, an increase in c_{CDS} therefore also increases the equilibrium price of the CDS market, but lowers the CDS trading volume. As some investors switch from selling CDS contracts to buying bonds, the bond price and demand rise. This induces fewer investors to conduct the hedged trade (hedging channel).

In summary, a simultaneous decrease of d and increase of c_{CDS} which characterizes the introduction of central clearing have one unambiguous effect: an increase in the CDS price $\hat{q}^*$. The effects on bond prices, and trading volumes of both CDS contracts and bonds depends on the relative size of the arbitrage and hedging channel. For a better illustration of the argument above we refer the reader to Appendix D where we discuss the comparative statics of this model in a numerical example. Which channel dominates, depends, in the end, on the set of parameter values and assumed changes in d and c_{CDS}.

Section 6.1 empirically investigates the outcomes for quantities and prices on the bond and CDS market. Taking these results as given, we can then ask if the model can qualitatively generate these outcomes and infer how large the two changes, and the associated channels, need to be in relation to each other to be consistent with the observed empirical results. To tackle this question, we calibrate the model in Section 6.2 to moments from our data set.

Having discussed in detail the implications of CC for prices and quantities in the CDS and bond market, can we make additional predictions about firm performance? Consider the firm to have a standard Cobb-Douglas production function with decreasing returns to scale and two inputs. These are capital (financed via debt) with price $1/p - 1$ and labor with wages w. The increase in the bond price p reduces the demand for capital (to equalize marginal returns to capital and its price). In turn, marginal returns to labor also decrease with less capital available, prompting firms to reduce the amount of labor to again equalize marginal returns and costs. Lastly, profits decrease with less production and higher input prices. Hence, a standard model of a firm would additionally predict less investment in capital, less employment and lower profits after firms become eligible for CC. We come back to these empirical predictions in Section 7.

6 Channel of Effect - Hedging or Arbitrage?

In this section we investigate the presence and relative strength of the two channels through which derivative market reforms could propagate to firms' capital structure postulated in Section 5: the hedging channel and the arbitrage channel.

6.1 Empirical results

The hedging channel builds on the idea of CDS spreads being hedging instruments for firm creditors (cf. Duffee and Zhou (2001) and others). Since the CDS is an insurance contract against default, creditors have a natural demand for this product. If the hedge becomes more expensive due to trading costs, lenders are less likely to provide the firm with funds as a portfolio with the same risk profile is now more expensive. Hence, the hedging channel translates to less debt and less CDS demand simultaneously. The hedging channel therefore postulates that CDS contracts are a complement to bonds.

The arbitrage channel builds on the similarity in payoff-profiles between buying a corporate bond and selling a CDS contract written on the same firm. In both cases, the investor receives regular coupons and loses money in case the firm defaults. Hence, there is a no-arbitrage condition between the two assets, deviations from which are measured by the CDS-bond basis (Duffie (1999)). As we have shown in Section 5, a decrease in counterparty risk on the CDS market and the associated price increase should therefore lead investors to switch from the (buying side of the) bond to the (selling side of the) CDS market. In this case, debt levels of firms and CDS trading volumes should move in opposite directions. The arbitrage channel therefore postulates that CDS contracts are a substitute to bonds.

Regardless of the relative size of the two channels, our model predicts that central clearing will positively affect CDS prices. To investigate this in our sample, we use the CDS spread as a LHS variable in estimating the staggered diff-in-diff specification in Equation 1 where we additionally employ the z-score as a control for the firm's default risk.[33] The result can be found in column (1) of Table 4.[34] The point estimate indicates a statistically significant increase in the CDS spread of around 20 basis points on average, as expected.

To analyze whether the price increase in the CDS spread is accompanied by a drop in demand for the firms' debt, we estimate Equation 1 using total outstanding bond debt, bond issuance and bond yields as the dependent variables. If available, we use multiple bonds per firm for the yield regression. The requirements for bonds are that they have a maturity of more than one year, are senior debt and dollar-denominated. We control for lagged values of the bond rating, its liquidity as measured by the bid-ask-spread and its return. Column (2) documents that the volume of outstanding bond debt, the quantity on the bond market, decreases by 2.2%. Column (3) shows that the issuance of bonds relative to total assets of affected firms

[33] The CDS spread is directly linked to the default probability of the firm for which the z-score is a proxy (cf. Hull, Predescu, and White (2004)). Hence, we will use the z-score as a control variable in all regressions related to the CDS market. Those are columns (1), (4), and (5) in Table 4.

[34] All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters as well as data before 2011 (see Tables F6 and F10).

Table 4: Market impact of clearing eligibility

The table presents results of running regression specification 1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	CDS spread	Outstanding bond debt	Bond issuance	Bond yield	CDS notional	CDS-bond basis
$Eligibility_i$	19.54**	-0.022**	-0.020*	0.300	0.033	4.05
	(7.95)	(0.009)	(0.010)	(0.291)	(0.042)	(5.62)
Matched sample	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1813	2363	2000	2455	1696	1281
adj. R^2 (within)	0.79	0.93	0.23	0.43	0.29	0.55

significantly decreases by two percentage points, on average.[35] That is, quantity decreases strongly, driven by a reduction in bond issuance. If demand remained stable, this would imply by simple intuition and by the equilibrium outcome of our model in Section 5 that the bond yield (price) goes down (up). However, column (4) of Table 4 shows that bond yields of eligible firms increased by 30 bps, on average, even though this coefficient is not statistically significant. That is, even though supply declines, interest rates withstand the downward pressure, consistent with a pronounced decline in the demand for bonds clearing the market. This is in line with the arbitrage channel. Investors switch from buying corporate bonds of eligible firms to selling CDS contracts for which one can now obtain a higher price (cf. column (1)).

In column (5) of Table 4, the LHS variable is the natural logarithm of outstanding CDS notional. The estimate is not statistically significant, while the point estimate is positive with 3.3% higher outstanding notional. Together with the higher price for CDS products observed in column (1), a stable quantity on this market implies that the demand for CDS products has gone up. The empirical findings are therefore consistent with the arbitrage channel, which thus dominates the hedging channel. We will investigate the relative strength

[35]The decrease in bond issuance without scaling by assets is almost 18%.

of the two channels in more detail in the model calibration in Section 6.2.

As a last piece of evidence for the validity of our model, we look at the CDS-bond basis. The literature has shown that the CDS-bond basis is often times different from zero, potentially allowing for arbitrage opportunities (cf. Bai and Collin-Dufresne (2019)). Consistent with limits-to-arbitrage arguments, market frictions prevent prices to perfectly adjust especially if structural differences between markets arise. If this in turn implies that prices do not adequately adjust after the structural shift induced by central clearing, market outcomes might change due to factors unrelated to the mechanisms laid out in our model. To investigate this, column (6) displays results of using a measure of the CDS-bond basis as the LHS variable.[36] Indeed, our results in column (6) of Table 4 confirm that the CDS-bond basis does not open up after CC eligibility. This lends credibility to our theoretical assumption that there is a smooth and frictionless transition to the new equilibrium after central clearing and the effects we observe can be due to the postulated channels.

6.2 Calibrating the model

In Section 5 we showed how CC, captured by a simultaneous decrease in the market maker's default probability and an increase in the CDS' trading costs, can generate an increase in the CDS spread. Furthermore, we argued that the model can generate a stable bond price as well as a decrease in the amount of outstanding bonds (when bond supply is elastic) which is consistent with our empirical findings. In this section, we want to ask what changes in the market maker's default probability and CDS' trading costs are qualitatively and quantitatively consistent with these findings given a calibrated set of parameters.

We use moments from our data set to estimate the parameter values.[37] For $\overline{\pi}$ (the average expected probability of a bond's default) we choose firm's average default probability implied by its average CDS spread according to Hull's formula[38] between 2010 and 2012. Δ (the range of believes about $\overline{\pi}$) is computed from the corresponding standard deviation in implied probabilities. We take c_{CDS} (the cost of trading CDS contracts) from Wojtowicz (2014) who estimates the average bid-ask spread for CDS. The bid-ask spread for bonds (c_b) is the

[36] We rely on Markit's estimation of the CDS-Bond basis.

[37] We focus on the case where bond supply is fixed to abstract from the issue of choosing an appropriate functional form for the bond supply curve.

[38] Hull's formula computes the probability of default (PD) with respect to the CDS/interest rate spread: $PD = 1 - exp(\frac{-m \cdot spread}{1-LGD})$ where m denotes the maturity in years.

average bid-ask spread in our bond sample. In our model, d represents the probability of default an investor. We choose the spread between the one year LIBOR rate and the one year treasury rate between 2010 and 2013 to compute the average implied probability of default in the interbank market (which includes all the major traders and dealer banks). This is a common measure in the literature to capture the risk of default in the banking sector. Lastly, λ (the Poisson rate governing maturity) is chosen to match the maturity of a CDS contract of 5 years. Table 5 presents the estimates.

Table 5: Parameter estimates

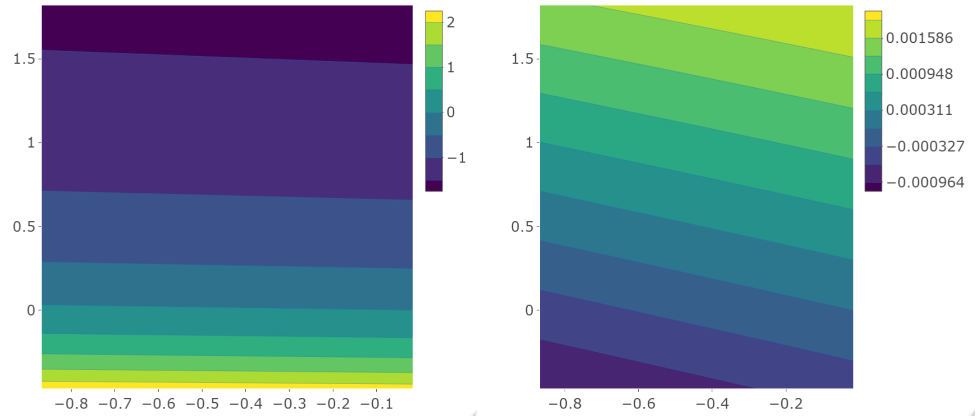
The table presents the parameter values used in calibrating the model and their sources.

Parameter	Estimate	Source
$\overline{\pi}$	0.129	Markit: average implied probability of default for firms between 2010 and 2013
Δ	0.112	Markit: standard deviation of implied probability of default for firms between 2010 and 2013
c_b	0.0065	TRACE: average bid-ask spread for bonds in our sample
c_{CDS}	0.0011	Wojtowicz (2014)
d	0.035	St. Louis Fed: implied probability of default from the one year LIBOR-treasury rate spread
λ	0.2	5 year maturity of CDS

Using these parameter values as our baseline, we can then simulate effects on prices and quantities when d and c_{CDS} change jointly. Since the CDS spread moves upward unambiguously and we assume the bond supply to be fixed, we investigate the effect on the CDS notional and the bond price. Figure 8 presents the contour plots for the changes in the bond price and the outstanding notional (relative to the baseline model). In both panels the horizontal axis denotes the change in d (in percent) while the vertical axis denotes the change in c_{CDS} (in percent), i.e. the point (0,0) denotes the baseline model with values for d and c_{CDS} as in Table 5.

First, consider Panel 8a. Darker colors denote a stronger decrease in the notional. Holding the change in d fixed, a stronger increase in c_{CDS} leads to a stronger decrease in the total outstanding notional. On the other hand, holding c_{CDS} fixed, a stronger decrease in d decreases the notional by less. In our empirical exercise we found that the outstanding CDS notional only marginally decreased if at all (Table 4). This outcome is not informative about the change in d while being consistent with an increase of c_{CDS} by a relatively small amount (5% to 10%).

Panel 8b shows the change in the bond price. Darker colors denote a decrease while lighter colors denote an increase in the bond price. Again, values on the axis are expressed as percentages. In Table 5 we found a slight increase in the yield (i.e. a decrease in the bond price) if any change at all. For the model to be consistent with this result and a small increase in c_{CDS} deduced from Panel A, we require a relatively strong decrease in d (roughly 30-50%).



(a) Change in notional

(b) Change in bond price

Figure 8: Change in the notional and bondprice when varying d and c_{CDS}

These figures show the impact on the calibrated model of jointly varying the market maker default probability d on the x-axis and the trading costs c_{CDS} on the y-axis. Changes on the axis are measured in relative terms such that -0.5 corresponds to a reduction by 50% and 1 corresponds to an increase by 100%. The lower right corner in both graphs represents the benchmark with the values for d and c_{CDS} calibrated using the pre-treatment sample.

Hence, we can infer from the model that our empirical observations are consistent with a relatively strong decrease in d by around 30-50% while the cost of trading c_{CDS} only increased by a relatively small amount (around 5% to 10%). The arbitrage channel is therefore outweighing the hedging channel by a significant margin. This is an important contribution to the understanding of the CCP reform. From a financial stability point of view, the reform seems to have provoked a large decrease in the (perceived) counterparty risk on the market for only a small increase in the trading costs (cf. Duffie et al. (2015)). These changes, however, imply non-trivial and adverse consequences for the funding situation of non-financial firms. Thus, we document a trade-off between financial stability and real economic activity to be inherent to the CCP reform.

7 Real effects

We have documented that clearing eligibility left its mark on the capital structure and size of firms. The reduction in the balance sheet size implies that firms disposed of some assets. Does this constitute an adverse effect for firms and the real economy in a normative sense? We answer this question by investigating firms' performance before and after treatment eligibility.

7.1 Firm input choices and performance

We showed in Section 5, assuming a Cobb-Douglas production function, that the effects on the CDS and bond market described above should imply a decrease in both inputs – capital and employment – and profits of the firm. To measure this, we estimate regression models as specified in Equation 1:

$$y_{it} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \delta y_{i,t-1} + \alpha_i + \alpha_t + u_t,$$

using the following LHS variables: plants, property and equipment (PPE; as a proxy for capital inputs), employment (as a measure of labor inputs), return on assets (as a measure of profits), and the stock price (as a market-based measure of the firms' performance). We employ the same empirical strategy as before, using the temporal variation in clearing eligibility and the matched sample from Section 4.2 to estimate the regression.

Table 6 displays the results.[39] Column (1) shows that PPE shrinks significantly by 1.5%. To alleviate any worries that cleared firms might be firms who coincidentally face higher depreciation, columns (2) looks at net PPE. The result is roughly the same with an estimate of 1.4%. Hence, eligible firms reduce their capital inputs to production.

Employment in column (3) drops by 3.6%, on average, implying that firms also have to reduce their labor input in line with our theoretical prediction although this estimate is not statistically significant.[40] Are firms less profitable? Column (4) indicates that the return on assets of eligible firms is roughly 0.23 percentage points lower than the one of non-affected firms, on average. This coefficient is statistically significant. In untabulated results we investigate the cause of the profitability decline. While revenues stay unaffected, net income declines. This suggests that production cost have gone up, and indeed we find costs of goods sold to be significantly higher. The effect on stock prices as a gauge of the outlook of the firm is also statistically significant, with the point estimate suggesting a decrease in stock market valuation of 3.3% for eligible firms.

[39] All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters as well as only data before 2011 (see Tables F7 and F11).

[40] The regression using the log of the number of employees on the LHS is on annual data because this variable is only available at yearly frequency.

Table 6: Real effects of clearing eligibility

The table presents results of running regression specification 1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)
	Gross PPE	Net PPE	Employment	ROA	Stock price
$Eligibility_i$	-0.015***	-0.014**	-0.036	-0.0023*	-0.033*
	(0.006)	(0.006)	(0.021)	(0.0013)	(0.018)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	2278	3000	552	3000	2913
adj. R^2 (within)	0.87	0.87	0.65	0.00	0.68

Summing up, the results suggest that becoming eligible for clearing – implying a loss in debt funding and a reduction of the balance sheet size – is not beneficial for the affected firms. They reduce their capital stock, become less profitable and suffer a decrease in stock market valuation. It is therefore important to stress that CC eligibility of firms does not only affect their capital structure but also their real economic performance.

7.2 Credit demand

Given that the loss of debt funding brought about by clearing eligibility has adverse consequences for firms, a natural question arises: did firms try to compensate for the loss of bond funding by demanding more bank loans? To answer this question, we examine the syndicated loan market in the US. For this purpose, we retrieve data from Refinitiv Dealscan and hand-match the borrowers to our matched sample. We allocate 100% of the loan to the lead arranger following other papers in the literature, e.g. Ivashina (2009).

We proceed in two steps. First, we estimate a specification similar to Equation 1:

$$Loan_{i,b,t} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \delta y_{i,t-1} + \alpha_i + \alpha_b + \alpha_t + u_{i,b,t} \tag{5}$$

with bank FEs (α_b), firm FEs (α_i), time FEs (α_t) and firm controls ($\mathbf{x_{i,t-1}}$). The dependent variable $Loan_{i,b,t}$ is the amount of loans extended from bank b to firm i at time t. This will help us understand whether cleared firms receive more credit than non-cleared firms, controlling for a host of confounding factors. However, this approach does not tell us whether firms increased demand for bank loans. Instead, it only shows the effect of CC on the equilibrium outcome. To avoid this issue, we run a second set of regressions in the spirit of Khwaja and Mian (2008) of the following form:

$$Loan_{i,b,t} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_{b,t} + u_{i,b,t}. \tag{6}$$

By including $bank \times time$ FEs we can control for the credit supply provided by bank b and time t. To identify this effect we only include banks that lend to more than one firm in every period. Since this is the case for most banks in our sample we are left with sufficient variation to identify the demand of firms for additional credit, captured by θ. We call this the "inverted" Khwaja and Mian (2008), since we control for supply instead of demand.[41]

The results can be found in Table 7 which displays the estimates for θ. In columns (1) and (2), we use exposures measured in USD between bank b and firm i as the dependent variable, in columns (3) and (4), we use log exposures, and in columns (5) and (6) we use the exposure scaled by the level of previous quarter assets of the borrower. All measures of credit paint a similar picture. Cleared firms receive more credit than non-cleared firms (columns (1), (3), and (5)). The coefficient in column (1) states that the loan size from bank b to firm i increases by around \$20 Mio. after the firm becomes eligible for clearing. This effect is statistically significant. Similarly, the log exposure increases by 0.27 points (column(3)) and the exposure in terms of total assets increases by 3.3% (column (5)). Again, these effects are statistically significant. These effects are relative to uncleared firms.

More importantly, in columns (2), (4) and (6), we see that credit growth is still significant after controlling for bank credit supply. That is, firms have been demanding significantly more credit from banks after becoming eligible for clearing. The demand from firm i for loans from bank b in dollars increases by \$27 Mio (column (2)). The log exposure increases by 0.34 points and the exposure in terms of total assets increases by 4%. All these effects are

[41] In Khwaja and Mian (2008) the authors estimate the effect of liquidity shocks on bank lending. For that purpose they need to control for credit demand by firms. By including only loans to firms, which have lending relationships with two or more banks the authors can control for credit demand by including firm×time FEs.

statistically significant.

Comparing the sizes of the coefficients between the two specifications (the equilibrium outcomes in the first set of regressions and the demand estimates in the second set of regressions), we note that the latter estimates are larger. This suggests that the increase in credit demand was larger than the amount of credit extended to the firms, i.e. firms could not compensate for the loss in bond funding to the extent that they wanted to.

Table 7: Overall loans

The table presents results of running regression specifications 5 and 6. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 383 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure	Exposure	Log Exposure	Log Exposure	Scaled Exposure	Scaled Exposure
$Eligibility_i$	20.456***	26.618**	0.274***	0.337***	0.033*	0.040*
	(7.331)	(9.973)	(0.080)	(0.099)	(0.018)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,658	35,658	35,658	35,658	35,658	35,658
adj. R^2 (within)	0.500	0.420	0.486	0.395	0.709	0.666

To better understand the exact reaction of firms, we split the loans into two groups: term loans and credit lines. A term loan is an actual on-balance sheet credit granted to the firm, which typically has a medium-term maturity (one to five years). A credit line is an off-balance sheet credit limit promised to the firm, which can be drawn down in the case of liquidity needs and converted to an on-balance sheet exposure. Credit lines usually have short-term maturities ($\leq$ one year). If firms need to secure additional short-term liquidity to compensate for the loss of funding on debt markets, it is more likely that they increased their demand via credit lines than term loans.

Table 8 shows the results for credit lines. All coefficients have a similar size as in Table 7. They are all statistically significant. The overall amount of credit lines increases by \$20 Mio. after becoming eligible for clearing (column (1)). The log exposure increases by 0.26 points (column (3)) and the amount in terms of total assets increases by 2.9% (column (5)). Similar to the previous table, the coefficients estimating the increase in demand are somewhat larger,

Table 8: Credit lines

The table presents results of running regression specifications 5 and 6 with the sample being restricted to loans that classify as credit lines. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 333 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	20.387***	26.569***	0.259***	0.300***	0.029**	0.031**
	(6.211)	(8.355)	(0.071)	(0.084)	(0.012)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,423	30,423	30,423	30,423	30,423	30,423
adj. R^2 (within)	0.528	0.464	0.503	0.420	0.749	0.715

indicating that their demand is not fully met. Overall demand for credit lines increases by \$27 Mio. (column (2)), by 0.3 points in log terms (column (4)) and by 3.1% in terms of total assets. One caveat in our analysis is that we cannot observe whether credit lines are actually drawn. Nevertheless, our results suggest that, even if credit lines are not used, firms' demand for access to short-term liquidity increases after becoming eligible. This interpretation is in line with our previous results. Firms want to have quick access to cash because they lost funding on the bond market. While all the effects documented in Table 7 can be reproduced for credit lines, no significant coefficients turn up in the term loan specification in Table 9. Thus, the demand increase of firms for loans is entirely driven by additional demand for credit lines, i.e. short-term liquidity.

Why have firms not been able to fully compensate for the loss of market-based funding by bank credit, as indicated by the total debt reduction on their balance sheet? This question is hard to answer with the data at hand. For one, as mentioned before, our results indicate that demand rose more than than supply, that is banks were not willing to provide more credit. Another possible explanation is that firms could not increase their demand for bank credit enough without facing higher, and potentially unfavorable, interest rates. Our data suggests that interest rates for the additional credit lines have not been significantly higher, implying

Table 9: Term loans

The table presents results of running regression specifications 5 and 6 with the sample being restricted to loans that classify as term loans. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 173 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure	Exposure	Log Exposure	Log Exposure	Scaled Exposure	Scaled Exposure
$Eligibility_i$	3.516	−12.197	0.025	−0.062	0.017	−0.007
	(4.160)	(9.349)	(0.026)	(0.054)	(0.018)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,235	5,235	5,235	5,235	5,235	5,235
adj. R^2 (within)	0.690	0.434	0.850	0.699	0.760	0.531

that firms just might have negotiated as much as they could without facing higher borrowing costs.[42]

Moreover, firms, even after observing the decrease in bond demand by investors after becoming eligible, might not have fully anticipated the extent of the drop in bond demand. As Section 4.3 shows, debt levels only decreased gradually over time with the effects picking up speed 5 to 6 quarters after eligibility. Hence, firms could have been – at least – partially surprised by the size of the effects and were thus unable to secure alternative (affordable) funding in time.

8 Conclusion

In this paper, we show that central clearing of single-name corporate CDS contracts has a sizeable effect on the capital structure of affected firm. After becoming eligible for clearing, firms decrease their debt levels by 2.7%, an effect that is even stronger for long-term debt. As a response, firms shrink their balance sheets by reducing total assets by around 1.6%. The effects we identify are both statistically and economically significant. Importantly, we

[42]To obtain this finding, we repeat the regressions of Table 7 with interest rates as the dependent variables. In untabulated results, we find no significance for the eligibility dummy.

document empirically that the impact of central clearing on the funding situation of firms has real economic effects as those firms decrease their capital stock, turn less profitable and lose in stock market valuation. To mitigate these effects, firms respond by demanding more bank loans. However, they are not able to fully compensate for the initial loss in funding.

We use a theoretical model for the CDS and corporate debt markets to describe how a change in the CDS market structure can affect demand for firms' debt. We introduce central clearing in this setup by focusing on two features: lower counterparty risk and higher trading costs. We obtain theoretical predictions which allow us to disentangle two channels of effect – the arbitrage and the hedging channel.

We show that the arbitrage channel (lower counterparty risk on the cleared market) appears to be the major part of the explanation. Our theory predicts that, due to lower risk on the CDS market, investors switch from the bond market to the CDS market driving bond demand down and CDS demand up. We empirically document both of these demand shifts. We calibrate our model to the pre-event time window of our sample and simulate a decrease in the default probability together with an increase in trading costs. We observe that a strong decrease in the default probability and a small increase in trading costs are consistent with our empirical observations. Thus, the arbitrage channel is outweighing the hedging channel by a significant margin.

These results have important implications. From a policy maker's perspective we demonstrate that there are potential trade-offs between financial stability (through more clearing of derivatives resulting in lower risk) and promoting real economic outcomes. Although derivative markets are, arguably, safer compared to before the GFC this comes at the cost of real economic externalities. Most likely, the implications for non-financial firms go beyond the credit derivative market that we explore in our paper as interest rate, exchange rate or weather derivatives are important financial products for the real economy, too. Policy makers need to keep such relationships in mind when augmenting existing and implementing new financial market regulation.

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A Central Clearing Counterparties - Overview and history

This section first describes CCPs in general. Then, we briefly discuss the history of central clearing.

A.1 How do CCPs work?

To illustrate the workings of a CCP first consider a traditional, bilateral over-the-counter (OTC) derivative market for CDS where participants directly trade with each other.[43] As an example, *Bank A* wants to insure its credit exposure to *Firm A*. To do so it enters into a trade with *Bank B*. Both parties agree that the former will make regular payments (the coupon, expressed as a spread over some benchmark interest rate) to the latter. In return, *Bank B* agrees to compensate *Bank A* for its losses in case *Firm A* defaults. Additionally, both banks may agree on initial margins and collateral. These two entities are not necessarily the only participants in the market. There may be other financial institutions which trade with each other, e.g. *Bank B* could insure itself against a default of *Firm A* and to earn a profit on the difference in coupon payments without taking on risk.

The result is a network of financial exposures with financial institutions as nodes. In such a network, every player is possibly exposed (on a gross basis) to everyone else. As long as financial conditions remain calm, this market structure works perfectly fine. However, once banks start to default, problems which initially affect a small number of institutions can spread through the entire network, leading to contagion. Coming back to the example, if *Firm A* is in trouble and defaults on its obligations, *Bank A* does not incur any losses since it is compensated by *Bank B*. However, if *Bank B* also defaults on its obligations to *Bank A*, *Bank A* is forced to write-off the credit to the firm, incurring capital losses. If these losses are large enough, *Bank A* will default as well on its obligations to other banks. The initially small problem spreads through the entire network. A popular example to illustrate this problem (e.g. Cont, 2015) is the ring structure depicted in Panel A of Figure A1. Arrows denote the direction of the exposure while the figures denote the size. A default by A imposes losses on B, which when defaulting, imposes losses on C. Hence, difficulties of one agent spread to other agents in the market.

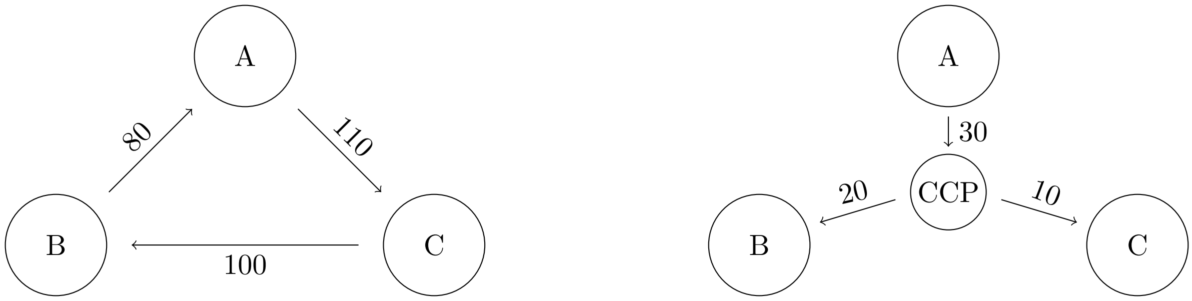
In contrast, a market structure with a central counterparty (CCP) can avoid this problem of

[43] For a more detailed overview see Duffie, Li, and Lubke (2010); Domanski, Gambacorta, and Picillo (2015).

contagion. As its name says, a CCP is the counterparty to every market participant. Going back to the first example, both banks A and B again agree on the terms of the CDS. However, instead of executing the trade themselves they go to the CCP which intercepts itself between the two. *Bank A* now pays the coupon to and is insured against credit losses by the CCP. At the same time, *Bank B* receives coupon payments from the CCP while insuring it against credit losses of *Firm A*. The CCP also imposes margin requirements. The advantage of this market structure is that a default by *Bank B* can be absorbed by the CCP (with proper risk management) such that *Bank A* remains unaffected. Additionally, in a market with more than two participants, a CCP can reduce gross exposure via netting (cf. Cont and Kokholm (2014)). This is illustrated in Panel B of Figure A1.

In practice, a CCP has several so-called members. These are large dealer banks. They are the only market participants that interact directly with the CCP. If some other entity would like to trade, it has to go through one of the members. For every trade, both parties are required to post initial margins (IM). Additional collateral may be needed, e.g. depending on the relative size of the position. The purpose of this collateral is to absorb losses and inject liquidity, in case a member defaults. During the lifetime of a derivative contract, members additionally receive and post variation margin (VM) on a daily basis, reflecting changing market valuations of the underlying contracts. Using VMs, a CCP transfers market losses/gains of a derivative contract to its members. A CCP itself is not affected by changing market valuations because for every position, it has an off-setting position.

The main advantage of a CCP comes from its improved risk management. If a member defaults, it has several "lines of defense" which are summarized in its default waterfall. First, losses are absorbed by the IMs. If this is not sufficient, part of a CCP's own capital is next in line ("skin in the game"). Its purpose is to incentivize the CCP to conduct proper risk management. If this still is not enough to absorb the losses there is an insurance fund (IF) available to which each clearing member has to contribute. If the defaulting members share of the IF is still not sufficient, the remaining fund may be used. These lines of defenses are common across CCPs, details may vary, however. For more details and the adequacy of the waterfall see Cont (2015); Faruqui, Huang, and Takats (2018).



(a) Panel A: Without CCP

(b) Panel B: With CCP

Figure A1: Stylized Derivatives Market without/with a CCP

These figures show stylized versions of derivative market structures. Panel a depicts a market where agents A, B, and C are directly exposed to each other. Panel b depicts a market where all the exposures between agents A, B, and C are intercepted and netted by the CCP.

A.2 History

This subsection describes the history of CCPs and how this affects the current regulatory environment. Clearing houses have existed, in some form, since at least 1853 in the USA. They were used by banks in New York City to settle daily claims against each other and to act as a lender of last resort. Gorton (1985) argues that this institution was the predecessor of the New York Fed. In its current form, as financial institutions in the derivative markets CCPs remained small actors for most of the 20th century. Nevertheless, there were three failures of CCPs in the 1970s and '80s. For more details see Bignon and Vuillemey (2020). CCPs came into the public spotlight again in the aftermath of the Great Financial Crisis. At the time of its failure, Lehman Brothers had large derivative positions outstanding with several clearing houses across the world (e.g. an interest rate swap portfolio with the London Clearing House with a notional of around \$9 trillion). These clearing houses were able to unwind the contracts using initial margins posted without any losses to its members. Faruqui et al. (2018) discuss this episode in more detail. On the other hand, the failure of a big institution in the (uncleared) OTC market for CDS had a severe impact. When AIG, a large issuer of CDS, failed in 2008, markets panicked. Due to the opaque nature of the OTC CDS market it was impossible to distinguish which banks and financial institutions had direct (or indirect) exposure to AIG. To avoid any further spillovers from defaults and to prevent credit markets from shutting down, the US government decided to bail out AIG (Commission et al., 2011).

After the GFC, regulators acknowledged the different performances of the two derivative markets with respect to their market structure. They drew the conclusion that cleared

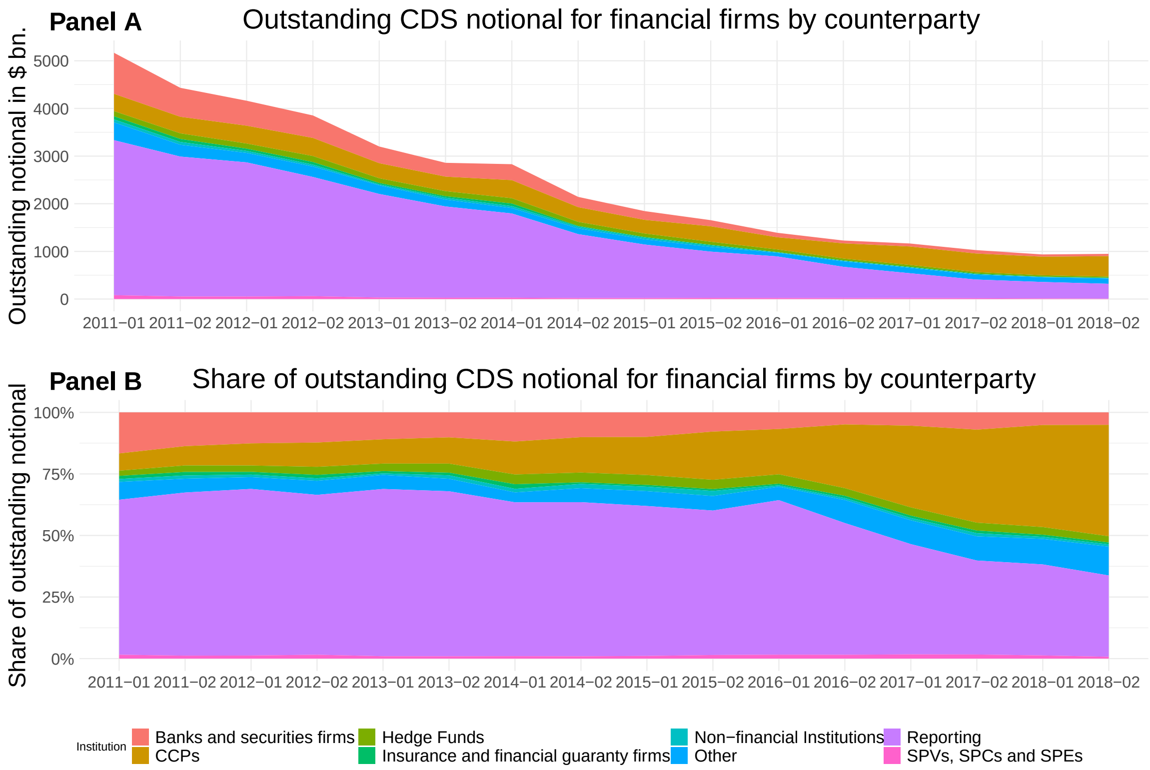


Figure A2: Outstanding CDS by Counterparty for Financial Firms

derivative markets perform better and are safer during times of crisis and hence, central clearing should be encouraged. This idea was implemented in the Dodd-Frank Act in 2010 in the US and somewhat later in the European Market Infrastructure Regulation (EMIR) in 2012 in Europe. Key points of this regulations were mandatory clearing requirements for several derivative classes such as interest rate swaps and index CDS (but importantly, not single-name CDS) as well as mandatory reporting requirements of all derivative trades to trade repositories. Hence, the legislation encouraged central clearing and caused a shift in trading activities away from OTC markets to CCPs (also for derivative classes not directly affected by the regulation). At the same time, derivative markets saw a reduction in the total outstanding notional due to more standardization of contracts which enabled more trade compression as well as netting of exposures within clearing houses, see e.g. Gündüz, Ongena, Tumer-Alkan, and Yu (2017).

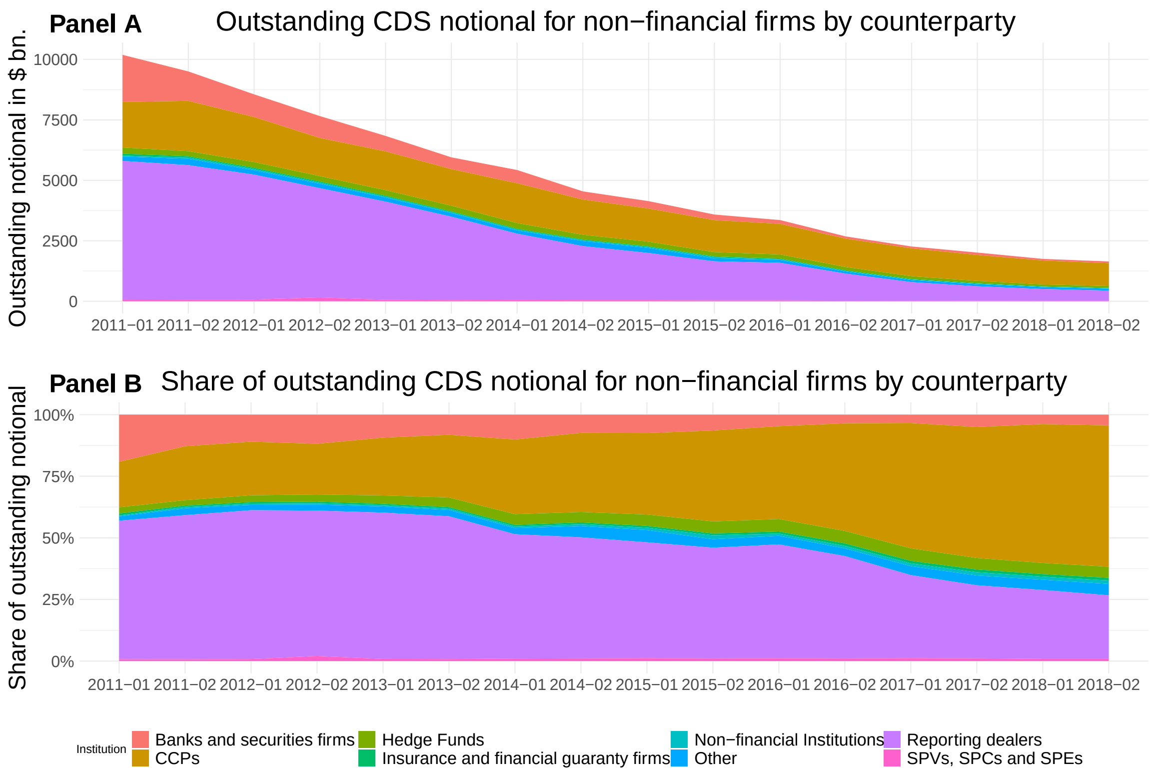


Figure A3: Outstanding CDS by Counterparty for Non-financial Firms

B Elastic bond supply

In the previous section we fixed supply at some value S. Although this approach allows for tractability when computing equilibrium prices, we cannot make any statements on how the level of firm debt varies when CC is introduced, which is a main focus of the empirical part of this paper. Hence, we loosen the initial assumptions of fixed bond supply. Assume that bond supply is given by a linear function

$$S(p) = \alpha p + \beta$$

with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$. That is, there is some fixed component β corresponding to outstanding debt and a variable component αp corresponding to rollovers and new debt issues increasing in prices. A higher bond price is equivalent to a lower interest rate for a bond with no coupon payments. All else equals this means that a firm will issue more bonds when interest rates are low, which is a reasonable assumption. Again, we can solve for the bond price by equating bond supply and demand:

$$\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\left(1-\overline{\pi}-p-\frac{c_b}{2}+d\frac{\Delta}{2}\right)+\frac{\lambda}{c_b}\left(1-p-\frac{c_b}{2}-\overline{\pi}\right)\right)\frac{\Delta}{2}+\frac{1}{2}\frac{\lambda}{c_b}\left(1-\overline{\pi}--p\frac{c_b}{2}\right)^2\right)=S(p)$$

Proposition 3 gives the equilibrium price.

Proposition 3. *When bond supply is given by $S(p) = \alpha p + \beta$ with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$ the equilibrium bond price is given by*

$$\hat{p} = 1-\overline{\pi}-\frac{c_b}{2}+\frac{\Delta}{2}+\Delta\frac{c_b}{\lambda}\alpha-\sqrt{\left(\frac{\Delta}{2}+\Delta\frac{c_b}{\lambda}\alpha\right)^2-d\frac{\Delta^2}{4}+2\Delta\frac{c_b}{\lambda}\gamma}$$

where $\gamma \equiv \alpha(1-\frac{c_b}{2}-\overline{\pi})+\beta$.

Proof: *See Appendix C.*

We can compute the equilibrium bond price in closed form. Note that setting $\alpha = 0$ and $\beta = S$ collapses the result to the case with fixed bond supply. Similar to Proposition 2, we can show that $\hat{p}$ decreases when d decreases.

Proposition 4. *A lower default probability d decreases the bond price $\hat{p}$ when bond supply is an elastic, linear function of p. The total amount of bonds issued decreases, when d decreases. If $\alpha(1-\overline{\pi}-\frac{c_b}{2})+\beta > S$ the price decrease with elastic supply is smaller than the price decrease when supply is fixed.*

Proof: *See Appendix C.*

The second part of Proposition 4 follows directly from the fact that the bond supply function has a positive slope. Lower bond prices make it more expensive for firms to issue bonds. Hence, they reduce their debt level. The third part of the proposition follows from the first two. The decline in d lowers bond prices. However, part of this decline is absorbed by the firm which issues fewer bonds. Hence, the price does not have to fall as much as would be the case with fixed supply. However, this only holds if the fixed part of the supply β is not too large. To give an intuition for this condition consider the case, where β is very large. Then, the change in d can barely have an effect on overall bond supply.

We can show that a decrease in d decreases both bond prices and quantities for a more general set of bond supply functions $S(\cdot)$. First define total bond demand $D()$ as a function of p and d. Note that $D(p, d)$ is increasing in d: $D(p, d) > D(p, \hat{d}) \forall d > \hat{d}$ and continuous. Then for any continuous, positively sloped bond supply function $S(p)$ we can define the excess demand function $D(p, d) - S(p)$ which equals zero at the equilibrium price p^* and is strictly decreasing. Then it follows from a simple continuity argument that for all $\hat{d} < d$ in a neighbourhood around d there exists $\hat{p} < p^*$ such that $D(\hat{p}, \hat{d}) - S(\hat{p}) = 0$. From the fact that supply is an increasing function (demand is a decreasing function) it also follows that the total amount of bonds decreases.

C Proofs

C.1 Proposition 1 - Proof

With $c_{CDS} = 0$, the equilibrium CDS price is $q^* = (1-d)\overline{\pi}$ and the equilibrium bond price is

$$p^* = 1 - \overline{\pi} - \frac{c_b}{2} + \frac{\Delta}{2} - \sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}$$

Proof: We first determine the equilibrium CDS price q^*. Solving $V_{buyCDS,i} = 0$ and $V_{buyCDS,i} = 0$ with $c_{CDS} = 0$ yields $q_i = (1-d)\pi_i$. At price q_i, investor i is indifferent between buying and selling CDS. Hence, all investors j with $\pi_j > \pi_i$ ($\pi_j < \pi_i$) get a positive payoff from buying (selling) the CDS, independent of μ_j.

Lastly, in equilibrium supply of CDS must equal demand. For that purpose, we follow Oehmke and Zawadowski (2015). Consider some $\overline{\mu} < \infty$. Equality between supply and demand is then given at $q^* = (1-d)\overline{\pi}$ where half of all investors (with $\pi_i < \overline{\pi}$) sell the CDS whereas the other have buys the CDS. Letting $\overline{\mu}$ go to infinity yields the desired result. Given that the CDS market is infinitely large we can take q^* as given to solve for p^*. Again we must equal supply and demand where bond demand is given by the area of the "Buy bonds" trapezoid and the "Basis" triangle in Figure 5 multiplied by the conditional density $\frac{1}{\Delta}$. The market clearing condition is given by:

$$\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\left(1-\overline{\pi}-p-\frac{c_b}{2}+d\frac{\Delta}{2}\right)+\frac{\lambda}{c_b}\left(1-p-\frac{c_b}{2}-\overline{\pi}\right)\right)\frac{\Delta}{2}+\frac{1}{2}\frac{\lambda}{c_b}\left(1-\overline{\pi}--p\frac{c_b}{2}\right)^2\right) = S.$$

Substituting $x \equiv 1 - \overline{\pi} - p - \frac{c_b}{2}$ yields a quadratic equation in x. Using standard methods we can then solve for x which gives

$$\begin{aligned} x &= -\frac{\Delta}{2} + \sqrt{\frac{\Delta^2}{2}(1-d) + 2\Delta S\frac{c_b}{\lambda}} \\ \Leftrightarrow 1 - \overline{\pi} - p - \frac{c_b}{2} &= -\frac{\Delta}{2} + \sqrt{\frac{\Delta^2}{2}(1-d) + 2\Delta S\frac{c_b}{\lambda}} \end{aligned}$$

Solving for p yields the desired result. □

C.2 Proposition 3 - Proof

When bond supply is given by $S(p) = \alpha p + \beta$ with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$ the equilibrium bond price is given by

$$\hat{p} = 1 - \overline{\pi} - \frac{c_b}{2} + \frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha - \sqrt{\left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}$$

where $\gamma \equiv \alpha(1 - \frac{c_b}{2} - \overline{\pi}) + \beta$.

Proof: The proof of Proposition 3 follows the same structure as in Proposition 1. The argument regarding the price of the CDS does not change. Only when solving for $\hat{p}$ we must consider that S is now a function of p. Hence the market clearing condition is given by

$$\begin{aligned}\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\left(1 - \overline{\pi} - p - \frac{c_b}{2} + d\frac{\Delta}{2}\right) + \frac{\lambda}{c_b}\left(1 - p - \frac{c_b}{2} - \overline{\pi}\right)\right)\frac{\Delta}{2} + \frac{1}{2}\frac{\lambda}{c_b}\left(1 - \overline{\pi} - -p\frac{c_b}{2}\right)^2\right) &= S(p) \\ &= \alpha p + \beta.\end{aligned}$$

We can rearrange the right hand side such that

$$S(p) = \alpha\left(p - 1 + \overline{\pi} + \frac{c_b}{2}\right) + \alpha\left(1 - \overline{\pi} - \frac{c_b}{2}\right) + \beta.$$

We define $\gamma \equiv \alpha\left(1 - \overline{\pi} - \frac{c_b}{2}\right) + \beta$ and substitute $x \equiv 1 - \overline{\pi} - p - \frac{c_b}{2}$ into the market clearing condition and solve the resulting quadratic equation in x using standard methods. Lastly, we solve for p which yields the desired result. □

C.3 Proposition 4 - Proof

A lower default probability d decreases the bond price $\hat{p}$ when bond supply is an elastic, linear function of p. The total amount of bonds issued decreases, when d decreases. If $\alpha(1 - \overline{\pi} - \frac{c_b}{2}) + \beta > S$ the price decrease with elastic supply is smaller than the price decrease when supply is fixed.

Proof: To show the first part of the proposition we compute the partial derivative of $\hat{p}$ w.r.t. d:

$$\frac{\partial \hat{p}}{\partial d} = \frac{\Delta^2}{8\sqrt{\left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}} > 0$$

To show the second part of the proposition consider two equilibria i and ii with varying d such that $d_i < d_{ii}$. From above we then know that $p_i < p_{ii}$ and $S(p_i) < S(p_{ii})$ because $\alpha > 0$. For the last part of the proposition compare $\frac{\partial \hat{p}}{\partial d}$ and $\frac{\partial p^*}{\partial d}$:

$$\begin{aligned}
\frac{\partial \hat{p}}{\partial d} &< \frac{\partial p^*}{\partial d} \\
\Leftrightarrow \frac{\Delta^2}{8\sqrt{\left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}} &< \frac{\Delta^2}{8\sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}} \\
\Leftrightarrow \frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S &< \left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma
\end{aligned}$$

Note that $\frac{\Delta^2}{4}(1-d) < \left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4}$. Hence, a sufficient condition for the inequality to hold is

$$\begin{aligned}
2\frac{c_b}{\lambda}\Delta S &< 2\Delta\frac{c_b}{\lambda}\gamma \\
&\Leftrightarrow S < \gamma \\
&\Leftrightarrow S < \alpha(1 - \overline{\pi} - \frac{c_b}{2}) + \beta
\end{aligned}$$

The desired result follows. $\square$

D Numerical example

In this section we discuss the effect of CC (a simultaneous decrease in d and an increase in c_{CDS}) in the model with positive c_{CDS}. Since we cannot solve the model analytically, we instead rely on an numerical example to illustrate the dynamics of the model. All results are qualitatively robust to changes in the basic parameters. We take the values for these parameters from Oehmke and Zawadowski (2015) with $\lambda = 0.2$, $\overline{\pi} = 0.1$, $\Delta = 0.12$, $c_b = 0.02$ and $S = 0.2$. For clarity of exposition we discuss the case with fixed supply. All results carry over to the case with elastic supply, albeit attenuated.

Before discussing the joint change in d and c_{CDS} we consider only isolated changes in these variables. First, we analyze decreasing the market maker's default probability d. We coined this channel the *arbitrage channel*. The lower counterparty risk raises the attractiveness of CDS contracts. This generates an inflow to the sell-side of the CDS market away from investors who have previously been buying the bond. Hence, both CDS prices and demand go up. Then in equilibrium it must hold that bond prices fall (with falling demand for bonds). In a version of the model with elastic bond supply, the total amount of bonds outstanding then also falls.

This is exactly what we find in Figure D4. First, consider the left panel (with $c_{CDS} = 0.006$). As in the cases discussed in Section 5 with $c_{CDS} = 0$, we can clearly see that the sign of change regarding prices remains the same. When d decreases, the price of the CDS contract increases, as before. The likelihood that the market maker honors the contract increases if the firm defaults and hence, the value and the price of the contract increases. The increased price changes the attractiveness of selling the CDS contract relative to buying the bond. To clear markets in equilibrium the price (interest rate) of the bond must therefore decrease (increase) such that it remains attractive to a sufficient amount of investors.

This change in prices is accompanied by a change in the amount of CDS contracts traded (bond supply remains fixed, otherwise it would decrease). First, consider the CDS notional (measure of CDS contracts bought/sold). Clearly, a decrease in d increases the total notional. CDS contracts become more attractive, in particular to investors who previously chose to hold cash. Optimistic investors (low π_i) now receive a higher price when selling the contract. More pessimistic investors also benefit because it is more likely that they will be repayed in case the firm defaults. Hence, the measure of investors who buy and sell CDS increases. The change in the measure of investors conducting the negative basis trade is *ex ante* unclear. A higher CDS price makes it less attractive to buy a CDS and a bond simultaneously, all else equal. The cost of hedging increases the price of the entire bundle. However, the bond price declines as well in equilibrium. This may counteract the higher hedging costs with higher expected returns. Additionally, a lower default probability d increases the expected payout if the firm defaults. As it turns out, the latter to effects dominate the first such that the total measure of investors in the basis trade increases, consistent with our proposed channel.

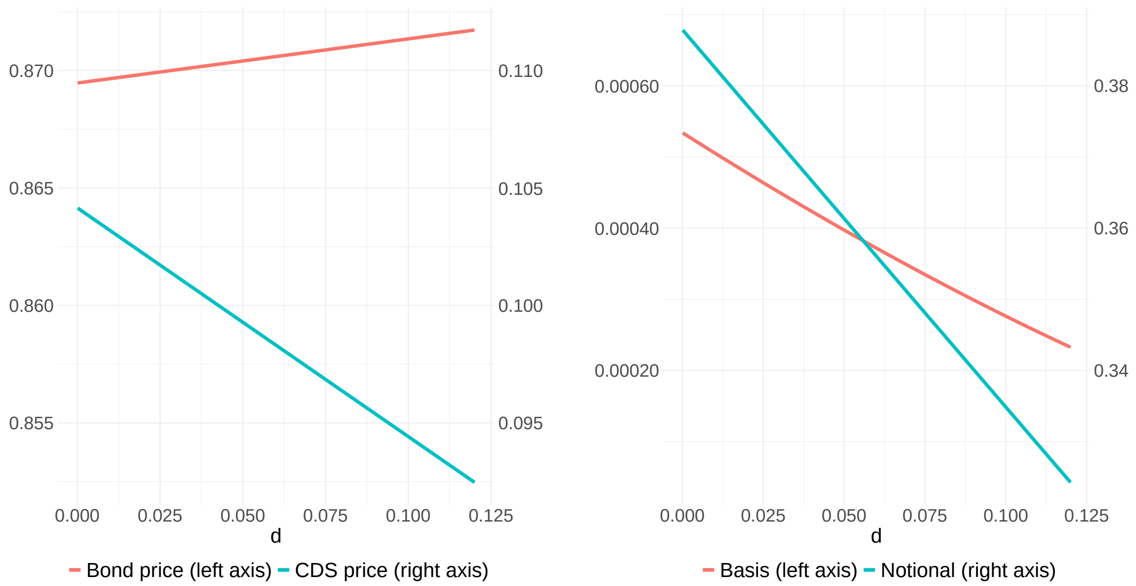


Figure D4: Numerical example - varying d

These figures show comparative statics of various equilibrium outcomes in response to a change in the market maker default probability d.

Next, we move on to analyze increases in c_{CDS} which corresponds to our proposed *hedging channel* where higher trading costs induce people to leave the CDS market and to switch to either bonds or cash. Since former CDS sellers have two alternatives (cash and buying bonds), but former CDS buyers only have one (cash), there are more sellers leaving the market than buyers. This creates an upward pressure on the CDS price. As some CDS sellers become bond buyers, there is upward pressure on the bond price which leads to fewer people conducting the hedged trade (the basis trade) of jointly buying the bond and the CDS contract. In sum, CDS prices go up and CDS demand goes down.

Figure D5 illustrates these relationships. First, consider the left panel which shows bond and CDS prices. Clearly, bond prices increase when c_{CDS} increases. Higher trading costs of the CDS decrease the expected payoff of the contract relative to buying bonds. Then in equilibrium, the price of bonds must increase to clear markets. At the same time, the price of the CDS contract also increases with c_{CDS}. Investors demand to be compensated for higher trading costs when buying/selling a CDS contract. Hence, both prices increase when c_{CDS} decreases.

Moving on to the right panel we note that both the notional and the measure of investors doing the basis trade decrease when c_{CDS} increases. The notional decreases because holding cash or buying bonds become relatively more attractive relative to selling CDS contracts (similarly holding cash becomes more attractive relative to buying CDS contracts). This holds particularly true for investors with shorter investment horizon (small μ_i). Hence, fewer investors are willing to buy/sell CDS. Note that for very small c_{CDS} we converge back to the baseline model (outlined in Section 5) with an infinite notional. The same argument holds for the measure of investors conducting the basis trade. Fewer are willing to bear the higher trading costs as it lowers their expected payoff (even with higher prices) when their investment horizon is short.

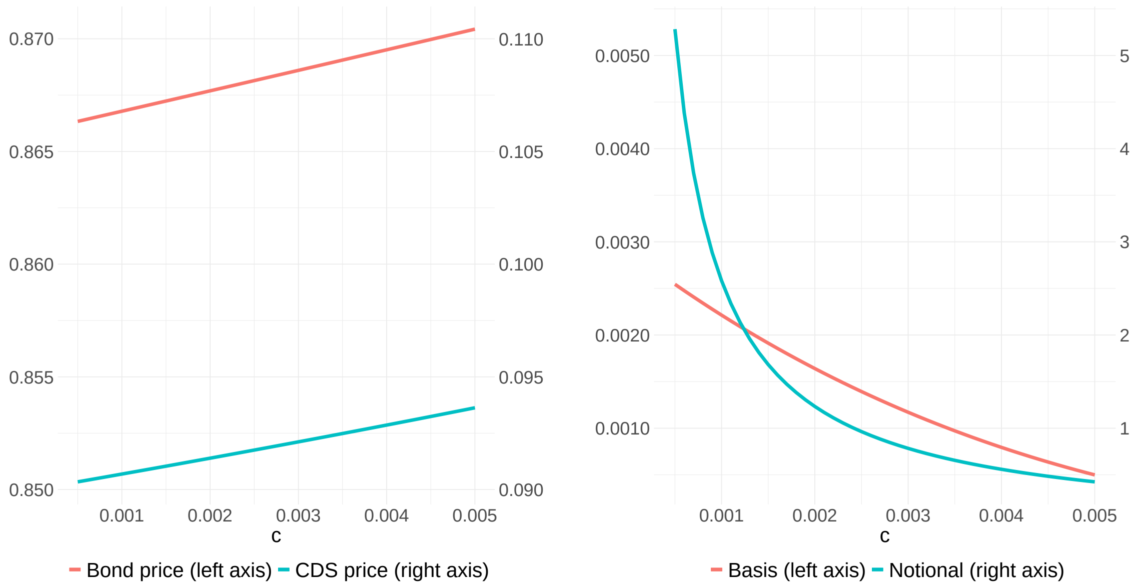


Figure D5: Numerical example - varying c_{CDS}

These figures show comparative statics of various equilibrium outcomes in response to a change in the CDS trading costs c_{CDS}.

Taking stock we note that both a decrease in d and an increase in c_{CDS} increases the price of the CDS. Assuming that there are no non-linearities at play a joint change in these two variables should therefore increase the price of the CDS as well. Regarding the other outcomes, however, effects go in different directions. Bond prices decreases with lower d while they increase with higher c_{CDS}. Similarly, the total notional and the measure of basis investors increases when d decreases while the opposite is true when c_{CDS} increases. Hence, it is *ex ante* unclear which of the two effects prevails under a joint change. In particular, the relative size of changes in the variables should determine which effect is stronger.

E Data appendix

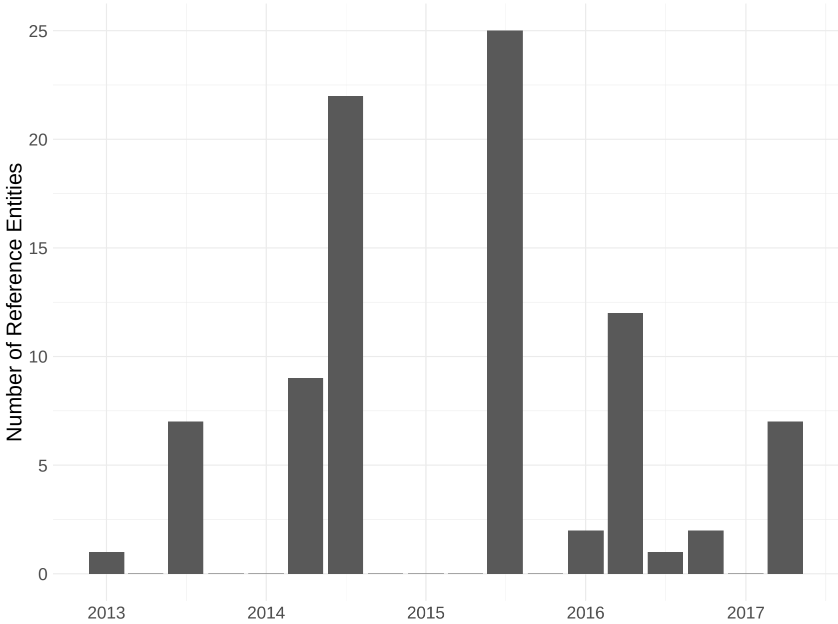


Figure E6: Number of newly eligible reference entities by quarter

Table E1: Clearing Eligiblity Dates

Clearing date	N	Reference Entity
25/03/2013	1	Mondelez International
30/09/2013	7	Avon Products, Block Financial, Caterpiller Financial Services Corporation, Ford Motor Company, Genworth Holdings, Boeing, The Gap,
27/06/2014	9	Ally Financial, Chesapeake Energy Corp, D.R. Horton, Frontier Communications, L Brands, Lennar Corp, Louisiana-Pacific Corp, PulteGroup, Royal Caribbean Cruises
11/07/2014	9	American Axle & Manufacturing, Avis Budget Group, Bombardier, Brunswick Corp, Dish DBS Corp, HCA, Hertz, New York Times, Universal Health Services
31/07/2014	11	Amkor Technology, Beam Suntory, Dean Foods, Host Hotels & Resorts, Kinder Morgan, Liberty Interactive, Olin Corp, Sealed Air Corp, Tenet Healthcare Corp, AES, Goodyear

04/08/2014	12	Cooper Tire & Rubber, CSC Holdings, Dillard's, Levi Strauss, Navient, Nova Chemicals Corp, NRG Energy, Pactiv, Smithfield Foods, Neiman Marcus Group, United Rentals (North America), Vulcan Materials Company
20/07/2015	9	AK Steel Corp, Beazer Homes USA, Domtar Corp, General Motors, K. Hovnanian Enterprises, KB Home, Meritor, United States Steel Corp, Weyerhaeuser Company
03/08/2015	10	Advanced Micro Devices, Enbridge, Iheartcommunications, J.C. Penney, MGM Resorts International, Rite Aid Corp, Supervalue, Teck Resources, The McClatchy Company, Toys "R" US
17/08/2015	6	CIT Group, Community Health Systems, First Data Corp, Level3 Communication, Radian Group, Sprint Communications
08/02/2016	1	General Electric
14/03/2016	1	Chubb Limited
30/05/2016	7	Best Buy, Chubb INA Holdings, Exelon Generation Company, Hess Corp, Johnson & Johnson, Owens-Illinois, Packaging Corporation of America
13/06/2016	4	Assured Guaranty Municipal Corp, Diamond Offshore Drilling, Ford Motor Credit Company, MGIC Investment Corp
27/06/2016	1	FIS Data Systems
04/07/2016	1	MGM Growth Properties Operating Partnership
14/11/2016	1	iStar
12/12/2016	1	Lamb Weston Holdings
03/04/2017	1	Uniti Group
10/04/2017	6	Bank of America, Citigroup, JPMorgan Chase, Morgan Stanley, Goldman Sachs, Wells Fargo

Table E2: Variable definitions and sources

Variable	Definition	Source
Firm balance sheet		
Cash	Natural logarithm of cash holdings	Compustat
Capex	Natural logarithm of capital expenditures	Compustat
Revenues	Natural logarithm of revenues	Compustat
ROA	Return on average assets (winsorized at the 1% and 99% level)	Compustat
Total Assets	Natural logarithm of total assets	Compustat
Total Debt	Natural logarithm of total debt	Compustat
Long−term Debt	Natural logarithm of debt with maturity $>$ 1 year	Compustat
Short−term Debt	Natural logarithm of debt with maturity $\leq$ 1 year	Compustat
Leverage	Ratio of total debt to total assets	Compustat
Equity	Natural logarithm of book value of common equity	Compustat
Stock price	Natural logarithm of close quote of company's traded stocks	Compustat
Employment	Natural logarithm of number of employees	Compustat
z−score	Altman z-score	Authors' calculation, Compustat
Gross PPE	Natural logarithm of gross expenditures for properties, plants and equipment	Compustat
Net PPE	Natural logarithm of net expenditures for properties, plants and equipment	Compustat
Debt and CDS markets		
CDS spread	Spread of 5-year CDS contract denominated in US dollar with CR credit event (winsorized at the 1% and 99% level)	Markit
Outstandingbonddebt	Natural logarithm of outstanding bond volume	TRACE
Bond issuance	Ratio between newly issued debt and total level of pre-period assets	Compustat
Bond yield	Yield of all bonds that are dollar denominated, senior debt, have a fixed coupon and maturity $>$ 1 year	TRACE
CDS notional	Natural logarithm of outstanding notional value of open CDS contracts	DTCC
CDS − bond basis	Difference between CDS spread and yield of senior, dollar denominated, fixed coupon bond with maturity closest to 5 years (winsorized at the 1% and 99% level)	Markit
Syndicated loans		
Loans	The sum of the credit volume of all syndicated loans extended to a specific borrower	Dealscan
Credit lines	The sum of the credit volume of syndicated loans extended to a specific borrower which classify as credit lines	Dealscan
Term loans	The sum of the credit volume of syndicated loans extended to a specific borrower which classify as term loans	Dealscan

Table E3: Descriptive statistics – matched sample

The table presents descriptive statistics of all relevant LHS and control variables for the matched sample. The statistics are calculated from 2012Q1 to 2019Q2.

Variable	Mean	Median	Std. Dev.	Min	Max
Cash	6.4500	6.4151	1.6359	0.5092	10.6656
Capex	5.5676	5.5787	1.6178	-2.3539	10.2808
Revenues	7.7372	7.6732	1.0006	5.1855	10.6445
ROA	0.0101	0.0092	0.0175	-0.0629	0.0736
Leverage	0.4211	0.3920	0.2661	0.0608	3.1794
Total Assets	9.4610	9.2484	1.1828	7.1261	12.4959
Total Debt	8.4529	8.3086	1.2438	5.7043	11.9736
Z-Score	3.9293	3.0963	3.3447	-2.6337	29.4609
CDS Spread	243.46	149.84	322.26	1.0000	2249.91
Bond Issuance	0.0945	0.0391	0.1630	0.0000	0.9786
Bond Yield	4.3258	3.8120	2.5022	-1.9820	32.64
CDS Notional	16.3762	16.3412	0.9592	14.7318	19.2316
CDS-Bond Basis	-30.610	-28.502	86.601	-204.30	170.60
Gross PPE	8.9040	8.9371	1.2598	4.0955	11.7000
Net PPE	8.1733	8.1005	1.5160	2.9707	11.5081
Employment	3.4695	3.5499	1.2009	0.4479	5.8081
Stock Price	3.5103	3.6014	0.9400	0.3500	9.0653

F Robustness checks

Table F4: Balance sheet impact of clearing eligibility – unmatched sample

The table presents results of running regression specification 1. The estimation is based on an unmatched sample of 72 treated and 148 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)
	Total debt	Long-term debt	Total assets	Leverage	Equity
$Eligibility_i$	-0.041***	-0.056***	-0.016***	-0.004	-0.026*
	(0.010)	(0.012)	(0.006)	(0.005)	(0.015)
Matched sample	No	No	No	No	No
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	6411	6445	6447	6411	6091
adj. R^2 (within)	0.76	0.69	0.86	0.81	0.75

Table F5: Balance sheet impact of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.023***	-0.017**	-0.013**	0.000	-0.017
	(0.008)	(0.008)	(0.005)	(0.003)	(0.016)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	5244	5242	5244	5244	4941
adj. R^2 (within)	0.85	0.82	0.90	0.90	0.79

Table F6: Market impact of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) CDS spread	(2) Outstanding bond debt	(3) Bond issuance	(4) Bond yield	(5) CDS notional	(6) CDS-bond basis
$Eligibility_i$	14.49**	-0.022**	-0.013	0.412	-0.019	4.94
	(6.57)	(0.010)	(0.008)	(0.344)	(0.040)	(4.81)
Matched sample	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3213	1945	3289	2030	2160	2485
adj. R^2 (within)	0.78	0.91	0.28	0.05	0.25	0.54

Table F7: Real effects of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)
	Gross PPE	Net PPE	Employment	ROA	Stock price
$Eligibility_i$	-0.01*	-0.01*	-0.002	-0.025	-0.042**
	(0.005)	(0.005)	(0.001)	(0.016)	(0.020)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	4092	5851	5244	5077	748
adj. R^2 (within)	0.90	0.91	0.05	0.80	0.63

Table F8: Overall loans – matched sample starting in 2011

The table presents results of running regression specifications 5 and 6. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. We identify 496 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure	Exposure	Log Exposure	Log Exposure	Scaled Exposure	Scaled Exposure
$Eligibility_i$	-7.275	-7.954	0.065	0.083	0.021	0.038
	(7.722)	(9.322)	(0.096)	(0.110)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	52,484	52,484	52,484	52,484	52,484	52,484
adj. R^2 (within)	0.507	0.445	0.575	0.516	0.729	0.706

Table F9: Balance sheet impact of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)
	Total debt	Long-term debt	Total assets	Leverage	Equity
$Eligibility_i$	-0.035***	-0.043***	-0.011	-0.003	0.012
	(0.009)	(0.010)	(0.007)	(0.005)	(0.021)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	2779	2786	2786	2779	2467
adj. R^2 (within)	0.81	0.79	0.85	0.85	0.71

Table F10: Market impact of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	CDS spread	Outstanding bond debt	Bond issuance	Bond yield	CDS notional	CDS-bond basis
$Eligibility_i$	26.82***	-0.027***	-0.027***	0.325	-0.015	-0.81
	(8.06)	(0.012)	(0.009)	(0.242)	(0.044)	(5.03)
Matched sample	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1725	1578	1827	1623	1305	1309
adj. R^2 (within)	0.77	0.94	0.27	0.10	0.27	0.54

Table F11: Real effects of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Gross PPE	(2) Net PPE	(3) Employment	(4) ROA	(5) Stock price
$Eligibility_i$	-0.01	-0.01	-0.001	-0.061**	-0.036
	(0.006)	(0.007)	(0.001)	(0.031)	(0.023)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	1930	2757	2786	2689	552
adj. R^2 (within)	0.85	0.84	0.01	0.67	0.48

Table F12: Overall loans – alternative matching with pre-quarter values

The table presents results of running regression specifications 5 and 6. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. We identify 430 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	20.456***	26.618**	0.274***	0.337***	0.033*	0.040*
	(7.722)	(9.322)	(0.096)	(0.110)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39,305	39,305	39,305	39,305	39,305	39,305
adj. R^2 (within)	0.463	0.379	0.487	0.399	0.676	0.626