The impact of central clearing on the market for single-name credit default swaps*

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Abstract

In this paper, we examine the impact of the voluntary central clearing scheme on the CDS market for North American firms during the period spanning 2009 to 2015. In order to address the endogeneity problem arising from the fact that central clearing is not mandatory for single-name CDSs, we use a methodology that relies on propensity-score matching combined with generalized difference-in-differences. Our empirical findings show that initiating the central clearing results in an increase in CDS spreads, while there is no evidence of an associated improvement in CDS market liquidity and trading activity or of a deterioration in the default risk of the underlying bond. These results suggest that the increase in CDS spreads of centrally cleared entities can be mainly attributed to the reduction in CDS counterparty risk, and that the magnitude of this price increase (19 bps) could be used as an assessment of counterparty risk in the non-cleared CDS market.

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1 Introduction

Credit default swaps (CDSs) are insurance contracts that act against the default of the issuer of an underlying bond. They were first introduced by J.P. Morgan in 1994 to meet the need for an instrument to manage and transfer credit risk. These contracts can also be used for speculation purposes, in order to benefit from a change in the credit quality of a particular reference entity. The CDS market gained momentum and grew rapidly during the 2000s. The total notional amount outstanding peaked in 2007 at $58.8[1] trillion, and then fell gradually to $9.9 trillion in 2016. When they were first introduced, CDSs were solely exchanged in the *over-the-counter* (OTC) market, until they were heavily criticized for their lack of transparency and for the role they consequently played in the 2007 financial turmoil. In the aftermath of the 2007–2008 global financial crisis, the large size of the CDS market, as well as the amount of inherent risk associated with it, made market participants more cautious about their existing positions and pushed regulators to step in and announce reforms, mainly aimed at standardizing the CDS market and introducing central clearing.

After the introduction of the Dodd-Frank Wall Street Reform and the Consumer Protection Act, central clearing became an alternative for single-name CDSs. By the end of 2009, clearing operations began in North America and Europe, conducted by the Intercontinental Exchange Clear Credit (ICECC). By stepping in as the buyer for every seller and the seller for every buyer, the clearinghouse plays the role of a counterparty to both traders. The introduction of central clearing was meant to reduce the counterparty risk of cleared contracts: while the default probability of the reference entity is normally not affected by the move to central clearing, the protection of the CDS holder should be enhanced, as long as the clearinghouse itself is well protected against default (see Acharya, Engle, Figlewski, Lynch, and Subrahmanyam 2009). This new scheme may also boost trading activity and attract new players to the market. However, to guarantee a good protection against default, the clearinghouse requires that its clients post daily margins in the form of cash or highly liquid assets in addition to paying administrative fees.

This paper is part of the ongoing research on the impact of introducing a central counterparty (CCP) that stands between buyers and sellers of default protection in the CDS market. We examine this impact on spreads, liquidity, and trading activity by considering CDS contracts written on North American reference entities over the 2009–2015 period. We also analyze this impact on the default risk of the underlying bond during the same period. Our contribution is twofold. First, we address the endogeneity problem originating from the voluntary choice of adhering to central clearing. The fact that under this new regulation adhesion is not mandatory for single-name CDSs may result in a potential bias when analyzing the differences between CDS contracts written on bonds issued by cleared and non-cleared entities. By combining propensity-score matching with generalized difference-in-differences (DID), our approach is better able to deal with this potential bias. Second, we find evidence that CDS spreads increase once a reference entity becomes centrally cleared. We show that this spread increase does not pertain to an improvement in CDS liquidity or trading activity, nor is the default risk of the underlying bond affected by CDS central clearing. We therefore argue that this increase in the CDS spreads provides an assessment of the magnitude of

[1] Source: Bank for International Settlements (BIS).

counterparty risk in the non-cleared CDS market.

The empirical literature on the impact of central clearing on the CDS market is still scarce. The papers focusing on this topic employ various methodologies and data sets, and reach different conclusions about the implications of introducing clearinghouses into the CDS market. Slive, Witmer, and Woodman (2012) find that the new clearing mechanism slightly increases CDS liquidity. They argue that this improvement is the result of two opposite effects: an increase in collateral requirements, generating higher clearing costs, and an increase in transparency and operational facilities, leading to better competition and a more liquid market. They also find an improvement in trading activity as measured by gross notional amounts. Loon and Zhong (2014), using an event study methodology, find that the spreads widen around the initiation of central clearing. This change is explained by a reduction in CDS counterparty risk and, to a lesser extent, by an improvement in CDS liquidity. They also combine a standard DID analysis with propensity-score matching to provide evidence of an improvement in CDS liquidity as well as in trading activity. Kaya (2017) reports an increase in CDS spreads after central clearing, in a limited sample of non-financial firms. He argues that this surge is not the result of a reduction in counterparty risk, but is rather due to an increase in clearing costs, which is passed on to end-users. Du, Gadgil, Gordy, and Vega (2018) examine the cross-sectional and time series variations of CDS spreads on confidential data from the Depository Trust and Clearing Corporation (DTCC) by using a panel regression and DID analysis respectively. They find no evidence of an increase in CDS spreads after central clearing and that cleared trades have lower spreads than uncleared interdealer trades. They argue that their result is consistent with the fact that counterparty risk has a modest impact on the pricing of CDS contracts and rather is managed by market participants.

Loon and Zhong (2014) were the first to investigate the impact of central clearing on CDS spreads, as well as on liquidity and trading activities in the CDS market. While the framework of our paper is close to theirs, our methodology, scope, and findings are different. In this paper, we focus on eliminating the selection bias and, more particularly, on studying the changes in CDS spreads. We also improve the matching technique and rely on generalized DID by including time and firm fixed effects. Table 1 summarizes the main features of the literature dealing with the impact of central clearing on the CDS market, highlighting the differences in methodologies and empirical results.

[Table 1 about here]

The remainder of this paper is organized as follows. Section 2 presents an overview of the CDS market and its regulatory reforms. Section 3 presents the framework and methodology applied in this paper. Section 4 is a description of the data. Section 5 reports our empirical results about the impacts of the introduction of central clearing on the CDS market. Section 6 is a conclusion.

2 The CDS market: Overview and regulatory reforms

2.1 CDS prices and their determinants

In a CDS contract, the buyer agrees to make regular payments, known as the *premium leg* of the contract, until the earliest between the contract maturity or the default event. The seller makes one contingent payment, known as the *protection leg*, if and when the default event occurs. This payment is considered compensation for the protection buyer's net loss. The most common methodology for pricing CDS contracts is to use a reduced-form setting and compute the fair spread, obtained by equalizing the values of the premium and protection legs, discounted at the inception date. As an illustration (see, e.g., Longstaff, Mithal, and Neis 2005), consider stochastic and independent interest-rate and default-intensity processes, denoted respectively by r_t and $_t$. Consider a bond with a unit par value, and assume that the buyer pays a continuous premium s and receives an amount w upon default (w is the so-called *loss given default* of the bond). The present value of the premium leg can be expressed as follows:

$$sE\left[\int_0^T exp\left(-\int_0^t (r_u + \lambda_u)\ du\right)\ dt\right], \tag{1}$$

where T is the maturity of the CDS contract and t is the default date of the underlying bond. Similarly, the present value of the protection leg can be expressed as

$$wE\left[\int_0^T \lambda_t exp\left(-\int_0^t (r_u + \lambda_u)\ du\right)\ dt\right]. \tag{2}$$

The premium s is then obtained by equalizing (1) and (2):

$$s = w\frac{E\left[\int_0^T \lambda_t exp\left(-\int_0^t (r_u + \lambda_u)\ du\right)\ dt\right]}{E\left[\int_0^T exp\left(-\int_0^t (r_u + \lambda_u)\ du\right)\ dt\right]}. \tag{3}$$

Formula (3) is obtained under the assumption that the price of the CDS contract is not affected by liquidity and counterparty risk. Longstaff et al. (2005) mention that the premium s should be lower if the protection seller might not be able to honor its contractual obligations. The authors also argue that CDS spreads are less sensitive to liquidity risk than are corporate bonds because of their contractual nature, and the authors hence consider the spread to be a pure measure of default risk. This assumption was challenged after the 2007 financial crisis.

Recent papers provide empirical evidence that CDS spreads contain a non-negligible liquidity premium. Tang and Yan (2007) document that this premium is on average 13.2 basis points (bps). Buhler and Trapp (2009), relying on a reduced-form approach that includes a liquidity discount factor, find that the liquidity premium accounts for 5% of the mid quotes. Junge and Trolle (2015) develop an asset pricing model to extract liquidity from CDS data, and estimate that liquidity risk represents about 24% of CDS spreads. Many other papers, using various methodologies, confirm the existence of a liquidity premium in non-centrally-cleared markets (see, for instance, Chen, Fabozzi, and Sverdlove 2010; Bongaerts, Jong, and Driessen 2011; Qiu and Yu 2012; Lesplingart, Majois, and Petitjean 2012; Kuate

Kamga and Wilde 2013; and Pires, Pereira, and Martins 2014). Since the premium varies cross-sectionally and over time, it is not straightforward to provide a general estimation for this component. In addition, numerous liquidity measures can be used, which may lead to different estimates. Nonetheless, our concern in this paper is not to measure how liquidity affects CDS spreads but rather to evaluate the relative magnitude of a potential liquidity premium between cleared and non-cleared markets.

On the other hand, trading-activity measures can disclose additional trading information that is not necessarily contained in liquidity measures. In fact, Kyaw and Hillier (2011) find that the relation between trading activity and liquidity is not always positive. They show that an increase in trading activity is associated with an improvement in liquidity for large stock portfolios, but with a reduction in liquidity for small stock portfolios. Moreover, Silva (2015) argues that the informational content of open-interest variables can be used as a predictor of CDS spread changes, by showing that open-interest measures contain private information that precedes CDS price movements. Hence, it is important to account for CDS trading-activity variables, since they may be used as an additional predictor of spreads.

Finally, the debate about the contribution of counterparty risk in the price of credit protection is still open, due to the difficulty of obtaining data that identifies the protection seller. Jarrow and Yu (2001) and Hull and White (2001) develop theoretical models that account for a possible correlation between the default of the reference entity and that of the seller of the credit protection, and show that CDS spreads decrease when this correlation increases. In their numerical illustrations, Hull and White (2001) find that an improvement in the credit rating of a protection seller, from BBB to AAA, increases CDS spreads by 5 to 36.1 bps, depending on the default correlation reflecting the counterparty risk in the CDS valuation. Empirically, Arora, Gandhi, and Longstaff (2012) document that the relation between the dealer's credit risk and the CDS spreads is statistically significant but economically very small. Specifically, they estimate that an increase of 645 bps in the dealer's credit risk results in a decrease of only 1 basis point in the price of protection. These results are supported by the analysis of Du et al. (2018), who also rely on panel regressions and argue that market participants manage counterparty risk by selecting dealers with a low credit risk. They estimate that a 100 bps increase in the dealer's credit spread reduces the CDS spread by about 0.6 bps.

Counterparty risk can also be analyzed from a different perspective, by quantifying the *Credit Value Adjustment* (CVA), which is defined as the difference between the value of a counterparty-risk-free portfolio and that of a comparable portfolio subjected to counterparty risk. The CVA, an adjustment made to compensate one party for the other's default risk, also represents the market value of the counterparty risk. Brigo and Chourdakis (2009) evaluate the CVA of CDS contracts, taking into account default correlation and credit spread volatility. In their illustrations, the CVA of CDS contracts ranges from zero to 91 bps when the correlation is very strong. In the case of a moderate correlation of 20%, the CVA ranges between 15 and 25 bps, depending on the credit spread volatilities of the reference entity and of the counterparty. These estimates are in line with those of Gregory (2011), who finds a range of zero to 48 bps, where the CVA increases with the level of correlation. Brigo, Capponi, and Pallavicini (2014) evaluate the counterparty risk of collateralized agreements. They find that the CVA is an increasing function of the default correlation, ranging from 10 to 60 bps, with a maximum of 20 bps for a moderate correlation of 20%.

2.2 Regulatory reforms and the CDS market

In recent years, the CDS contract has become a very attractive tool to hedge a credit exposure or take a speculative position without having to purchase the underlying reference bond. The market grew dramatically after the beginning of the 2000s, reaching a peak in 2007, and then gradually declined afterwards. Figure 1 reports on the total notional amount outstanding in the CDS market, growing from \$6.4 trillion in 2004 to \$58.2 trillion in 2007, and dropping to \$9.9 trillion by the end of 2016[2]. Vause (2010) argues that the decrease in the notional value of the CDS market since 2007 is due to trade compression and the creation of central counterparties.

[Figure 1 about here]

Because of the large size of their market and because of their interconnectedness with other derivatives, CDSs play an important role in the stability of the financial system; hence, the importance of monitoring the risks associated with CDS trading, and more specifically, counterparty risk. In fact, the failure of Lehman Brothers, Bear Stearns, and other major financial institutions raised concerns about the vulnerability and efficiency of the existing market infrastructure when dealing with counterparty risk. As a result, following the 2007 financial crisis, regulatory authorities took new measures to control counterparty risk and increase market transparency.

The most important regulatory change for CDS trades was the introduction of central clearing, as recommended by the Dodd-Frank Act in 2009. A clearinghouse acts as an intermediary between seller and buyer, and its main role is to mitigate counterparty risk. Indeed, the CCP becomes the counterparty to both traders and has its own methods of reallocating the risk of the trade, including netting and loss mutualization. The CCP also continuously collects collateral in the form of margins, and guarantees payment in the event of default. ICECC is the market leader in Europe and North America for clearing CDS trades. It started clearing CDS indices in March 2009 and single-name CDSs in December 2009. Other clearinghouses, such as LCH Clearnet and CME, offer similar services but their market share is still small compared to that of ICECC. At present, the clearing of most CDS indices is mandatory, whilst that of single-name CDSs remains done on a voluntary basis. The new system has become increasingly popular since its inception, and a growing number of reference entities have adhered to it. Investors are also increasingly aware of the benefits of trading through a clearinghouse with respect to counterparty risk. According to BIS data, the proportion of notional amount outstanding with CCPs increased from around 15% in 2010 to 44% in 2016 (see Figure 1).

The CDS market underwent other regulatory changes in early 2009, known as the *CDS Big Bang*, introduced by the International Swaps and Derivatives Association (ISDA). The main goal of this protocol was to push toward standardization in order to facilitate operational efficiency and pave the way for the implementation of central clearing. This standardization has mainly affected the CDS premium and maturity dates. In addition, *determination committees* have been created to oversee various aspects of credit events, such as identifying them and determining how to define the list of eligible deliverable bonds. Another important

[2]Source: BIS.

regulatory change was the obligation to report to trade repositories, which helped restore public confidence and created more transparency.

All the above reforms, and many others, impacted not only the CDS market but all classes of derivatives. Their objective was to minimize the overall counterparty-risk exposure and avert another financial meltdown. Most of these regulations had taken effect before the introduction of central clearing, and hence, do not affect our results.

2.3 The principles of central clearing

The concept of a CCP is not really new, as exchanges for futures trading have existed since the 19th century. The OTC market coexisted with exchanges at that time, and gained popularity because it allowed for trading of a wider class of derivatives. However, the important development of credit instruments and their inherent risk—particularly after the 2007 financial crisis—triggered the urgent need to mitigate CDSs' counterparty risk and raised the appeal of central clearing. By replacing the original contract with two distinct ones, the CCP becomes the counterparty to both parties. Once a trade is cleared, each party is unaffected by any default by the other. If a market participant defaults, the CCP honors its exposures and shares the losses with the other CCP members instead of letting one institution bear all the damage alone. The remaining counterparty risk is limited to the default of the CCP itself, which is highly unlikely, given the strong risk-management procedures it applies[3].

The viability of a CCP is measured by its ability to absorb the losses caused by the default of one or more of its members. This is generally achieved by imposing strict collateral requirements in the form of margins or contributions to specific funds. Additionally, clearinghouses rely on a waterfall approach with several layers of protection, to be able to respond to extreme events. The first layer consists of the membership criteria. To become a cleared member, an entity must meet certain requirements of financial stability and operational capabilities. The second protection layer consists of margin requirements. Members must make an upfront payment, known as the *initial margin*, which may be used to close out the positions of a defaulting member without losses. Daily adjustments to this amount, or *variation margins*, are made to mark-to-market losses or gains. Intra-day margin calls can also be made in case of a large price movement. The potential determinants of the margin are the volatility of the underlying asset, default risk, liquidity risk, interest-rate risk, correlation with other CCP members, and size of the position. Concentration charges are also applied for large positions that exceed a certain threshold. Margins should be sufficient to offset the losses of a defaulting member and cannot be used to cover the losses of another member or of the CCP itself. Under extreme market scenarios, clearinghouses rely on a third layer of protection, known as the *guaranty fund*. Members contribute to this fund by posting additional amounts of collateral, which help in mutualizing losses if the two first layers are insufficient. The CCP holds the assessment rights and may ask its members for additional contributions to the guaranty fund. All of the aforementioned measures are supposed to guarantee sufficient financial resources to bring confidence to the market and reduce the counterparty risk associated with bilateral trades.

[3]We refer the reader to Gregory (2014) for a detailed discussion of the structure and mechanics of clearinghouses.

Trading through a central clearinghouse presents many other advantages in addition to reducing counterparty risk. On the one hand, different contracts can easily be netted, which not only reduces the total notional exposure but also the margin costs relative to bilateral transactions. Moreover, since a CCP works closely with regulators, it is able to follow the best practices in the market, leading to legal and operational efficiency. Clearinghouses are also required to provide, on a daily basis, an accurate valuation of the derivatives they are clearing, for margin calculation purposes. This procedure helps improve market transparency. On the other hand, members of clearinghouses are required to set aside significant amounts of cash and liquid assets as collateral, which may represent a liquidity concern.

Finally, note that to be suitable for central clearing, an instrument should present a good level of standardization. One consequence of the 2009 Big Bang was the standardization of CDS contracts, which made the introduction of central clearing in the CDS market possible.

3 Methodology

In order to study the impact of central clearing, we compare the spreads of single-name CDS contracts in two groups of firms, namely, cleared reference entities that are members of the clearinghouse and non-cleared reference entities; this comparison is undertaken before and after adhesion to the CCP, in a DID framework.

The DID methodology has been widely used in various areas of application to evaluate the impact of an exogenous event or of a policy change. The classical two-by-two design uses data from a treatment group and from a control group, measured at two different dates: before treatment and after treatment. This methodology is flexible and can be generalized to the case of multiple groups and multiple time periods (see, e.g., Bertrand, Duflo, and Mullainathan 2004; Imbens and Wooldridge 2009; and Gormley and Matsa 2011). In our case, since we are dealing with multiple treatment (clearing) dates, a generalized DID framework is required.

Since its introduction in 2009, central clearing for single-name CDSs has been conducted on a voluntary basis. Note that when the assignment to treatment and control groups is not random, and subjects have the choice of taking the treatment or not, the two groups are more likely to differ, and therefore, estimates may be biased if this endogeneity problem is not addressed.[4]

Moreover, not all reference entities are eligible to become clearinghouse members; firms must meet some capital requirements and show sufficient financial strength in order to be accepted for central clearing.

To alleviate these endogeneity and heterogeneity concerns, we rely on propensity-score matching (see Rosenbaum and Rubin 1983; Heckman, Ichimura, and Todd 1997; and Dehejia and Wahba 2002) to construct treatment and control groups. Propensity-score matching allows us to construct a sample of cleared and non-cleared firms that have similar pre-clearing characteristics, before applying a generalized DID approach.

The combination of these two methodologies has been used in many fields, including finance (Greenaway and Kneller 2008; Lemmon and Roberts 2010; Hofmann 2013; Bandick,

[4]We refer to Li and Prabhala (2005) and Roberts and Whited (2012) for a detailed discussion on this subject.

Gorg, and Karpaty 2014; Sari and Osman 2015; and Amiram, Beaver, Landsman, and Zhao 2016), but has not yet been applied to analyze the impact of central clearing on CDS spreads.

The first step consists of constructing a sample of candidate control entities and treatment entities, and computing their propensity scores on the basis of pre-clearing characteristics. Specifically, we consider the 29 clearing dates enumerated in Table 2 as the various possible times for adhering to a CCP. These treatment dates can be interpreted as hypothetical events for the control group. Each non-cleared firm thus generates up to 29 firm-date entities. The sample also contains the cleared firms along with their clearing date.

[Table 2 about here]

We then estimate the following Probit model, using the sample of cleared and non-cleared firm-date entities and the corresponding observable variables that are relevant to clearinghouses:

$$Pr(Y = 1|X) = \Phi(X \cdot \beta), \tag{4}$$

where Y is a binary random variable that equals 1 if the firm is centrally cleared and 0 otherwise, Φ is the standard normal cumulative distribution function, X is the vector of regressors that influence the outcome Y, $\cdot$ is the inner product operator, and β is a vector of parameters. The vector β is estimated by maximum likelihood and is used to estimate the probability, for each firm-date entity, of being accepted for central clearing. This probability is the *propensity score* and is associated to a combination of a firm and a clearing date. The event windows used for the estimation of the regressors are $[-8, -2]$ months before the relevant clearing date, where the two months immediately before the clearing date are excluded to make sure the data does not contain any market anticipation. The propensity score of a control firm-date entity indicates the probability of a control firm being selected for central clearing, if it decided to adhere to a CCP at the given clearing date.

The second step consists of matching cleared and non-cleared entities to obtain a treatment and a control group containing firms that have similar characteristics just before the treatment event. We match with replacement each cleared firm with its closest neighbor from the non-cleared group, on the basis of the propensity scores. Our final sample is then composed of matched firm-date entities. A detailed example of the matching procedure is provided in Appendix A.

Note that the period over which the independent variables are constructed is very important for the performance of the matching operation. In a similar setting, Loon and Zhong (2014) use data prior to December 2009 to match all firms, including firms cleared by the end of 2011. Clearly, a firm's financial situation can change considerably over time. Relying on firm-date identifiers allows us to obtain a better match for the treatment and control groups, obtaining matched entities that are similar along many dimensions, thereby eliminating the potential selection bias.

The third and last step is to apply generalized DID regression to the matched sample in order to test for the presence of statistically significant impact factors. Using the generalized DID framework allows us to account for the different treatment times of CDS contracts. To isolate the effect of central clearing, we estimate the following DID equation:

$$Factor_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{5}$$

where β_0 is a constant term. The dependent variable $Factor_{i,t}$ will take four different definitions in order to investigate the impact of central clearing on CDS spreads, liquidity, and trading activity, as well as on bond default spreads. Subscripts i and t denote the firm (i) and date (t) combination. The main explanatory variable $cleared_{i,t}$ is a binary variable that indicates whether the reference entity i is centrally cleared or not on clearing date t. This variable is the equivalent of the interaction term in the classic two-by-two DID design. The treatment effect is given by the corresponding coefficient β_1. The fixed effects of the generalized DID setting help control for unobserved heterogeneity across time and reference entities, thereby alleviating concerns about any omitted variables that might affect both groups in the same way. The firm fixed effect, α_i, captures differences across firms that are constant over time, while the time fixed effect, γ_t, captures differences over time that are common to all firms. We deliberately do not control for specific time-varying variables to avoid confounding estimates of β_1, since these variables might also be affected by the move to central clearing. In all our regressions, the standard errors are clustered by firm.

4 Data

We use seven years of CDS data on North American firms, observed from January 2009 to December 2015, and compiled from different sources. From Markit, we obtain daily CDS spreads of five-year senior unsecured contracts denominated in USD. We follow the market convention for North American contracts since April 8, 2009, and focus on contracts with a no-restructuring clause (XR). We delete observations with a missing five-year spread and keep only reference entities with at least 20 observations. We also obtain from Markit the *Composite Depth,* which is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread.

4.1 Liquidity data

Our liquidity measures are mainly collected from Markit Liquidity. This database contains data that starts in April 2010 and was updated in November 2011 to include new variables. Specifically, we obtain bid-ask spreads from Markit Liquidity, and supplement the missing pre–April 2010 information from CMA mainly, and where necessary, from Bloomberg to obtain a larger coverage. We then construct the *Relative Quoted Spread* (RQS), computed as the bid-ask spread divided by the spread midpoint. In addition, we rely on other liquidity measures from Markit Liquidity, depending on data availability. From April 2010 to December 2015, we use the *Upfront five-year bid-ask spread* and the *Markit liquidity score*, defined on a scale from 1 to 5, where 1 indicates the highest liquidity. During this period, we also have the *Quotes count* and the *Dealers count*, defined as the total number of unique quotes for a reference entity and the total number of distinct dealers quoting the reference entity across all available tenors, respectively. From November 2011 to December 2015, we have more detailed information about the quotes and dealers count. We obtain the *Five-year quotes count* and the *Five-year dealers count*, defined respectively as the total number of unique quotes for a reference entity and the total number of distinct dealers quoting the reference entity for the five-year tenor. Data about the remaining tenors is given by the variables *Non five-year quotes count* and *Non five-year dealers count*.

4.2 Trading activity data

The data on trading activity is obtained from the Depository Trust and Clearing Corporation (DTCC), which covers approximately 98% of all credit derivative transactions in the global marketplace. For each entity, we have weekly information on the gross and net notional amounts outstanding, as well as the number of contracts outstanding. The first available report is for the week that ended on October 31, 2008. DTCC also publishes market risk transfer activity in terms of gross notional value and number of contracts. This activity captures transaction types that result in a change in the market risk position of market participants and is meant to exclude transactions that do not represent market activity, such as moving bilaterally cleared trades to a CCP and portfolio compression. The market risk transfer activity data is available on a weekly basis, starting from the week that ended on July 16, 2010. We end up with the five following variables defining the CDS trading activity: *Gross notional amounts*, *Net notional amounts*, *Contracts*, *Gross notional—Risk transfer*, and *Contracts—Risk transfer*.

In Table 3, we provide the list of all the variables obtained from Markit, Markit Liquidity, and DTCC. These variables will be used in the DID equation to evaluate the impact of central clearing. Clearinghouses are expected to reduce counterparty risk, and boost liquidity and trading activity. Therefore, CDS contracts in the treatment group are anticipated to have higher spreads and higher liquidity following central clearing, as compared to the control group. This translates into a positive sign for the coefficient (β_1) of the interaction term in the case of CDS spreads, liquidity, and trading-activity variables and a negative sign for this coefficient in the case of illiquidity variables.

[Table 3 about here]

4.3 Central clearing data

We identify the name of the entities that were centrally cleared as well as the corresponding clearing date by using the official list on the ICECC website and the regularly published circulars announcing the single-name CDSs that are going to be cleared. We also check whether the entity has gone through any type of restructuring event that might affect its CDS spread. In such cases, the entity is excluded from the list, since we want to focus exclusively on the impact of central clearing. Other reference entities that have experienced a merger or were acquired by another company are also eliminated. If an entity had a renaming event, we keep it on the list, and its first clearing date is that of the first entity with the old name since this type of event is unlikely to affect the spreads. We finally merge DTCC with Markit by name and then identify centrally cleared entities with the Markit redcode. After this filtering and merging process, we obtain a total of 607 reference entities.

4.4 Bond data

For additional tests, we also analyze the impact of central clearing on the default probability in the underlying bond market. The data is mainly obtained from TRACE, which provides information about the prices, and FISD, which contains the different characteristics of the bonds. We keep only straight and redeemable bonds in FISD and we apply the Dick-Nielson filter to TRACE data before merging the two datasets in order to eliminate reporting errors. Our objective is to have a unique bond for each issuer and therefore we choose, among bonds with maturities between three to ten years, the bond with the maturity closest to five years. First, we limit the range of maturities to [3 - 10] years and then keep only the bond with the closest maturity to five years. We complement this dataset with the bond ratings obtained from S&P to be able to classify bonds into investment grade and high yield. To avoid losing observations, we replace any missing information with Moody's rating.

5 Empirical results

5.1 Matching procedure

First, we have to choose the appropriate variables to include in the Probit estimation. These variables should have an impact on the decision of a CCP about accepting a firm for central clearing. Intuitively, a CCP selects liquid contracts that have a low default risk so that it will be able to liquidate the position quickly and efficiently in the case of an undesirable event. Therefore, according to this criteria, cleared contracts should have lower CDS spreads and should be traded more often than the other contracts. To support this intuition, Slive et al. (2012) conduct a Cox survival analysis and find that CCPs are more likely to accept contracts with larger notional amounts outstanding, higher liquidity, and smaller CDS spreads. In addition, Loon and Zhong (2014) confirm, after communicating with ICECC, that liquidity and open interests (available through DTCC data) are important criteria to accept obligors for central clearing. Hence, we take into account variables that fall into the above categories to construct the two groups. We compute the six-month mean of each variable over the relevant event window and fit the Probit model described in equation (4) on cleared and non-cleared firms, to compute propensity scores that represent probabilities of being selected for central clearing.

In Table 4, we present four different specifications by including a different combination of variables each time, in order to find the best model. The variable *CDS spread* reflects the riskiness of the reference entity. The variables *Contracts* and *Net notional* measure the trading activity, and their respective squared terms help account for possible nonlinear effects. However, we cannot include these two variables in the same regression because they are correlated. We also include *Relative quoted spread* and *Composite depth* as liquidity measures. Lastly, we add industry dummies to our estimations since ICECC generally clears many firms from the same sector on the same date. Specifically, we consider the ten following sectors: telecommunications services, healthcare, technology, basic materials, utilities, industrials, financials, energy, consumer services, and consumer goods. In line with the ICECC requirements, all the variables are statistically significant and have the expected sign. The higher the CDS spread, the lower is the probability of being accepted for central clearing, because the firm has a higher default risk. Moreover, we confirm that reference entities with more liquid contracts and larger open interests have higher probabilities of being accepted by a CCP. We finally select Model 3 since it has the highest log likelihood ratio and it includes the important determinants of central clearing.

[Table 4 about here]

After matching with replacement each cleared entity with its nearest neighbor from the control group, we need to evaluate the quality of this matching and see whether a selection bias is present. In Table 5, we present various statistics to examine the overall balancing between the treatment group and the control group.

For each variable included in the model, we compute in Panel A its mean in the treatment and control groups, both before and after the matching. We expect the matching procedure to substantially reduce the difference between the two means. We compute the standardized bias, which is the difference between the means of the two groups, scaled by the average standard deviations. A well-performed matching procedure should reduce the bias to a low level. Before the matching, we notice that the cleared firms differ from the non-cleared firms, and that their characteristics are in line with ICECC selection criteria. After the matching, and for all the variables, the two means are closer for the matched sample, and the bias is clearly lower. All bias reductions are higher than 81%, which indicates that the characteristics of the two groups are very similar.

In Panel B, we perform additional tests to assess the matching quality. Specifically, we fit the Probit model again, this time on the matched sample. If the two groups are well matched, then we should obtain a bad fit. In fact, the variables that were useful for deciding if a company is eligible for central clearing should no longer do so, since the non-cleared firms resemble the cleared ones along the key dimensions relevant for central clearing. This intuition is confirmed by our results. We obtain a very low likelihood ratio and pseudo R^2, as shown in Table 5. Furthermore, we can no longer reject the null hypothesis that all the variables are jointly nonsignificant ($p\text{-}value = 0.905$). The mean and median biases (4.9 and 3.4, respectively) are also greatly reduced, compared to the Probit estimation with the unmatched sample (25.4 and 16.5, respectively). All the above results suggest that the selection bias is substantially reduced across the two samples and that we have more balanced groups. In the next sections, we rely on the matched sample to study the implications of joining a CCP.

[Table 5 about here]

5.2 Impact of central clearing

5.2.1 Impact on CDS spreads

Here, we examine the impact of clearing on CDS spreads. Specifically, we test the following hypothesis:

H1: CDS spreads increase when the reference entity becomes centrally cleared.

Our sample consists of 198 cleared firms and 100 control firms. Matches with insufficient data were eliminated to ensure that each treated firm has a good match that covers the full event window. We start by plotting in 2 the daily mean CDS spread for the treatment and control groups during a period of $[-250, 50]$ days around the commencement of central clearing (day 0). First, we notice that both groups have the same pre-treatment trend, which again confirms the matching quality and makes it possible to graphically verify the parallel trend assumption of the difference-in-differences model. Second, we observe that the CDS spread of cleared entities was initially lower, and then increased following the event date. This is consistent with the idea of CCPs accepting entities with a lower default risk. Figure 2 also suggests that the spread of cleared entities increases gradually after the move to central clearing, and shows that the difference between the two groups reaches approximately 28 bps by the end of our event window. This behavior could be the result of increased confidence in the clearinghouse as an entity able to protect the investor against the seller's default and to mitigate counterparty risk. Market participants are willing to pay more to benefit from this advantage.

[Figure 2 about here]

Next, we test the previous finding by conducting a difference-in-differences analysis on the matched sample. We estimate Equation (5) with CDS spreads as the dependent variable and we focus on the coefficient β_1 of the variable *Cleared*. In the first column of Table 6, we start with a large event window of [-250, 50] days and we find that the coefficient β_1 is positive and statistically significant. Our results show that moving a CDS contract from the OTC market to a clearinghouse increases its spread by 19.2 bps on average. Despite the difference in the applied methodologies, this result is in accordance with the findings of Loon and Zhong (2014) and Kaya (2017) that the spreads rise with the initiation of central clearing. Kaya (2017) estimates this increase to around 24 bps, by using a sample of nonfinancial firms. To check the robustness of our estimations, we consider different event windows of various lengths. All the specifications lead to a positive and statistically significant coefficient, with a lower magnitude for shorter event windows.

[Table 6 about here]

Considering the main purpose of creating a central counterparty and the magnitude of the increase in CDS spreads, we can presume that this change is more likely to be a reflection of a reduction in counterparty risk. The estimation of the coefficient β_1 is in the range provided by the papers that study the pricing of counterparty credit risk in CDS spreads. For instance, Brigo and Chourdakis (2009) find a range of 15 to 25 bps in the case of a moderate default correlation. The CCP has several layers of protection that make the contract more reliable, and thus, more expensive. However, other factors, such as a possible improvement in liquidity, or trading activity resulting from central clearing, may also contribute to this observed surge in the CDS spreads. We assess the potential effects of these other two factors in the following subsections.

5.2.2 Impact on liquidity

The introduction of central clearing may help improve CDS liquidity by attracting more market participants. In fact, the mitigation of counterparty risk, the increased transparency, and the reduction of operational risk may all encourage more institutions to get involved in CDS trading, thus rendering the market more liquid. At the same time, the elevated costs of this new scheme and particularly the margin requirements could prevent some participants from having access to clearinghouses. Not all investors can afford to pay collateral demands on a daily basis and to set aside a non-negligible amount of capital as a contribution to the default fund. According to Cont (2017), the collateral maintained by CCP members in the form of liquid assets was more than 400 billion USD in 2016. Hence, the overall impact on market liquidity is still unclear. If the first effect prevails, then an improvement in CDS liquidity will widen CDS spreads. The second effect might also be sizeable and compensate for the benefits of the first improvement. We expect, however, an improvement in liquidity, as shown by Slive et al. (2012) and Loon and Zhong (2014).

By applying the same methodology as in the previous section, consisting of comparing groups matched on the basis of propensity scores, we empirically test the following hypothesis:

H2: Central liquidity improves CDS liquidity.

We have a total of 10 liquidity measures, mainly obtained from Markit Liquidity. In Figures 3 and 4, we plot the evolution of the daily mean of the control group against the treatment group during a period of $[-250, 50]$ days around the initiation of central clearing for the variables *Relative quoted spread* and *Composite depth*. Since liquidity is a key dimension for accepting a reference entity for central clearing, it is very important to have similar pre-clearing trends for both groups. The figures show that the two graphs are very similar and have the same trend over the whole event window. Unlike the previous analysis of CDS spreads, where the cleared entities had a different behavior after the event date, none of our liquidity measures exhibit a divergence in trend following the move to a clearinghouse. For instance, the average number of dealers providing CDS quotes, as measured by the composite depth, oscillates around 6.5 before and after the event date for both cleared and non-cleared entities. The two graphs representing the liquidity score computed by Markit also remain relatively stable and oscillate between 1.5 and 2. Overall, this preliminary investigation seems to indicate that CDS liquidity is not affected by the clearing event. Figures comparing the graphs for other liquidity measures are presented in the appendix and show similar behavior.

[Figures 3–4 about here]

We apply the difference-in-differences analysis to each measure by changing each time the dependent variable in Equation (5). We mainly focus on the *Relative quoted spread* and *Composite depth* because they fully cover our sample period. For these two measures, we fit the regression equation using different event windows. For all the specifications in Tables 7 and 8, none of the coefficients of the binary variable *Cleared* are statistically significant, suggesting that central clearing does not have any impact on CDS liquidity. The positive effects caused by the increased competition in the market are probably counterbalanced by the high costs of daily margining. It might also be the case that the accepted contracts are already liquid, which makes them less likely gain any additional liquidity benefit. As a robustness check, we estimate the same equation using the remaining liquidity measures on an event window of $[-250, 50]$ days and report the results in Table 9. With the exception of the variable *Liquidity score*, which is significant at the 10% level, all the other coefficients β_1 are negligibly small and statistically nonsignificant. This shows that cleared reference entities do not experience any improvement in their liquidity following central clearing.

Nonetheless, these results do not necessarily mean that liquidity is not priced in CDS contracts, but rather that the pricing is homogeneous among cleared and non-cleared contracts.

[Tables 7–9 about here]

5.2.3 Impact on trading activity

Since it has been shown that CCPs have a preference for contracts with large open interests, we find it interesting to check whether the introduction of central clearing affects trading-activity variables. Open interest indicates how much debt is insured with CDSs, and thus, could be considered a good measure of the market participants' demand. On the one hand, the trading activity could increase if participants wanted to benefit from the reduction in counterparty risk following central clearing. This behavior could raise the demand and exert an upward pressure on CDS spreads. On the other hand, informed traders may start looking for alternative derivatives and more opaque markets because of the increased transparency brought by clearinghouses. In such a case, demand for credit protection could decrease and drive CDS spreads down. We expect the first effect to dominate, given the numerous advantages of trading through a clearinghouse. Therefore, we propose the following hypothesis to test the overall impact of the introduction of central clearing on trading activity:

H3: Central clearing improves CDS trading activity.

We examine all weekly CDS position variables published by DTCC. We have information on the gross and net notional amounts on each reference entity, i.e., the par amount of credit protection that is bought or sold. The gross notional amount includes all the contracts on a given firm, even if a new position offsets another, thus increasing the amount with every trade. The net notional amount can be considered an adjustment of the previous measure, since it takes into account offsetting trades, which makes it a better proxy for the actual amount insured by CDS contracts. DTCC also discloses weekly data about market risk transfer activity, which only includes transactions that result in a change in the market risk position, such as new trades, the termination of an existing transaction, and the assignment of an existing transaction to a third party. These measures exclude moving bilateral trades to CCPs, portfolio compression, and back-loaded trades, since they do not change the risk profile.

We employ the same methodology to analyze the five variables provided by DTCC. We construct weekly means for the control and treatment groups matched with propensity scores over a period of $[-50, 10]$ weeks around the event date. Figures 5 and 6, illustrating gross and net notional amounts, respectively, show that the two graphs move together during the pre-treatment period, which again shows that both groups have similar pre-clearing characteristics. After the move to a clearinghouse, we do not observe any change in the behavior of open-interest measures except for *Gross notional amounts.* There is no increase in the number of traded contracts or in the net notional amounts. Even the number of contracts and the other variables measuring the market risk transfer do not exhibit any trend change in the post-clearing period (see Appendix B). For instance, the gross notional amount involving a market risk transfer keeps oscillating between 72 and 225 million dollars, without any particular increase around day 0. However, Figure 5 shows a surge in the gross notional amount of the treatment group by around 7%, while the control group maintains the same trend for the whole event window. This increase is essentially due to the move to central clearing itself, that is, the transfer of the contracts to a clearinghouse.

[Figures 5–6 about here]

To confirm these preliminary findings based on graphical representations, we analyze the results of the difference-in-differences regression, which we report in Table 10. In each model, a different open-interest measure is used as the dependent variable in Equation (5). We find that the gross notional amount is the only variable having a positive and statistically significant coefficient for the interaction term. All the remaining variables, which represent a better proxy for the amounts outstanding, have nonsignificant coefficients. Consequently, our results suggest that central clearing does not have any impact on trading activity.

[Table 10 about here]

5.2.4 Impact on bond default spread

The CDS and bond markets are strongly related since the CDS contract is essentially used to hedge bond positions. Therefore, we need to check whether the increase in CDS spreads is due to a change in the default risk of the underlying bond, by testing the following hypothesis:

H4: Central clearing increases the bond default risk.

Bond issuers may take riskier positions if they know that their associated CDSs are more protected against counterparty risk once they are centrally cleared. A similar moral-hazard situation was documented in the banking industry, where bank managers became less risk averse when their customers obtained a deposit insurance protecting them from a bank default event (Diamond and Dybvig, 1983). In fact, this moral-hazard effect is often used to justify banking regulations (Crouhy, Galai, and Mark, 2000). The first step in testing the previous hypothesis is to construct a default spread measure, since it is not observed in the market. To do so, we implement the J.P. Morgan Par Equivalent CDS Spread (PECS) methodology and perform the following steps for each observation:

- Bootstrap default probabilities from the CDS market quotes.
- Compute the present value of the bond, using the implied default probabilities.
- Apply a parallel shift to the default probability curve so that the previously computed present value matches the bond's market price. The shift is obtained by solving a minimization problem.
- Compute the PECS by using the new default probabilities.

Since most of the bonds in the data are callable, they need a special treatment to be included in the analysis of *H4*. For investment-grade bonds, we keep the original maturity since the bonds are not likely to be called. For high-yield bonds, we compute a new maturity based on the Yield-To-Worst (YTW), defined as the minimum between the Yield-To-Call, computed for each possible call date, and the Yield-To-Maturity (YTM), assuming no prior default. If one or more call dates have passed and the bond is not yet called, then the calculation of the YTW is based on all the remaining call dates. The new maturity reflects the worst scenario for a bondholder and will be considered the maturity of the high-yield bond for the computation of the PECS. This approach could be considered a simple and efficient approximation for computing the PECS for bonds with call features.

For each CDS contract, we now have an associated bond and its daily default spread measure. We compute the daily PECS means for the control and treatment groups over the period $[-250, 50]$ around the central clearing date. Figure 7 shows that there is no trend change after the event, suggesting that the default spread of cleared entities is the same before and after joining the clearinghouse. We confirm this result by estimating the DID described in Equation (5) and using the PECS as a dependent variable. For all the estimation windows reported in Table 11, the coefficient of the binary variable *Cleared* is not statistically significant, which supports the previous finding[5]. The results clearly indicate that the default risk of the underlying bond did not increase, once again confirming that the surge in CDS spreads is caused by a change in the CDS market and not in the bond market.

[Figure 7 about here]
[Table 11 about here]

5.3 Summary of empirical results

All our empirical findings indicate that neither CDS liquidity, nor trading activity, nor bond default risk is affected by the introduction of clearinghouses. In addition, note that clearing fees should not represent a burden for those trading cleared contracts. The clearing fees charged by ICECC to its clients and members amount, respectively, to $20 per million of notional for single-name CDSs, and $15 per million of notional. Clearly, these fees are negligible for market participants and are very unlikely to affect the CDS spreads. Consequently, after eliminating the potential factors that may be affected by central clearing and may themselves affect the CDS spreads, our results suggest that the surge in CDS spreads following adhesion to a CCP can be mainly attributed to the reduction in counterparty risk. The magnitude of this increase could therefore be used as a measure of the counterparty risk present in the market before a reference entity joins central clearing. We find that this risk could reach up to 19 bps of the total CDS spread, which is in the range of what was found in the literature. Participants in clearinghouses have higher trust in a central counterparty and less concern about the possibility of a default event. Hence, they could be willing to pay more to buy better credit protection. The ability of a CCP to prevent default contagion and to continuously monitor the risks arising from trading CDS contracts helps establish a safe and robust clearing environment. This was one of the main goals of the Dodd-Frank Wall Street Reform and Consumer Protection Act, and we believe this reform has managed to reach this goal through the introduction of clearinghouses.

[5]Similar results are obtained when we add bond rating dummies as control variables.

6 Conclusion

In this paper, we study the impact of central clearing on single-name CDSs. The opportunity of voluntarily joining a CCP to trade these contracts has been effective since December 2009. This new scheme, mandated by the Dodd-Frank Act, aims to reduce the overall risk in the market and enforce new regulations to avoid another financial crisis. The clearinghouse uses multiple layers of protection and strong risk-management strategies to prevent a potential domino effect. Members need to post initial margins as well as daily variation margins that should be sufficient to cover their losses in case of default.

Despite the economic importance of this regulatory change, little empirical evidence has been provided about its implications. In this work, we perform a generalized difference-in-differences analysis on samples matched with propensity scores. This type of matching ensures that the cleared and non-cleared groups have similar pre-clearing characteristics, and it alleviates the concern about the selection bias arising from the voluntary choice to adhere to central clearing. Our results indicate that the CDS spread increase resulting from a reference entity joining the clearinghouse could reach as high as 19 bps. We test whether this price change is due to various factors by separately analyzing the impact on liquidity and trading activity, but we find that central clearing does not cause any change in these two factors. We argue that this surge is therefore an indication of the amount of counterparty risk that was reduced thanks to the clearinghouse. In addition, our findings regarding the underling bond market corroborate the fact that this change in CDS spreads is only due to the reduction in counterparty risk.

The impact of central clearing is not only limited to liquidity, trading activity, and counterparty risk. In fact, central clearing helps to improve netting efficiency and to reduce the total exposure by offsetting bilateral positions. However, these advantages come at the expense of an increase in collateral demand to guarantee maximum protection against defaults. Blocking a non-negligible amount of highly liquid assets might have long-term negative effects on market liquidity. Moreover, the overall effects could change over time, particularly when the number of cleared entities increases, leaving only a small proportion for the OTC market.

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Figure 1: CDS Trading Volumes.

This figure plots the notional amounts outstanding in trillion dollars for single-name CDS contracts as well as the proportion of notional amounts cleared by central counterparties. The data is obtained from the Bank for International Settlements (BIS).

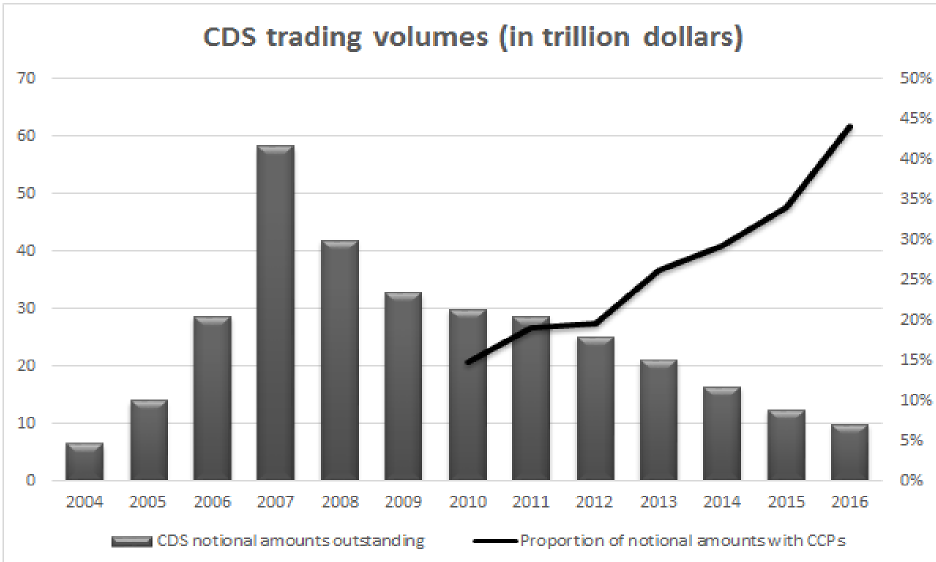

Figure 2: Comparison of CDS Spreads.

This figure compares the CDS spreads of cleared and non-cleared entities. *CDS spread* is the composite spread for the five-year tenor and is obtained from *Markit*. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the average daily CDS spread of the treatment group and the control group respectively. Both groups are constructed based on propensity score matching.

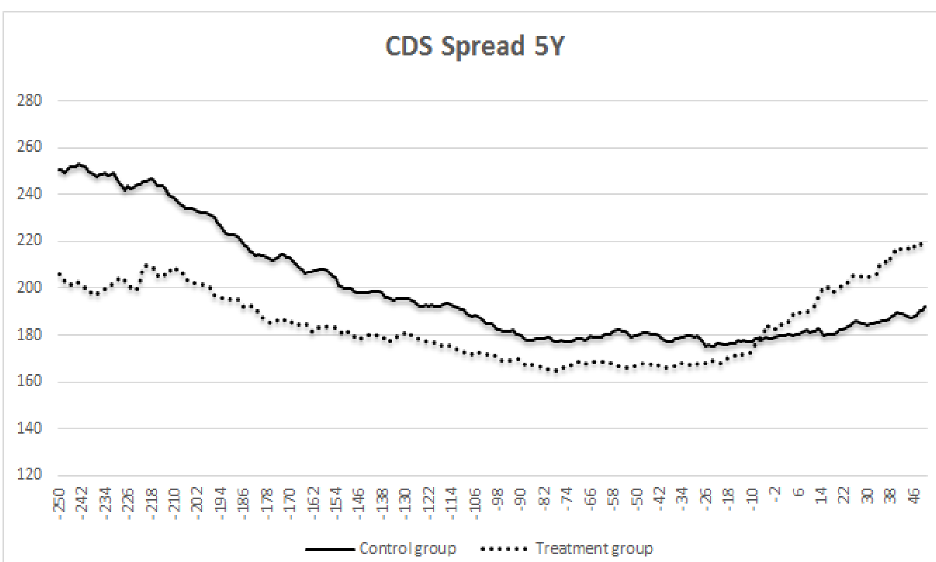

Figure 3: Comparison of Relative Quoted Spreads.
This figure compares the RQS of cleared and non-cleared entities. *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the average daily RQS of the treatment group and the control group respectively. Both groups are constructed based on propensity score matching.

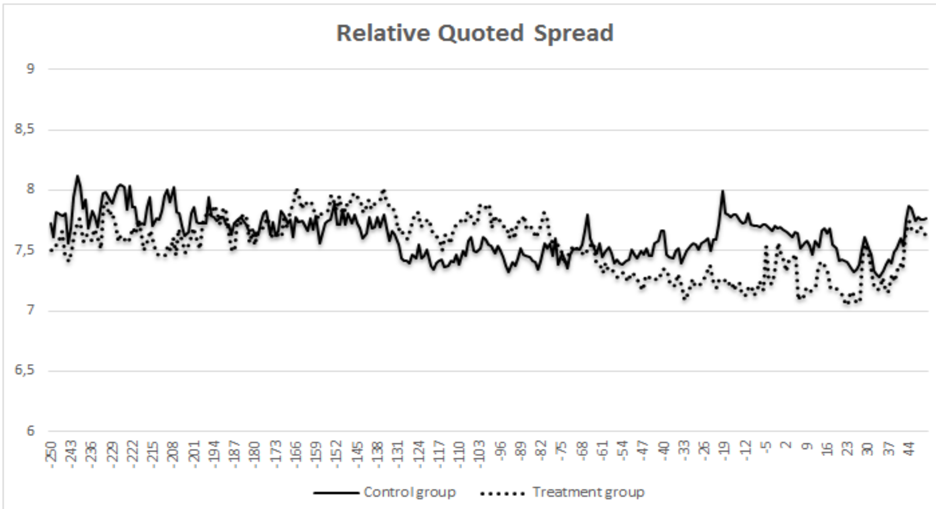

Figure 4: Comparison of Composite Depths.
This figure compares the Composite Depths of cleared and non-cleared entities. *Composite depth* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the average daily composite depth of the treatment group and the control group respectively. Both groups are constructed based on propensity score matching.

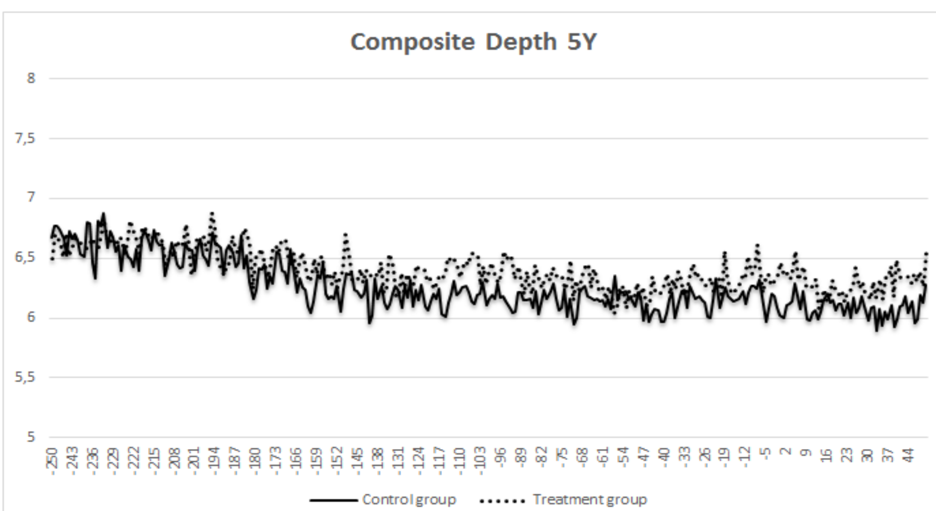

Figure 5: Comparison of Gross Notional Amounts.
This figure compares the gross notional amounts of cleared and non-cleared entities. This variable represents the sum of CDS contracts bought (or equivalently sold) for each reference entity. The data is on a weekly basis and is obtained from *DTCC*. The x-axis represents the event time in weeks where 0 denotes the week of beginning of central clearing. The dotted and solid lines represent the weekly average gross notional amounts of the treatment group and the control group respectively. Both groups are constructed based on propensity score matching.

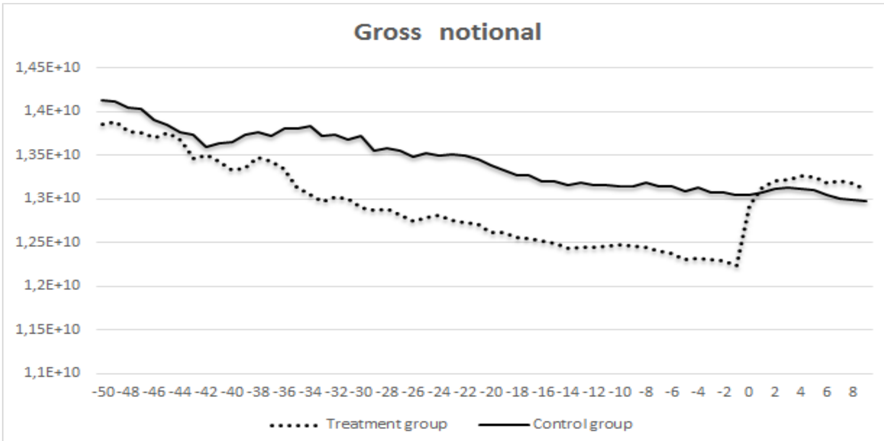

Figure 6: Comparison of Net Notional Amounts.
This figure compares the net notional amounts of cleared and non-cleared entities. This variable represents the sum of the net protection bought by net buyers (or equivalently sold by net sellers). The data is on a weekly basis and is obtained from *DTCC*. The x-axis represents the event time in weeks where 0 denotes the week of beginning of central clearing. The dotted and solid lines represent the weekly average net notional amounts of the treatment group and the control group respectively. Both groups are constructed based on propensity score matching.

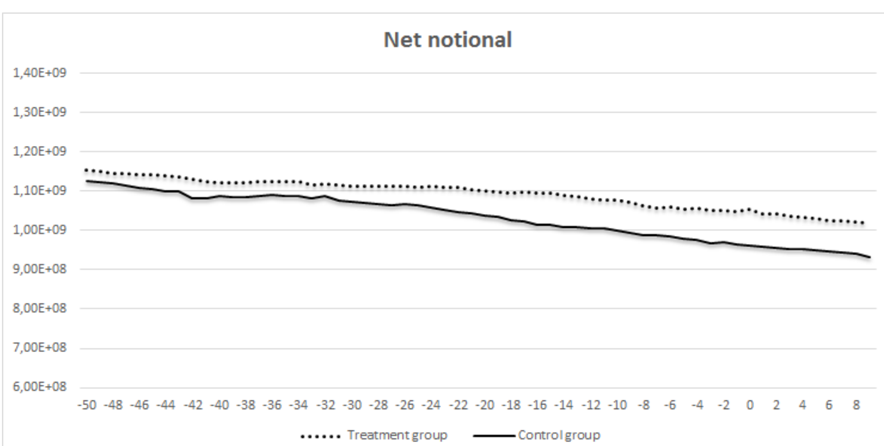

Figure 7: Comparison of Par Equivalent CDS Spreads.

This figure compares the Par Equivalent CDS Spreads (PECS) of cleared and non-cleared entities. This variable measures the default spread of the underlying bond and is computed using the J.P. Morgan methodology. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average PECS of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

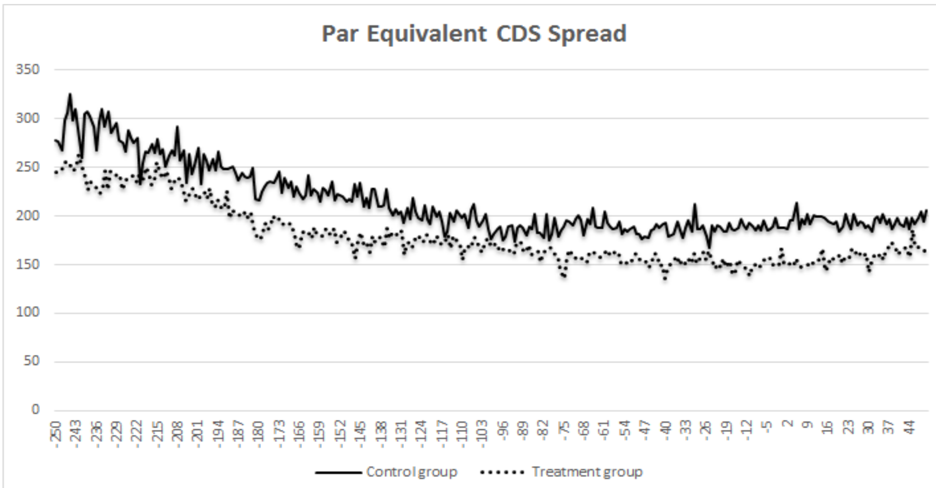

Table 1: Impact of Central Clearing

This table summarizes the different empirical results about the impact of central clearing on the CDS market. Cells indicate the findings of each paper, the source and the range of data, and the employed methodology.

	Slive et al. (2012)	**Loon and Zhong (2014)**	**Kaya (2017)**	**Du et al. (2018)**	**This work**
Period & CDS Data	11/2008 - 07/2011 DTCC + Markit + Bloomberg + ICECC	01/2009 - 12/2011 DTCC + Markit + CMA + ICECC	01/2009 - 06/2013 Bloomberg + ICECC	01/2010 - 12/2013 DTCC + Markit	01/2009 - 12/2015 DTCC + Markit + Bloomberg + CMA + ICECC
Impact on CDS spreads		Increase Methodology : event study	Increase Methodology : panel regression	No change / Decrease Methodology : DID and panel regression	Increase Methodology : Generalized DID + PS matching
Impact on liquidity	Slight Improvement Methodology : Event study + PS matching	Improve Methodology : DID + PS matching			No change Methodology : Generalized DID + PS matching
Impact on trading activity	Improve Methodology : event study + PS matching	Improve Methodology : DID + PS matching			No change Methodology : Generalized DID + PS matching
Impact on bonds default risk					No change Methodology : Generalized DID + PS matching
Impact on counterparty risk		Reduced Methodology : panel regression	No change Methodology : panel regression		
Impact on costs			Increase Methodology : panel regression		

Table 2: Clearing Dates.

This table presents the clearing dates and the number of cleared entities per date for North-American firms cleared from 2009 to 2015. This information is obtained from *ICECC*.

Clearing date	Number of cleared entities
21-Dec-09	2
11-Jan-10	3
01-Feb-10	2
15-Feb-10	14
08-Mar-10	9
29-Mar-10	15
19-Apr-10	8
10-May-10	12
07-Jun-10	1
06-Jul-10	1
09-Aug-10	7
30-Aug-10	8
28-Mar-11	9
11-Apr-11	8
02-May-11	7
13-Jun-11	9
14-Nov-11	3
09-Oct-12	5
22-Oct-12	6
05-Nov-12	8
19-Nov-12	1
30-Sep-13	7
23-Jun-14	9
07-Jul-14	9
21-Jul-14	11
04-Aug-14	12
20-Jul-15	9
03-Aug-15	10
17-Aug-15	7

Table 3: List of Variables.

This table presents the list of all the variables, their definitions and the prediction for the interaction term in the DID regression. The variables are obtained from Markit, Markit liquidity, CMA, Bloomberg and DTCC.

Variable	Symbol	Definition	Prediction for the interaction term
Five-year CDS spread	CDS spread	Composite spread for the five-year tenor	Positive
Composite depth	Comp depth	Number of contributors whose CDS spreads have been used to calculate the five-year CDS spread	Positive
Relative quoted spread	RQS	The bid-ask spread divided by the spread midpoint for the five-year tenor	Negative
Upfront five-year bid-ask spread	Upf 5Y BA spread	Bid-ask spread in upfront points for the five-year tenor	Negative
Dealers count	Dealers count	Total number of distinct dealers quoting the reference entity across all available tenors	Positive
Quotes count	Quotes count	Total number of unique quotes for a reference entity, all tenors combined	Positive
Liquidity score	Liquidity score	Defined on a scale from 1 to 5 where 1 indicates the highest liquidity	Negative
Five-year dealers count	5Y dealers count	Total number of distinct dealers quoting the reference entity for the five-year tenor	Positive
Five-year quotes count	5Y quotes count	Total number of unique quotes for a reference entity for the five-year tenor	Positive
Non five-year dealers count	Non 5Y dealers count	Total number of distinct dealers quoting the reference entity for the non five-year tenors	Positive
Non five-year quotes count	Non 5Y quotes count	Total number of unique quotes for a reference entity for the non five-year tenors	Positive
Gross notional amounts	Gross not	Sum of CDS contracts bought (or equivalently sold) for each reference entity	Positive
Net notional amounts	Net not	Sum of the net protection bought by net buyers (or equivalently sold by net sellers)	Positive
Contracts	Contracts	Number of contracts outstanding for each CDS contract	Positive
Gross notional - Risk transfer	Gross not risk	Captures transaction types that result in a change in the market risk position	Positive
Contracts - Risk transfer	Contracts risk	Number of contracts involved in market risk transfer	Positive
Par Equivalent CDS Spread	PECS	Bond default risk measure based on the J.P. Morgan methodology	Positive

Table 4: Probit Estimation.

This table presents four probit estimations including each time a different combination of variables and fitted on cleared and non-cleared entities.

$$Pr(Y = 1|X) = \Phi(X^T\beta)$$

Y is a binary variable that equals 1 if the firm is centrally cleared by ICECC during 2009-2015 and 0 otherwise, Φ is the cumulative distribution function of the standard normal distribution and X^T is the transpose of the vector of regressors that influence the outcome Y. The vector of parameters β is estimated by maximum likelihood. We use data in the six-month period defined by the firm-semester to compute the average of each regressor. *CDS spread* is the composite spread for the five-year tenor. *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. *Composite depth* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. *Contracts* is the number of contracts outstanding for each CDS contract. *Contracts*^{2} is the squared of *Contracts*. *Net Not* is the sum of the net protection bought by net buyers (or equivalently sold by net sellers). *Net Not*^{2} is the squared of *Net Not*. *Industry dummies* are constructed based on the ten following sectors: telecommunications services, healthcare, technology, basic materials, utilities, industrials, financials, energy, consumer services and consumer goods. N is the number of firm-semesters. Numbers in parentheses are standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	Model 1	Model 2	Model 3	Model 4
CDS spread	-0.00145***	-0.00143***	-0.00141***	-0.00127***
	(0.000218)	(0.000218)	(0.000217)	(0.000208)
Contracts	7.77e-05***	0.00157***	0.00152***	
	(2.39e-05)	(0.000151)	(0.000156)	
Contracts^2		-2.70e-07***	-2.64e-07***	
		(2.96e-08)	(2.99e-08)	
RQS	-0.106***	-0.0904***	-0.0899***	-0.0946***
	(0.0127)	(0.0132)	(0.0132)	(0.0129)
Comp depth			0.0379	0.0913***
			(0.0316)	(0.0297)
Net not				7.91e-10***
				(1.24e-10)
Net not^2				-1.8e-19***
				(3.00e-20)
Constant	-0.597***	-2.391***	-2.571***	-1.620***
	(0.216)	(0.275)	(0.314)	(0.276)
Industry dummies	Yes	Yes	Yes	Yes
Pseudo R^2	0.121	0.2155	0.2163	0.1645
LR Chi^2	219.54	391.12	392.56	298.67
Log likelihood	-797.80	-712.02	-711.30	-758.24
N	7,102	7,102	7,102	7,102

Table 5: Balancing Tests.

This table presents balancing tests between the treated and matched samples. In Panel A we compare the means of the two groups and we compute the standard bias which is the difference between the means of the two groups scaled by the average standard deviations. *CDS spread* is the composite spread for the five-year tenor. *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. *Composite depth* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. *Contracts* is the number of contracts outstanding for each CDS contract. *Contracts*^{2} is the squared of *Contracts*. In panel B, we fit the Probit model first on the unmatched sample and then on the matched sample to test if the same variables that were useful to decide if a company is eligible for central clearing are still able to perform the same task after matching.

Panel A : Mean comparison

Variable	Sample	Mean Treated	Mean Control	% bias	% bias reduction
CDS Spread	Unmatched	173.2	241.01	-13.6	81.9
	Matched	173.2	185.47	-2.5	
Contracts	Unmatched	2260.2	1511.5	61.6	
	Matched	2260.2	2280.9	-1.7	97.2
Contracts^2	Unmatched	6,00E+06	4,30E+06	20.2	
	Matched	6,00E+06	6,10E+06	-1	94.9
RQS	Unmatched	7.672	12.339	-74.3	
	Matched	7.672	7.459	3.4	95.4
Comp depth	Unmatched	6.3666	5.2254	81.2	
	Matched	6.3666	6.236	9.3	88.6

Panel B : Probit estimations

Sample	Pseudo R^2	Likelihood ratio Chi^2	p>Chi^2	Mean bias	Median bias
Unmatched	0.216	392.56	0.000	25.4	16.5
Matched	0.014	7.69	0.905	4.9	3.4

Table 6: Difference-in-Differences Analysis for CDS Spreads

This table presents the estimates of the generalized DID equation. The dependent variable *CDS spread* is the composite spread for the five-year tenor. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. In each column we estimate the equation using a different estimation window around the central clearing date. In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$CDS\ Spread_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

CDS Spread	[-250 , 50]	[-250 , 20]	[-100 , 50]	[-100 , 20]
Cleared	19.2**	18.2**	10.1*	8.37*
	(8.38)	(7.79)	(5.57)	(4.70)
Constant	385.4***	386.6***	166.4***	164.1***
	(73.2)	(72.2)	(18.4)	(18.8)
Observations	102,691	93,139	53,035	42,777
Number of firms	298	298	298	298
R-squared	0.224	0.224	0.260	0.247
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 7: Difference-in-Differences Analysis for the Relative Quoted Spread.

This table presents the estimates of the generalized DID equation. The dependent variable *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. In each column we estimate the equation using a different estimation window around the central clearing date. In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$RQS_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

RQS	[-250 , 50]	[-250 , 20]	[-100 , 50]	[-100 , 20]
Cleared	-0.0194	-0.0161	0.0173	-0.00285
	(0.151)	(0.0612)	(0.149)	(0.0609)
Constant	5.21***	7.00***	9.95***	6.70***
	(0.763)	(1.67)	(1.18)	(0.410)
Observations	102,591	93,07	52,947	42,720
Number of firms	298	298	298	298
R-squared	0.159	0.019	0.174	0.031
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 8: Difference-in-Differences Analysis for Composite Depth.

This table presents the estimates of the generalized DID equation. The dependent variable *Composite depth* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. In Each column we estimate the equation using a different estimation window around the central clearing date. In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Composite\ depth_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Comp depth	[-250 , 50]	[-250 , 20]	[-100 , 50]	[-100 , 20]
Cleared	-0.0171	0.0264	0.00627	0.0376
	(0.0273)	(0.0295)	(0.0457)	(0.0327)
Constant	5.965***	6.651***	7.150***	5.686***
	(0.460)	(0.460)	(0.571)	(0.800)
Observations	102,691	93,139	53,035	42,777
Number of firms	298	298	298	298
R-squared	0.018	0.019	0.266	0.028
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 9: Difference-in-Differences Analysis for Liquidity Measures.

This table presents the estimates of the generalized DID equation by using different liquidity measures obtained from *Markit Liquidity*. In each column, the dependent variable *Factor* is replaced with a new liquidity measure. The estimation window is [-250, 50] days around the central clearing date. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. *Upf 5y BA spread* is the bid-ask spread in upfront points for the five-year tenor. *Dealers count* is the total number of distinct dealers quoting the reference entity across all available tenors. *Quotes count* is the total number of unique quotes for a reference entity, all tenors combined. *Liquidity score* is calculated by Markit and is defined on a scale from 1 to 5 where 1 indicates the highest liquidity. *5Y Dealers count* is the total number of distinct dealers quoting the reference entity for the five-year tenor. *5Y Quotes count* is the total number of unique quotes for a reference entity for the five-year tenor. Data about the remaining tenors is given by the variables *Non 5Y Dealers count* and *Non 5Y Quotes count.* In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Liqduidity\ measure_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Liquidity measures	Upf 5Y BA spread	Dealers count	Quotes count	Liquidity score	5Y Dealers count	5Y Quotes count	Non 5Y Deal count	Non 5Y Quot count
Cleared	6.55e-05	-0.269	-1.114	0.0553*	-0.0655	-0.397	-0.118	0.0764
	(4.27e-05)	(0.181)	(1.578)	(0.0293)	(0.120)	(0.819)	(0.315)	(0.788)
Constant	0.00599***	7.428***	55.69***	0.974***	6.847***	26.81***	23.83***	32.87***
	(4.54e-05)	(0.208)	(2.268)	(0.0361)	(0.197)	(1.486)	(0.399)	(0.928)
Observations	74,167	74,167	74,167	74,167	39,699	39,712	34,577	34,578
Number of firms	212	212	212	212	123	123	123	123
R-squared	0.023	0.022	0.023	0.024	0.047	0.047	0.050	0.046
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: Difference-in-Differences Analysis for the Open Interest Measures.

This table presents the estimates of the generalized DID equation by using different open interest measures obtained from *DTCC*. In each column, the dependent variable *Factor* is replaced with a new open interest measure. The estimation window is [-50, 10] weeks around the central clearing date. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. *Gross not* is the sum of CDS contracts bought (or equivalently sold) for each reference entity. *Net not* is the sum of the net protection bought by net buyers (or equivalently sold by net sellers. *Contracts* is the number of contracts outstanding for each CDS contract. *Gross not Risk* Captures transaction types that result in a change in the market risk position. *Contracts Risk* is the number of contracts involved in market risk transfer. In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Open\ interest\ measure_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Trading Activity	Gross Notional	Net Notional	Contracts	Gross Notional Risk	Contracts Risk
Cleared	1.072e+09***	-1.303e+06	19.29	5.039e+06	-1.117
	(1.509e+08)	(1.539e+07)	(18.88)	(7.264e+06)	(1.386)
Constant	1.472e+10***	1.388e+09***	2,312***	9.570e+07***	21.71***
	(6.617e+08)	(5.805e+07)	(73.83)	(1.625e+07)	(3.545)
Observations	20,389	20,389	20,389	12,452	12,452
Number of firms	296	296	296	237	237
R-squared	0.403	0.386	0.433	0.301	0.317
Firm FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Table 11: Difference-in-Differences Analysis for the Par Equivalent Spread.

Table 8 reports the estimates of the generalized DID equation. The dependent variable *PECS* measures the bond's default risk and is measures using the J.P. Morgan methodology. Subscripts i and t denote the firm i and day t. $Cleared_{i,t}$ is a binary variable that indicates if the reference entity i is centrally cleared at day t or not. α_i is the firm fixed effects and γ_t is the daily fixed effects. β_0 is a constant term. In Each column we estimate the equation using a different estimation window around the central clearing date. In all our regressions, the standard errors are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$PECS_{i,t} = \beta_0 + \beta_1 cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

PECS	[-250 , 50]	[-250 , 20]	[-100 , 50]	[-100 , 20]
Cleared	3.025	2.533	-6.317	5.900
	(8.503)	(8.311)	(4.476)	(3.943)
Constant	528.0***	526.3***	365.2***	369.9***
	(24.33)	(25.64)	(21.11)	(20.70)
Observations	36,659	33,292	19,263	15,568
Number of firms	121	121	121	121
R-squared	0.443	0.453	0.338	0.319
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Online Appendix

Appendix A : Matching example

In this appendix, we present a detailed example of the matching procedure. For illustration purposes, let us assume that we have data about a small sample of four firms, A, B, C, and D, for the 2009–2015 period. Firms A and B were centrally cleared on December 21, 2009 and on March 28, 2011, respectively. Firms C and D were not centrally cleared during our sample period. Since our event window is $[-8, -2]$ months before the clearing date, we consider data from 21/04/2009 to 21/10/2009 for firm A, and from 28/07/2010 to 28/01/2011 for firm B. On the other hand, we assume that firms C and D have the possibility of being centrally cleared on either December 21, 2009, or March 28, 2011. Therefore, we create the following firm-semesters:
C_1: From 21/04/2009 to 21/10/2009, the new firm-semester if C decided to adhere to central clearing on December 21, 2009
C_2: From 28/07/2010 to 28/01/2011, the new firm-semester if C decided to adhere to central clearing on March 28, 2011
D_1: From 21/04/2009 to 21/10/2009, the new firm-semester if D decided to adhere to central clearing on December 21, 2009
D_2 : From 28/07/2010 to 28/01/2011, the new firm-semester if D decided to adhere to central clearing on March 28, 2011

A and B constitute our treatment group and could be matched to any firm-semester in the control group: C_1, C_2, D_1, and D_2. We apply the Probit model to the set of our six firm-semesters and match each firm in the treatment group based on the closest propensity score. For instance, if A is matched to D_1 and B is matched to C_2, then the new control group is D_1 and C_2. The treatment group remains the same (A and B), and the control firms that are not matched are dropped from the sample. Next, we generalize this reasoning to our full sample. This procedure allows us to construct a new control group that exhibits similar pre-clearing characteristics to the treatment group, and thus eliminate the potential selection bias.

Appendix B : Additional figures

Figure B.1: Comparison of Upfront 5Y bid-ask spread

This figure compares the upfront five-year bid-ask spreads of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the bid-ask spread in upfront points for the five-year tenor. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average upfront bid-ask spread of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

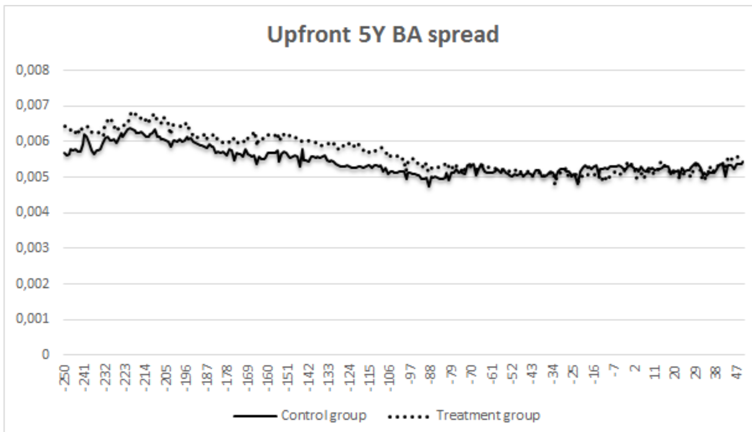

Figure B.2: Comparison of Liquidity scores

This figure compares the liquidity scores of cleared and non-cleared entities. This variable is calculated by *Markit Liquidity* and is defined on a scale from 1 to 5 where 1 indicates the highest liquidity. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average liquidity score of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

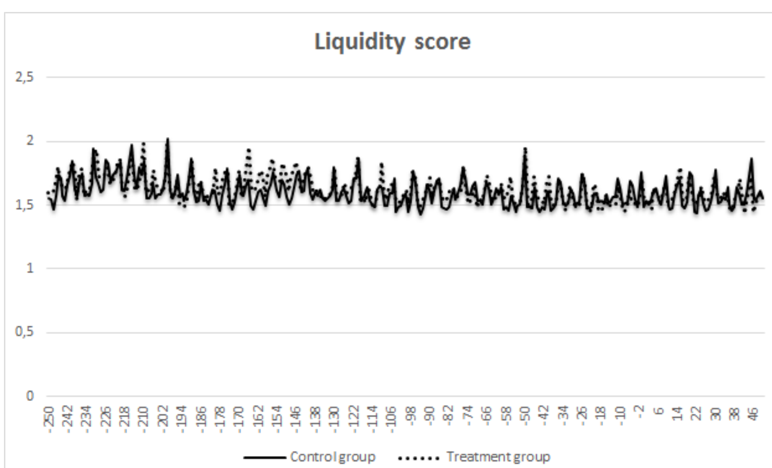

Figure B.3: Comparison of Quotes count

This figure compares the quotes count of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of unique quotes for a reference entity, all tenors combined. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average quotes count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

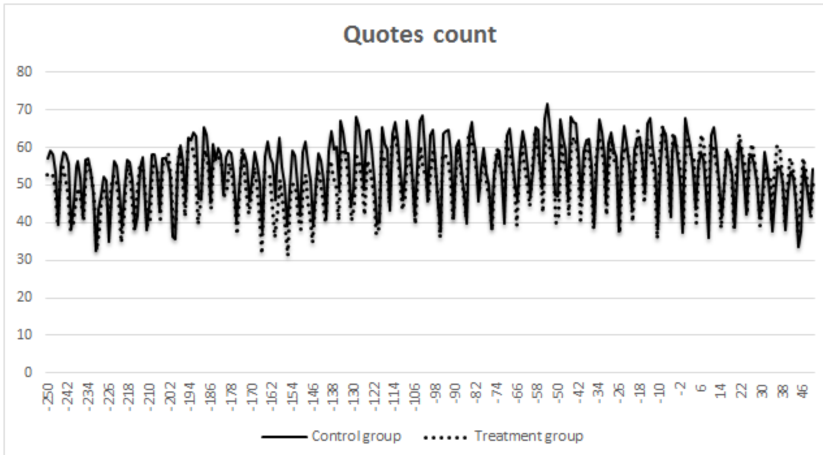

Figure B.4: Comparison of Dealers count

This figure compares the dealers count of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of distinct dealers quoting the reference entity across all available tenors. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average dealers count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

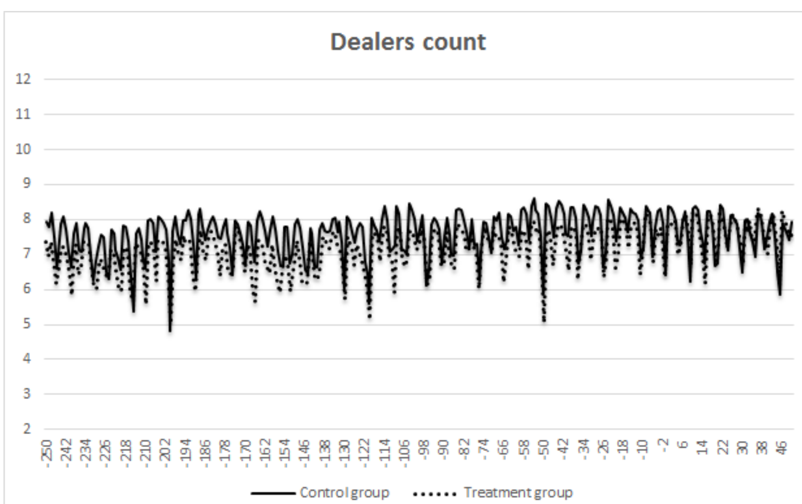

Figure B.5: Comparison of Dealers count 5Y

This figure compares the dealers count for the five-year tenor of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of distinct dealers quoting the reference entity for the five-year tenor. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average of the five-year dealers count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

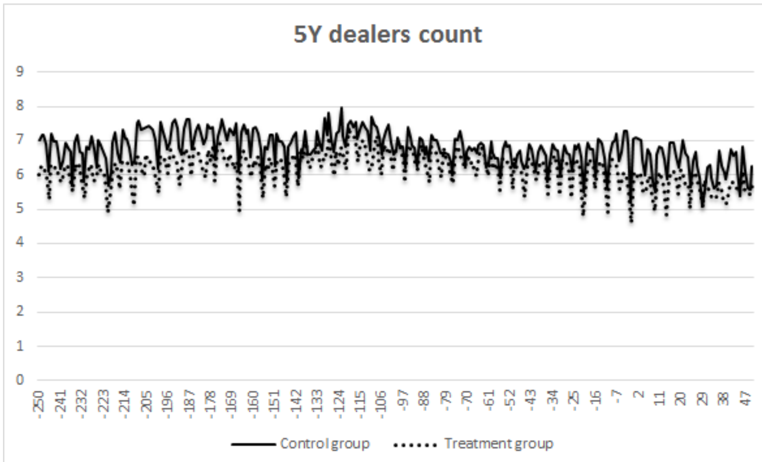

Figure B.6: Comparison of Quotes count 5Y

This figure compares the quotes count for the five-year tenor of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of unique quotes for a reference entity for the five-year tenor. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average of the five-year quotes count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

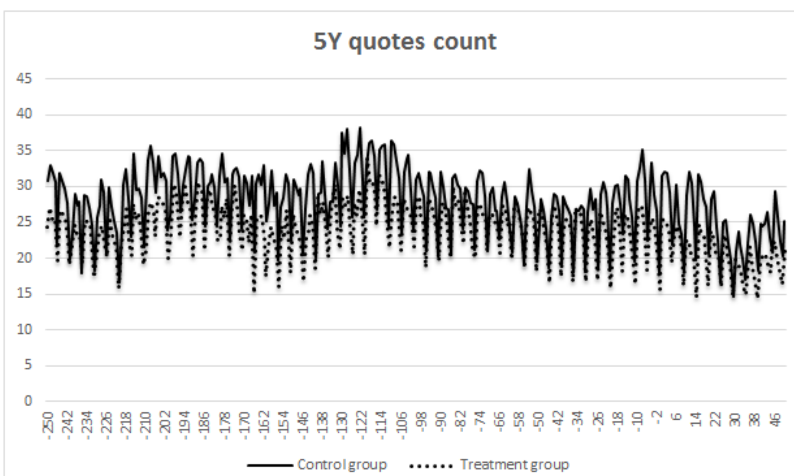

Figure B.7: Comparison of Dealers count non 5Y

This figure compares the dealers count for the non-five-year tenors of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of distinct dealers quoting the reference entity for the non-five-year tenors. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average of the non-five-year dealers count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

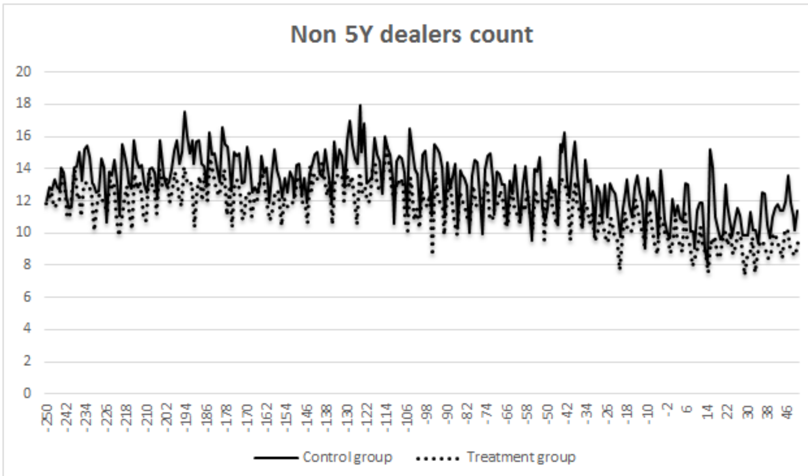

Figure B.8: Comparison of Quotes count non 5Y

This figure compares the quotes count for the non-five-year tenors of cleared and non-cleared entities. This variable is obtained from *Markit Liquidity* and represents the total number of unique quotes for a reference entity for the non-five-year tenor. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the daily average of the non-five-year quotes count of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

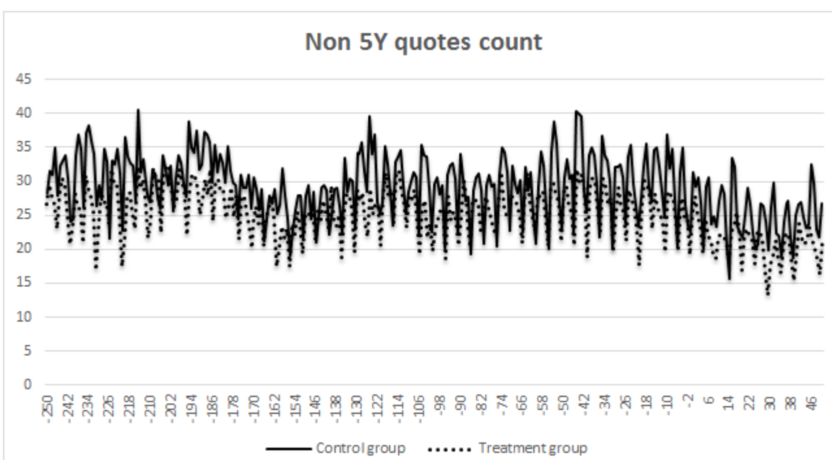

Figure B.9: Comparison of the number of contracts

This figure compares the number of contracts outstanding for each CDS contract of cleared and non-cleared entities. The data is on a weekly basis and is obtained from *DTCC*. The x-axis represents the event time in days where 0 denotes the day of beginning of central clearing. The dotted and solid lines represent the weekly average number of contracts of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

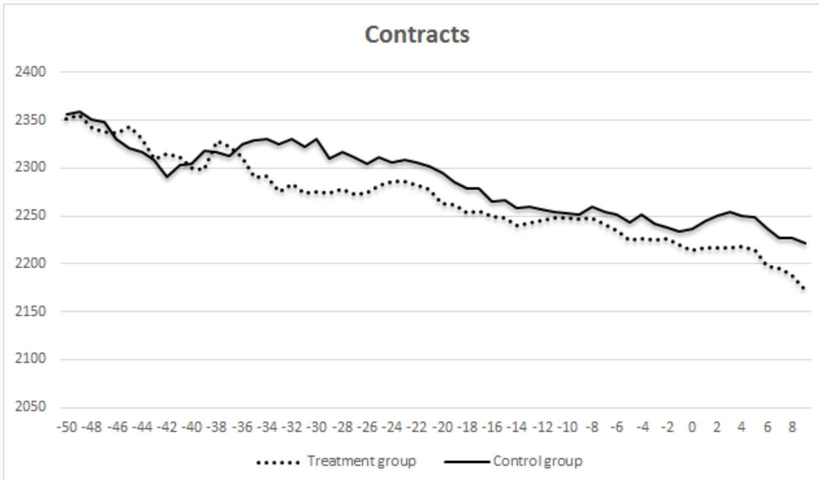

Figure B.10: Comparison of Gross notional amounts - Risk transfer

This figure compares the gross notional amounts of cleared and non-cleared entities. This variable represents the sum of CDS contracts bought (or equivalently sold) for each reference entity and captures transaction types that result in a change in the market risk position. The data is on a weekly basis and is obtained from *DTCC*. The x-axis represents the event time in weeks where 0 denotes the week of beginning of central clearing. The dotted and solid lines represent the weekly average gross notional amounts of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.

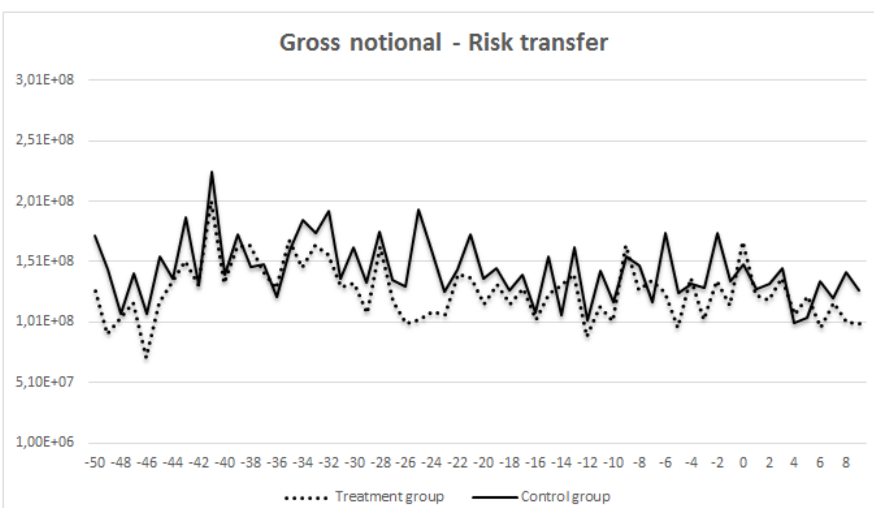

Figure B.11: Comparison of the number of contracts involved in a risk transfer activity
This figure compares the number of contracts outstanding for each CDS contract of cleared and non-cleared entities. This variable captures contracts involved in a market risk transfer activity. The data is on a weekly basis and is obtained from *DTCC*. The x-axis represents the event time in weeks where 0 denotes the week of beginning of central clearing. The dotted and solid lines represent the weekly average number of contracts of the treatment group and the control group respectively. The two groups are constructed based on propensity score matching.