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

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Abstract

In this paper, we revisit the impact of the voluntary central clearing scheme on the CDS market. In order to address the endogeneity problem, we use a robust methodology that relies on dynamic propensity-score matching combined with generalized difference-in-differences. Our empirical findings show that central clearing results in a small increase (estimated at 19 bps) 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 can be mainly attributed to a reduction in CDS counterparty risk.

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Keywords: Credit default swaps, central clearing, counterparty risk, liquidity, trading activity, bond default spread, difference-in-differences.

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1 Introduction

Credit default swaps (CDS) 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. When they were first introduced, CDS 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 (see Acharya, Philippon, Richardson & Roubini 2009 and Acharya, Engle, Figlewski, Lynch & Subrahmanyam 2009). 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 that mainly consisted of 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 CDS. 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. In a generalized difference-in-difference setting, we revisit 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 bonds during the same period. Our contribution is twofold. First, in order to address the endogeneity problem originating from the voluntary choice of adhering to central clearing, we propose the use of a different propensity-score matching approach. This matching approach allows us to account for a variety of treatment dates and is therefore better suited to the structure of the data set. We then show that the choice of a matching approach plays a significant role in the evaluation of the impact of the introduction of a CCP, and that differences between our results and those obtained in the previous literature are mainly explained by differences in methodology. 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 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) use an event study and 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. Kaya (2017), using panel regression in a limited sample of non-financial firms, reports an increase in CDS spreads after central clearing. 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 that is passed on to end-users. Du, Gadgil, Gordy, and Vega (2018) investigate the impact of counterparty credit risk on the pricing of CDS using confidential data from the Depository Trust and Clearing Corporation (DTCC). They analyze the effects of the introduction of central clearing on CDS prices using a panel regression of cross-sectional variations of CDS spreads. Their findings show that counterparty risk has negligible effects on CDS spreads and that centrally-cleared trades have significantly lower spreads than uncleared interdealer trades. They argue that this latter result could be attributed to the impact of a more transparent centrally-cleared market on the competitive structure. They also conclude that this finding is consistent with market participants' managing counterparty risk, which would result in a modest impact of counterparty risk on the pricing of CDS contracts.

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. They use an event study methodology and 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 then combine a DID approach with a static propensity-score matching to provide evidence of an improvement in CDS liquidity as well as in trading activity.

While the framework of our paper is close to theirs, our methodology, scope, and findings are different. We focus on the changes in CDS spreads using the DID methodology. Our approach aims at eliminating the selection bias by proposing two improvements. First, we improve the matching technique, relying on firm data just prior to the move to central clearing, instead of using a fixed estimation period to match all the firms. Second, we estimate a generalized DID model including time and firm fixed effects. As in Loon and Zhong (2014), we obtain an increase in CDS spreads. The main difference between our results and theirs is that we do not find any significant impact of the move to central clearing on CDS liquidity, nor on trading activity. We show that this difference in results can be attributed to the improvements in the methodology. Finally, we also consider the effect of central clearing on bond default spread and find no effect.

Table 1 summarizes the main features of the literature dealing with the impact of central clearing on the CDS market, highlighting the differences in data sets, 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 and discusses other potential factors that may have affected the CDS spread. Section 6 is a conclusion.

2 The CDS market

2.1 CDS prices and their determinants

In a credit default swap 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*, when the default event occurs. This payment is considered as a 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 λ_t. Given a bond with a unit par value, 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 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 equilibrium premium s is 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 contract is not affected by liquidity, trading activity, or 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 they 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 (i.e., the so-called *wrong-way risk*), 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 subject 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 The principles of central clearing

In recent years, CDS contracts have become very attractive tools 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[1].

[Figure 1 about here]

Because of the large size of their market and because of their interconnectedness with other derivatives, CDS 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. 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. 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. 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[2].

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 CDS 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 CDS remains 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. 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).

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

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

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. 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 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 application areas 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, we opt for a generalized DID framework with firm and time fixed effects.

Since its introduction in 2009, central clearing for single-name CDS has been conducted on a voluntary basis. Note that when subjects can choose to take the treatment or not, the two groups are more likely to differ and, therefore, estimates may be biased due to this endogeneity issue.[3]

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 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, 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.

3.1 Generalized DID with dynamic matching

To apply DID, we need to compose a treatment and a control group containing firms that have similar characteristics just before the treatment event. The first step consists of constructing a sample of candidate treatment and control entities, and computing their propensity scores on the basis of pre-clearing characteristics. Specifically, we consider the 29 clearing dates

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

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-event entities. The sample also contains the cleared firms, paired with the event corresponding to their clearing date.

[Table 2 about here]

We then estimate the following Probit model, using the sample of cleared and non-cleared firm-event 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 obtained by maximum likelihood and is used to estimate the probability, for each firm-event entity, of being accepted for central clearing. This probability is the *propensity score* associated to a combination of a firm and a possible clearing date. We estimate the regressors by averaging them over a window of $[-8, -2]$ months before the relevant event, where the two months immediately prior to the clearing date are excluded so that the data does not contain any market anticipation. The propensity score of a given control firm-event entity thus indicates the probability of the firm being selected for central clearing, were it to decide to adhere to a CCP at the corresponding clearing date.

The second step consists of matching cleared and non-cleared entities on the basis of the propensity scores. We match with replacement each cleared firm with its closest neighbor from the group of non-cleared firm-event entities. Our final sample is then composed of matched firm-event entities. A detailed example of the matching procedure is provided in Appendix A.

We then apply generalized DID regression to the matched sample in order to test for the presence of statistically significant impact factors. Using a generalized DID framework allows us to account for the different treatment times of CDS contracts. More specifically, to isolate the effect of central clearing on a given factor, 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 subscript i denotes a firm-event entity and subscript t denotes a date in the event window. The dependent variable $Factor_{i,t}$ will take various definitions in order to investigate the impact of central clearing on CDS spreads, liquidity, trading activity, as well as on bond default spreads. The main explanatory variable $Cleared_{i,t}$ is a binary variable that indicates whether the reference entity i is centrally cleared or not on 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.

3.2 Standard DID with static matching

In order to assess the robustness of our findings to the choice of methodology, we apply to our sample the methodology used in Loon and Zhong (2014) to analyze liquidity and trading activity. This methodology consists of using data from a fixed period (a window prior to December 2009) to estimate the Probit model (4) and then matching with replacement each cleared entity with the five noncleared entities that have the closest propensity score.

The difference-in-difference is then evaluated by comparing, around the treatment date, the change in the relevant factor of a cleared firm with the average change in the corresponding matched firms. We call this procedure *static matching*; under this matching procedure, a firm cleared in 2011, for example, is matched with a control firm that had similar characteristics to it in 2009.

We argue that the period over which the independent variables are measured is important for the performance of the matching operation and the elimination of the selection bias. Clearly, a firm's financial situation can change considerably over time, making a good match in 2009 no longer valid two years later. The dynamic matching procedure outlined above matches cleared firms with firms that are similar to them at the moment of their decision to adhere to central clearing. Our experiments indicate that the differences between our findings and those of Loon and Zhong (2014) can be mainly explained by the difference in methodology.

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 (CDS_Spr). 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 ($Comp\_Dep$), 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 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 (*Upf_BA*) and the Markit liquidity score (*Liq_sc*), defined on a scale from 1 to 5, where 1 indicates the highest liquidity. During this period, we also have the Quotes count (*Quotes*) and the Dealers count (*Dealers*), 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 (*5Y_Quotes*) and the Five-year dealers count (*5Y_Dealers*), 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 (*Non_5Y_Quotes*) and Non five-year dealers count (*Non_5Y_Dealers*).

4.2 Trading activity data

The data on trading activity is obtained from the Depository Trust and Clearing Corporation, which covers approximately 98% of all credit derivative transactions in the global marketplace. The first available report is for the week that ended on October 31, 2008.

For each entity, we have weekly information on the gross and net notional amounts outstanding, i.e., the par amount of credit protection that is bought or sold, as well as the number of contracts outstanding. 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 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, 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 all these trades do not change the risk profile. 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 (*Gross_Not*), Net notional amounts (*Net_Not*), Contracts (*Contr*), Gross notional–Risk transfer (*Gross_Not_Risk*), and Contracts–Risk transfer (*Contr_Risk*).

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 CDS 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. We keep entities that had a renaming event since this 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, of which 198 are centrally cleared. Our sample for the Probit estimation contains 7,102 firm-events. The final matched sample for the DID consists of the 198 cleared firms and their corresponding non-cleared firm-events.[4]

4.4 Bond data

To analyze the impact of central clearing on the default probability in the underlying bond market, we need to construct a bond default spread measure, since default spread is not observed in the market. To do so, we implement the J.P. Morgan Par Equivalent CDS Spread (PECS) methodology.

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. 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.

Since most of the bonds in the data set are callable, we need to apply a correction to the maturity in the computation of the PECS. For investment-grade bonds, we keep the original maturity since the bonds are not likely to be called. For callable 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 has not yet been called, then the calculation of the YTW is based on all the remaining call dates. This adjusted maturity reflects the worst scenario for a bondholder.

[4] Because the match is made with replacement and because a firm can be matched at various event dates, the total number of control firms in the final sample is 100.

We then compute the daily default spread measure of the bond associated to each CDS contract using the following steps:

- Bootstrap default probabilities from the associated 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 computed present value matches the bond's market price. The shift is obtained by solving a minimization problem.
- Compute survival probabilities using these implied probabilities and use the traditional CDS pricing equation (3) to compute an implied CDS spread. This spread is the variable $PECS$, which is a measure of bond default risk.

4.5 Variables

Table 3 provides the list of all the variables used in our analysis, along with the expected sign of the interaction term in the DID regression. 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, liquidity and trading activity following central clearing, as compared to the control group. This translates into a positive sign for the coefficient (β_1) in equation (5) for the case of CDS spread, liquidity, and trading-activity variables and a negative sign for this coefficient in the case of illiquidity variables.

[Table 3 about here]

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 criterion, 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.

In Table 4, we present four different specifications, including different combinations of variables, in order to select the best model. In all four specifications, variables are statistically significant and have the expected sign, in line with the ICECC requirements. 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, which has the highest log likelihood ratio and 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 evaluate the quality of this matching and investigate whether a selection bias is present, using various statistics presented in Table 5. Panel A compares the mean of each variable included in the model in the treatment and control groups, both before and after the matching. We also compute the standardized bias, which is the difference between the means of the two groups, scaled by the average standard deviations. After the matching, and for all the variables, the 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 be, since the non-cleared firms are similar to 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 by using the generalized DID methodology. Specifically, we test the following hypothesis:

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

We start by plotting in Figure 2 the daily mean CDS spread for the treatment and control groups during a period of $[-250, 50]$ days around the central clearing event (day 0). We first note that both groups have the same pre-treatment trend, which confirms again the matching quality and makes it possible to graphically verify the parallel trend assumption of the difference-in-differences model. We also observe that the mean CDS spread of cleared entities is initially lower, and then increases following the event date. This is consistent with the notion 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, where market participants are willing to pay more to benefit from this advantage. We also observe that the trend increase in the spreads of cleared entities starts on average one week before the clearing date. This pattern could reflect an anticipatory effect by market participants.

[Figure 2 about here]

We then test hypothesis H1 by conducting a difference-in-differences analysis on the matched sample. We estimate Equation (5) with *CDS_Spr* 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 methodology and sample size, this result is in accordance with most of the findings in the literature. Loon and Zhong (2014), using an event study with 132 cleared firms find that the spreads rise with the initiation of central clearing. Kaya (2017), using panel regression, estimates this increase to around 24 bps in a sample of 85 nonfinancial firms. Du et al. (2018) find a decrease in CDS spreads using panel regression with 142 cleared firms.[5]

[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 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 provides 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, or an increase in the underlying bond default risk, may also contribute to this observed surge in the CDS spreads. We assess the potential effects of the other 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 incite more institutions to get involved in CDS

[5] To check the robustness of our estimations, we consider different event windows of various lengths, including the $[-250, 20]$ days considered by Du et al. (2018). All the specifications lead to a positive and statistically significant coefficient, with a lower magnitude for shorter event windows.

trading. On the other hand, the demands 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 of central clearing 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 Figure 3, we plot the evolution of the daily mean of the variables *RQS* and *Comp_Dep* in the control group against that of the treatment group during a period of $[-250, 50]$ days around the central clearing event. 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. Figure 3 shows that the two graphs are very similar and have the same trend over the whole event window. Figures comparing the graphs for other liquidity measures are presented in Appendix B and show similar behavior. Unlike the previous analysis of CDS spreads, where the cleared entities had a different behavior after the clearing event date, none of our liquidity measures exhibit a divergence in trend following the move to a clearinghouse. Overall, this preliminary investigation seems to indicate that CDS liquidity is not affected by the clearing event.

[Figures 3 about here]

We now apply the difference-in-differences analysis to each liquidity measure, used as the dependent variable in Equation (5). We mainly focus on the *RQS* and *Comp_Dep* variables because they fully cover our sample period. For these two measures, we fit the regression equation using different event windows. For all the specifications, presented in Table 7, none of the coefficients of the binary variable *Cleared* are statistically significant, suggesting that central clearing does not have any impact on CDS liquidity.

As a robustness check, we estimate the same equation using the remaining liquidity measures. The results for an event window of $[-250, 50]$ days are reported in Table 8.[6] All interaction coefficients β_1 are negligibly small and statistically nonsignificant, except for the coefficient of the variable *Liq_sc*, which is significant at the 10% level.

Our results suggest that cleared reference entities do not experience any improvement in their liquidity following central clearing. The positive effects caused by the mitigation of counterparty risk and increased transparency may be counterbalanced by the inconvenience of daily margining. It might also be the case that the accepted contracts are already liquid, which makes them less likely to gain any additional liquidity benefit. 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 7–8 about here]

These results differ from those of Slive et al. (2012), who find a slight improvement in liquidity, and, most notably, from those of Loon and Zhong (2014) who find an improvement in liquidity using standard DID with static matching.

To show that the difference in our results may be explained by methodology, we first omit the fixed effects α_i and γ_t from the DID estimation in Equation (5), and find a significant impact for the liquidity variables *RQS* and *Comp_Dep*. We then apply the methodology used in Loon and Zhong (2014) to our data. The results, provided in Table 10, indicate a significant impact for the liquidity variables *RQS* and $Dealers$.

[6] Results for smaller event windows are qualitatively the same.

[Table 10 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 CDS, and 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 increases CDS trading activity.

We employ the same methodology to analyze the five variables provided by DTCC. We construct weekly means for these variables in the control and treatment groups matched with propensity scores over a period of $[-50, 10]$ weeks around the clearing event date. Figure 4, illustrating gross and net notional amounts, respectively, shows that the means in the two groups move together during the pre-treatment period, which again shows that both groups have similar pre-clearing characteristics.

Panel A of Figure 4 shows a surge of around 7% of the mean gross notional amount in the treatment group, while the control group maintains the same trend for the whole event window. Note that this increase is essentially due to the event itself, that is, the transfer of the contracts to a clearinghouse.

For all other trading activity measures, we do not observe any change in trend following the clearing event. There is no increase in the number of traded contracts, in the net notional amounts, nor in the market risk transfer variables (see Appendix B).

[Figures 4 about here]

To confirm these preliminary findings, based on graphical representations, we perform difference-in-differences regressions, using each trading activity variable as the dependent variable in Equation (5). The results corresponding to a window of $[-50, 10]$ weeks around the clearing event are reported in Table 9.[7] We find that $Gross\_Not$ (the gross notional amount) is the only variable having a positive and statistically significant coefficient for the interaction term. For all the remaining variables, which represent better proxies for trading activity, coefficients of the interaction term are nonsignificant. Consequently, our results suggest that central clearing does not have any significant impact on trading activity.

[Table 9 about here]

Again, our findings differ from those of Loon and Zhong (2014) who find an improvement in trading activity. Table 10 reports the results obtained by applying the same methodology as in Loon and Zhong (2014) to our data. These results show a significant increase in the number of contracts and net notional amount, and suggest an improvement in trading activity after joining a clearinghouse. We conclude that the difference in our findings is due to the difference in methodology.

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. Bond issuers may take riskier positions if they know that their associated CDS are 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

[7]Results for smaller event windows are qualitatively the same.

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).

We now check whether the increase in CDS spreads may be 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.

We compute the daily mean of the variable $PECS$ for the control and treatment groups over the period $[-250, 50]$ around the clearing event date. Figure 5 shows that there is no trend change after the event, suggesting that the default spread of bonds of cleared entities is the same before and after joining the clearinghouse. We confirm this observation by estimating the DID in Equation (5) using $PECS$ as a dependent variable. For all the estimation windows reported in Table 11, the coefficient of the interaction term is not statistically significant, which indicates that the default risk of the underlying bond does not increase due to a move to central clearing,[8] confirming that the surge in CDS spreads is not caused by a change in the bond market.

[Figure 5 about here]

[Table 11 about here]

5.2.5 The issue of clearing costs

Reducing counterparty risk comes at the expense of higher margin requirements relative to OTC transactions. As argued by Kaya (2017), the increase in the CDS spreads following central clearing could be partially explained by an increase in clearing costs that is passed on to end-users. However, as documented in the literature, clearinghouses do not necessarily ask for larger collateral amounts and such a contribution to the increase in the CDS spread should be small. Evidence in that direction is provided, for instance, in the following publications:

- Duffie, Scheicher and Vuillemey (2015) take a snapshot on December 30, 2011 of the CDS bilateral exposures provided by DTCC and show that central clearing helps lower

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

collateral demand relative to the OTC market, as long as there is no significant proliferation of central counterparties. In fact, the benefits of multilateral netting and diversifications outweigh the increased initial margin requirements.

- Mello and Parsons (2012) present a replication argument and show that the cost of initial margin requirements is insignificant. They find that there is no additional cost with the margin mandate but that the credit risk associated with the derivative is accounted for separately.

- According to the Committee on Global Financial System (2013), variation margin is not as costly as some argue. It represents a transfer of resources and does not affect the net demand for collateral.

Finally, clearing fees themselves 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 CDS, and $15 per million of notional. We therefore argue that the clearing fees and additional margin requirements should not affect significantly the CDS spreads.

5.3 Summary of empirical results

Our empirical findings indicate that neither CDS liquidity, nor trading activity or bond default risk are affected by the introduction of clearinghouses, while CDS spreads do increase. In addition, clearing costs are small and should not impact the spreads significantly. Consequently, our results suggest that the surge in CDS spreads following adhesion to a CCP can be mainly attributed to the reduction in counterparty risk. Assuming that the counteparty risk of a CCP to be small (see, e.g., Cruz Lopez, Harris, Hurlin & Perignon 2017 on central 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, which is in the range of what is 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.

6 Conclusion

In this paper, we study the impact of central clearing on single-name CDS. 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 at reducing the overall risk in the market and enforcing 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.

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 with fixed effects on samples matched with propensity scores computed just prior to the clearing event. This type of dynamic matching ensures that the cleared and non-cleared groups have similar pre-clearing characteristics, and 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 on trading activity, but we find that central clearing does not cause any significant change in these two factors. We also find that the clearing event has no significant impact on the underlying bond market. In addition, according to the recent literature it does not seem that important additional costs are passed on to end-users. Therefore, we argue that the change in CDS spreads can be used as an indication of the amount of counterparty risk that is reduced thanks to the clearinghouse.

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Figure 1: CDS Trading Volumes.
This figure plots the notional amounts outstanding in trillion dollars for single-name CDS contracts (left axis) as well as the proportion of notional amounts cleared by central counterparties (right axis). The data is obtained from the Bank for International Settlements.

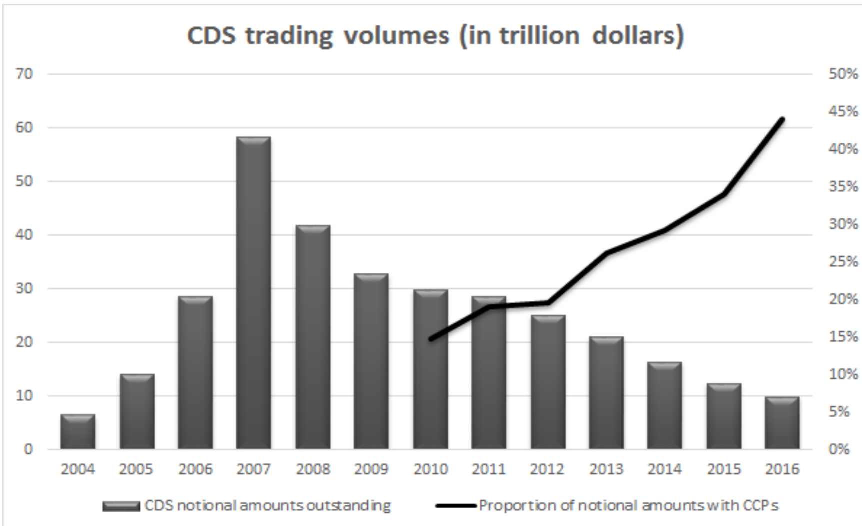


Figure 2: Comparison of CDS Spreads.
This figure compares the CDS spreads of cleared and non-cleared entities. CDS_Spr is the composite spread for the five-year tenor and is obtained from Markit. The horizontal axis represents time in days where date 0 denotes the central clearing event. The dotted and solid lines represent the average daily CDS spread of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

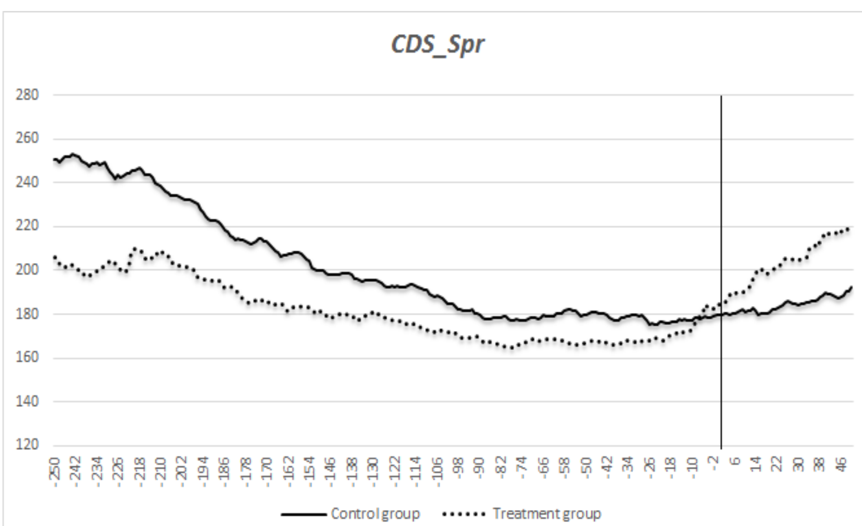
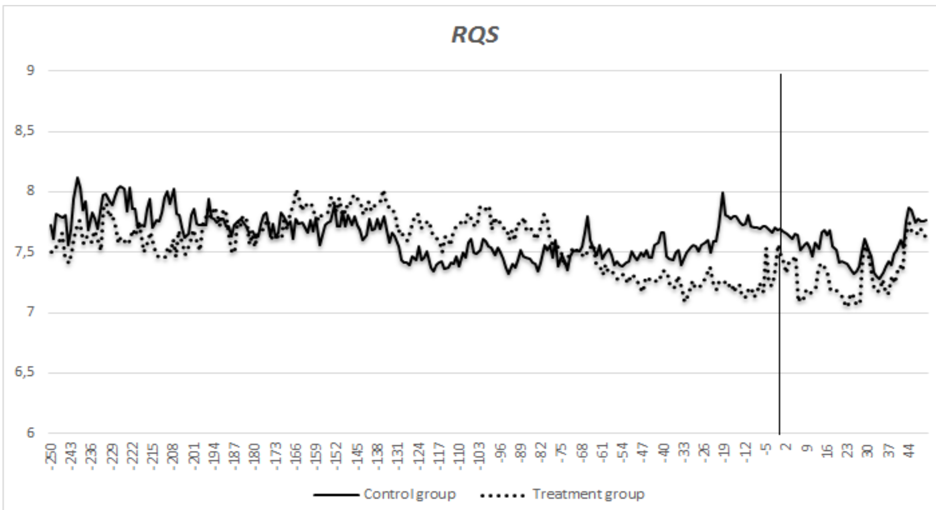


Figure 3: Comparison of liquidity measures.
This figure compares the liquidity measures of cleared and non-cleared entities. *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. *Comp_Dep* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. The horizontal axis represents time in days where date 0 denotes the central clearing event. The dotted and solid lines represent the average daily liquidity measure of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

Panel A : Comparison of Relative Quoted Spreads.



Panel B : Comparison of Composite Depths.

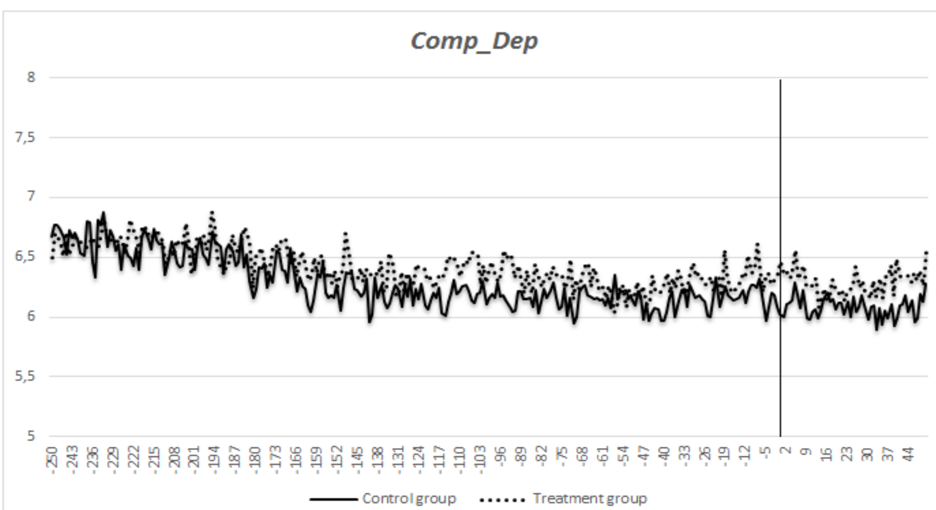
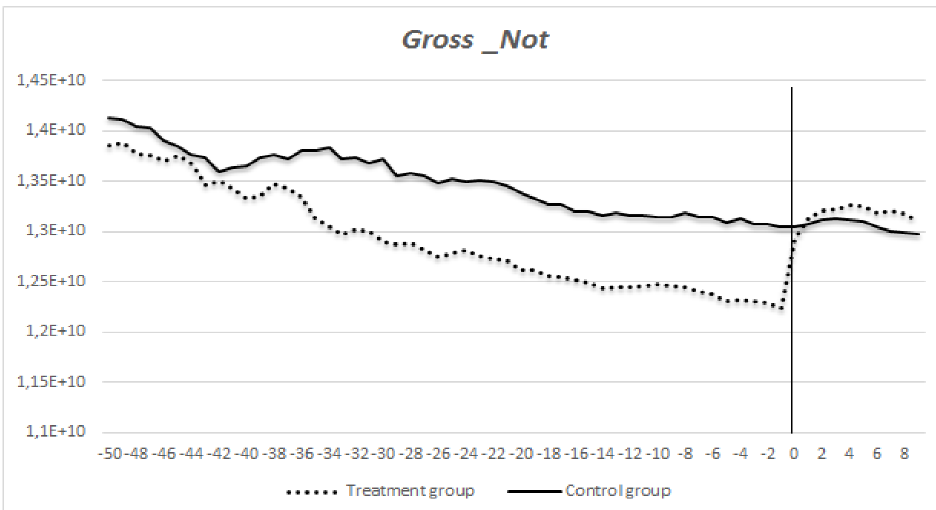


Figure 4: Comparison of trading activity measures

This figure compares the trading activity measures of cleared and non-cleared entities. *Gross_Not* represents the total notional 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). The data is on a weekly basis and is obtained from DTCC. The horizontal axis represents time in weeks where date 0 denotes the central clearing event. The dotted and solid lines represent the weekly average trading activity measure of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

Panel A : Comparison of Gross Notional Amounts.



Panel B : Comparison of Net Notional Amounts.

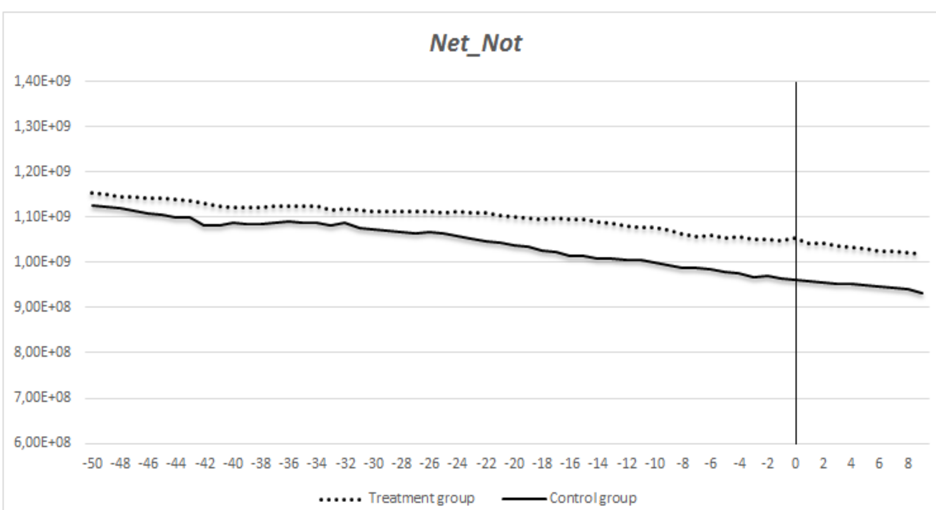


Figure 5: Comparison of Par Equivalent CDS Spreads.
This figure compares the Par Equivalent CDS Spreads ($PECS$) of cleared and non-cleared entities. This variable measures the default spread of the underlying bond and is computed using the J.P. Morgan methodology. The horizontal axis represents time in days where date 0 denotes the central clearing event. The dotted and solid lines represent the daily average PECS of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

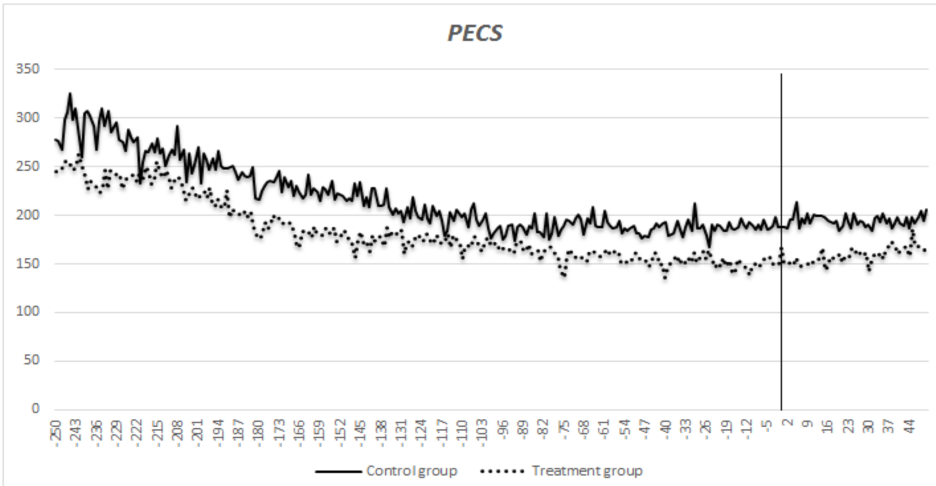


Table 1: Impact of Central Clearing

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. Static PS matching consists of computing propensity scores during a fixed period whereas dynamic PS uses the period prior to each firm's clearing date.

	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
Number of cleared firms	113 from North America and 102 from Europe	132 from North America	85 from North America	142 from North America	198 from North America
Impact on CDS spreads		Increase Methodology : event study	Increase Methodology : panel regression	Decrease Methodology : panel regression	Increase Methodology : Generalized DID + dynamic PS matching
Impact on liquidity	Slight Improvement Methodology : Event study + Static PS matching	Improve Methodology : standard DID + static PS matching			No change Methodology : Generalized DID + dynamic PS matching
Impact on trading activity	Improve Methodology : event study + Static PS matching	Improve Methodology : standard DID + static PS matching			No change Methodology : Generalized DID + dynamic PS matching
Impact on bonds default risk					No change Methodology : Generalized DID + dynamic PS matching
Impact on counterparty risk		Reduced Methodology : panel regression	No change Methodology : panel regression		Reduced Methodology : By elimination
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, DTCC, TRACE, FISD, S&P and Moody's.

Variable	Symbol	Definition	Prediction for the interaction term
Five-year CDS spread	*CDS_Spr*	Composite spread for the five-year tenor	Positive
Composite depth	*Comp_Dep*	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_BA*	Bid-ask spread in upfront points for the five-year tenor	Negative
Dealers count	*Dealers*	Total number of distinct dealers quoting the reference entity across all available tenors	Positive
Quotes count	*Quotes*	Total number of unique quotes for a reference entity, all tenors combined	Positive
Liquidity score	*Liq_sc*	Defined on a scale from 1 to 5 where 1 indicates the highest liquidity	Negative
Five-year dealers count	*5Y_Dealers*	Total number of distinct dealers quoting the reference entity for the five-year tenor	Positive
Five-year quotes count	*5Y_Quotes*	Total number of unique quotes for a reference entity for the five-year tenor	Positive
Non five-year dealers count	*Non_5Y_Dealers*	Total number of distinct dealers quoting the reference entity for the non five-year tenors	Positive
Non five-year quotes count	Non_5Y_Quotes	Total number of unique quotes for a reference entity for the non five-year tenors	Positive
Gross notional amounts	*Gross_Not*	Sum of all notional 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	*Contr*	Number of contracts outstanding for each CDS contract	Positive
Gross notional - Risk transfer	*Gross_Not_Risk*	Sum of all notional CDS contracts for transaction types that result in a change in the market risk position	Positive
Contracts - Risk transfer	*Contr_Risk*	Number of contracts involved in a market risk transfer activity	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 involving different combinations of variables and fitted on cleared and non-cleared entities, where the dependent variable is a binary variable that equals 1 if the firm is centrally cleared by ICECC during 2009-2015 and 0 otherwise, The vector of regressors' coefficients is estimated by maximum likelihood. We use data in the six-month period defined by the firm-event entity to compute the average of each regressor. *CDS_Spr* 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. *Comp_Dep* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. *Contr* is the number of contracts outstanding for each CDS contract. $Contr^2$ is the squared value of *Contr*. *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 value of *Net_Not*. Industry dummies are included in all the models and 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-event entities. Numbers in brackets 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_Spr	-0.00145***	-0.00143***	-0.00141***	-0.00127***
	(0.000218)	(0.000218)	(0.000217)	(0.000208)
Contr	7.77e-05***	0.00157***	0.00152***	
	(2.39e-05)	(0.000151)	(0.000156)	
$Contr^2$		-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_Dep			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)
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 control groups in the unmatched and matched samples. In Panel A we compare the means of the two groups and we compute the standard bias, that is, the difference between the means of the two groups scaled by the average standard deviations. *CDS_Spr* 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. *Comp_Dep* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. *Contr* is the number of contracts outstanding for each CDS contract. $Contr^2$ is the squared value of *Contr*. In panel B, we fit the Probit model first on the unmatched sample and then on the matched sample to test if variables that were useful in predicting the probability of a firm being eligible for central clearing in the full sample are still significant in the matched sample.

Panel A : Mean comparison

Variable	Sample	Mean Treated	Mean Control	% bias	% bias reduction
CDS_Spr	Unmatched	173.2	241.01	-13.6	81.9
	Matched	173.2	185.47	-2.5	
Contr	Unmatched	2260.2	1511.5	61.6	
	Matched	2260.2	2280.9	-1.7	97.2
$Contr^2$	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_Dep	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 coefficients in the generalized DID equation where the dependent variable *CDS_Spr* is the composite spread for the five-year tenor. Observations are pairs of firms (i) and dates (t). $Cleared_{i,t}$ is a binary variable that indicates if the firm i is centrally cleared at date t or not. The constant term includes firm and time fixed effects (α_i and γ_t respectively). In each column, we estimate the equation using a different estimation window around the clearing event date. In all the regressions, the standard errors (in brackets) are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$CDS\_Spr_{i,t} = \beta_0 + \beta_1 Cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

CDS_Spr	[-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

Table 7: Difference-in-Differences Analysis for the liquidity measures.

This table presents the estimates of the coefficients in the generalized DID equation. In panel A, the dependent variable *RQS* is the five-year relative quoted spread computed by dividing the bid-ask spread by the mid spread. In panel B, the dependent variable *Comp_Dep* is the number of contributors whose CDS spreads have been used to calculate the five-year CDS spread. Observations are pairs of firms (i) and dates (t). $Cleared_{i,t}$ is a binary variable that indicates if the firm i is centrally cleared at date t or not. The constant term includes firm and time fixed effects (α_i and γ_t respectively). In each column, we estimate the equation using a different estimation window around the clearing event date. In all the regressions, the standard errors (in brackets) are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Liquidity\_measure_{i,t} = \beta_0 + \beta_1 Cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Panel A : Difference-in-Differences Analysis for the Relative Quoted Spread.

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

Panel B : Difference-in-Differences Analysis for the Composite Depth.

Comp_Dep	[-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

Table 8: Difference-in-Differences Analysis for other liquidity measures.

This table presents the estimates of the coefficients in the generalized DID equation where, in each column, the dependent variable is a liquidity measures obtained from Markit Liquidity. *Upf_BA* is the bid-ask spread in upfront points for the five-year tenor. *Dealers* is the total number of distinct dealers quoting the reference entity across all available tenors. *Quotes* is the total number of unique quotes for a reference entity, all tenors combined. *Liq_Sc* is calculated by Markit and is defined on a scale from 1 to 5 where 1 indicates the highest liquidity. *5Y_Dealers* is the total number of distinct dealers quoting the reference entity for the five-year tenor. *5Y_Quotes* 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* and *Non_5Y_Quotes*. Observations are pairs of firms (i) and dates (t). $Cleared_{i,t}$ is a binary variable that indicates if the firm i is centrally cleared at date t or not. The constant term includes firm and time fixed effects (α_i and γ_t respectively). The estimation window is [-250, 50] days around the clearing event date. In all the regressions, the standard errors (in brackets) are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Liquidity\_measure_{i,t} = \beta_0 + \beta_1 Cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Liquidity measures	*Upf_BA*	*Dealers*	*Quotes*	*Liq_Sc*	*5Y_Dealers*	*5Y_Quotes*	Non_5Y_Dealers	Non_5Y_Quotes
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

Table 9: Difference-in-Differences Analysis for the trading activity measures.

This table presents the estimates of the coefficients in the generalized DID equation where, in each column, the dependent variable is a trading activity measure obtained from DTCC. *Gross_Not* is the sum of all notional 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. *Contr* 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. *Contr_Risk* is the number of contracts involved in market risk transfer. Observations are pairs of firms (i) and dates (t). $Cleared_{i,t}$ is a binary variable that indicates if the firm i is centrally cleared at date t or not. The constant term includes firm and time fixed effects (α_i and γ_t respectively). The estimation window is [-50, 10] weeks around the clearing event date. In all the regressions, the standard errors (in brackets) are clustered by firm. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$Trading\_activity\_measure_{i,t} = \beta_0 + \beta_1 Cleared_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

Measure	*Gross_Not*	*Net_Not*	*Contr*	*Gross_Not_Risk*	*Contr_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

Table 10: Impact of central clearing on CDS liquidity and trading activity using Loon and Zhong (2014) methodology

This table presents the results of the estimation of the impact of central clearing on CDS liquidity and trading activity using the same methodology as in Loon and Zhong (2014). For each measure, we compute the change between the event period average and pre-event period average. The pre-event and post-event windows are [-250, -21] and [0,20] days for liquidity measures and [-52, -5] and [0, 4) weeks for trading activity measures. The difference-in-differences is then computed as $DID = \Delta - \Delta_M$, where Δ is the change in liquidity or trading activity measures of a cleared firm around central clearing and Δ_M is the average change for the matched sample. We report the cross sectional mean (median) of Δ, Δ_M and DID and we test wether the mean (median) of DID is different from zero using t-tests (non parametric sign tests). The definition of all the liquidity and trading activity measures can be found in Table 3. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

		Mean			Median		
Measure	N	Δ	Δ_M	DID	Δ	Δ_M	DID
Illiquidity measures							
RQS	174	-0,005	0,002	-0,007***	-0,004	0,004	-0,008***
Upf_BA	126	4,447e-05	-1,432e-04	1,877e-04	1,617e-04	-3,781e-05	1,995e-04
Liq_sc	126	0,079	0,114	-0,035	0,146	0,153	-0,007
Liquidity measures							
Comp_Dep	174	-0,128	-0,186	0,057	-0,138	-0,156	0,018
Dealers	126	-0,161	-0,463	0,301***	-0,155	-0,520	0,365**
Quotes	126	-1,870	-2,520	0,650	-1,246	-1,939	0,693
5Y_Dealers	69	-0,595	-0,637	0,041	-0,696	-0,588	-0,108
5Y_Quotes	69	-2,771	-3,226	0,455	-2,616	-3,085	0,469
Non_5Y_Quotes	69	-2,282	-2,327	0,046	-0,721	-1,612	0,892
Non_5Y_Dealers	69	-2,335	-1,313	-1,022***	-2,507	-1,284	-1,223
Trading activity measures							
Gross_Not	174	2,497e+08	-6,325e+08	8,823e+08***	4,210e+08	-5,067e+08	9,277e+08***
Net_Not	174	-7,056e+07	-8,427e+07	1,371e+07	-7,243e+07	-8,478e+07	1,236e+07**
Contr	174	-58,308	-89,003	30,694**	-51,962	-74,031	22,069*
Contr_Risk	107	0,750	0,100	0,651	4,093	2,571	1,523
Gross_Not_Risk	107	3,645e+06	-1,004e+06	4,649e+06	2,273e+07	1,400e+07	8,728e+06

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

This table presents the estimates of the coefficients in the generalized DID equation where the dependent variable *PECS* measures the bond's default risk using the J.P. Morgan methodology. Observations are pairs of firms (i) and dates (t). $Cleared_{i,t}$ is a binary variable that indicates if the firm i is centrally cleared at date t or not. The constant term includes firm and time fixed effects (α_i and γ_t respectively). In each column we estimate the equation using a different estimation window around the clearing event date. In all the regressions, the standard errors (in brackets) 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

Appendix

Appendix A : Matching example

In this appendix, we present a detailed example of the dynamic propensity score matching procedure. For illustration purposes, consider a small sample of four firms, A, B, C, and D over the 2009–2015 period. Firms A was centrally cleared on December 21, 2009 and Firm B on March 28, 2011. Firms C and D were not centrally cleared during the sample period. Suppose that the 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. We then assume that firms C and D had the possibility of being centrally cleared on December 21, 2009, or on March 28, 2011. Therefore, we create the following firm-event entities:

C_1: Data for Firm C from 21/04/2009 to 21/10/2009; the firm-event corresponds to the possibility of Firm C adhering to central clearing on December 21, 2009

C_2: Data for Firm C from 28/07/2010 to 28/01/2011; the firm-event corresponds to the possibility of Firm C adhering to central clearing on March 28, 2011

D_1: Data for Firm D from 21/04/2009 to 21/10/2009; the firm-event corresponds to the possibility of Firm D adhering to central clearing on December 21, 2009

D_2 : Data for Firm D from 28/07/2010 to 28/01/2011; the firm-event corresponds to the possibility of Firm D adhering to central clearing on March 28, 2011

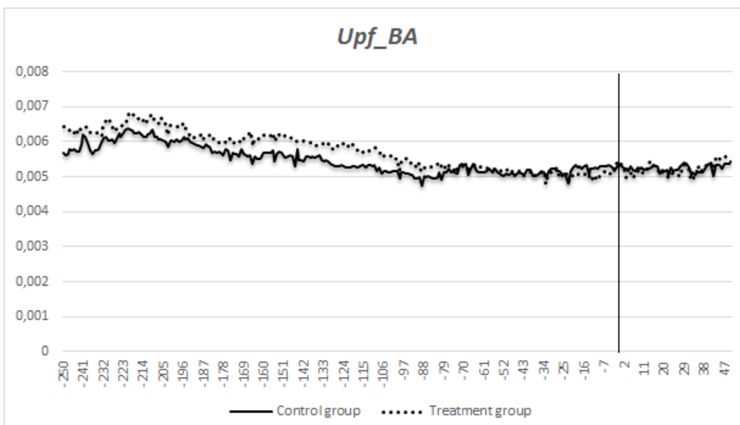
A and B constitute the treatment group and could be matched to any firm-event in the control group: C_1, C_2, D_1, or D_2. We apply the Probit model to the sample of six firm-events and match each firm in the treatment group to a firm in the control group having the closest propensity score. For instance, if A is matched to D_2 and B is matched to C_1, then the control group is D_2 and C_1. The firms in the control group that are not matched are dropped from the sample. This procedure allows us to construct a control group that exhibits pre-clearing characteristics that are similar to that of the treatment group, and thus eliminate the potential selection bias.

Appendix B : Additional figures

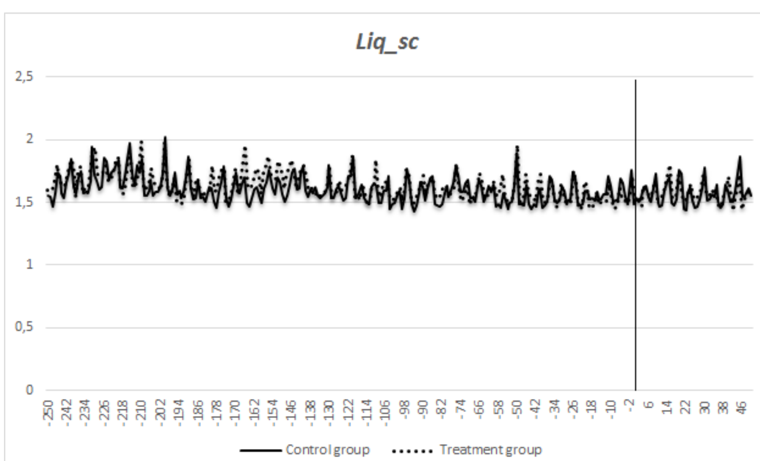
Figure B.1: Comparison of other liquidity measures.

This figure compares other liquidity measures of cleared and non-cleared entities. All these variables are obtained from Markit Liquidity. *Upf_BA* represents the bid-ask spread in upfront points for the five-year tenor. *Liq_Sc* is a score defined on a scale from 1 to 5 where 1 indicates the highest liquidity. *Quotes* is the total number of unique quotes for a reference entity, all tenors combined. *Dealers* is the total number of distinct dealers quoting the reference entity across all available tenors. *5Y_Dealers* is the total number of distinct dealers quoting the reference entity for the five-year tenor. *5Y_Quotes* is the total number of unique quotes for a reference entity for the five-year tenor. *Non_5Y_Dealers* is the total number of distinct dealers quoting the reference entity for the non-five-year tenors. *Non_5Y_Quotes* is the total number of unique quotes for a reference entity for the non-five-year tenor. The horizontal axis represents the event time in days where 0 denotes the beginning of central clearing. The dotted and solid lines represent the daily average of the liquidity measure of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

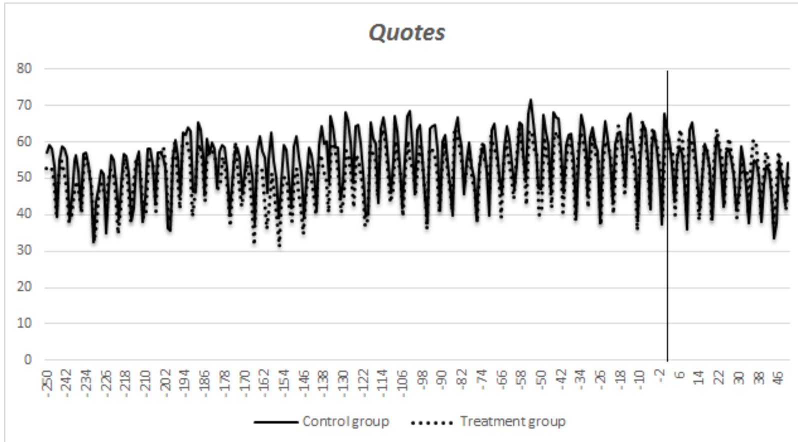
Panel A : Comparison of Upfront 5Y bid-ask spread.



Panel B : Comparison of Liquidity scores.

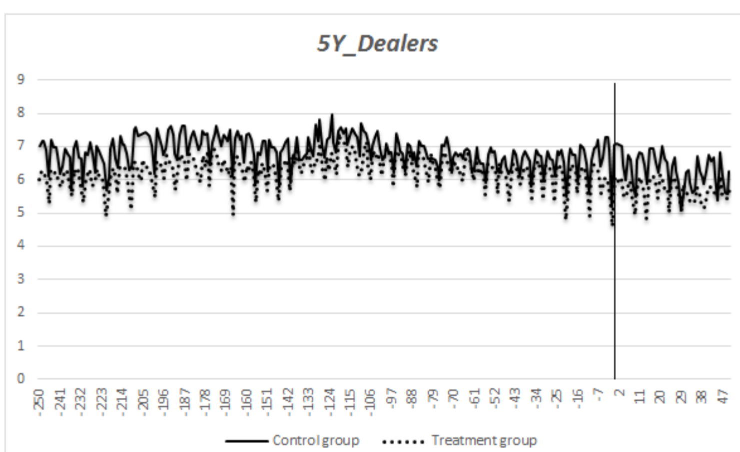


Panel C : Comparison of Quotes count.

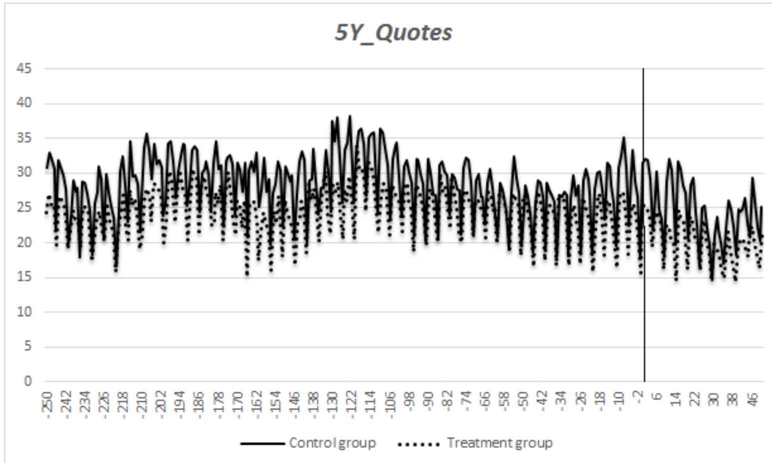


Panel D : Comparison of Dealers count.

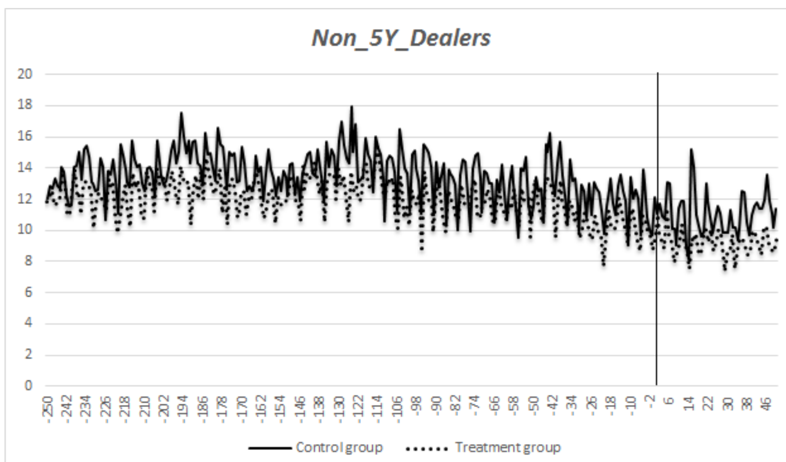
Panel E : Comparison of 5Y Dealers count.



Panel F : Comparison of 5Y Quotes count.



Panel G : Comparison of Non 5Y Dealers count.



Panel H : Comparison of Non 5Y Quotes count.

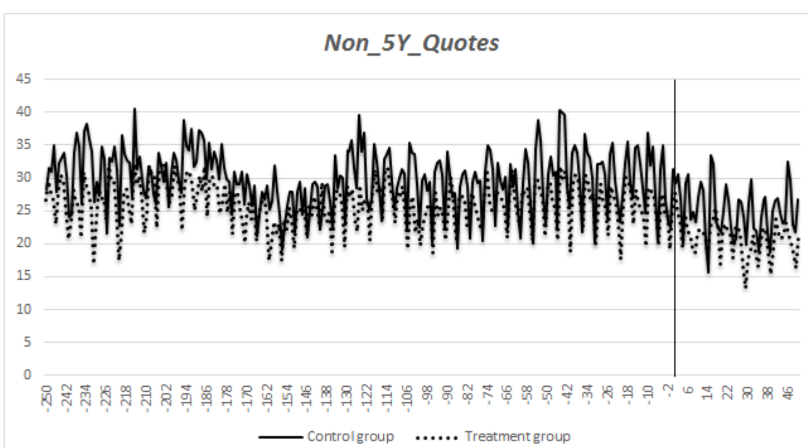
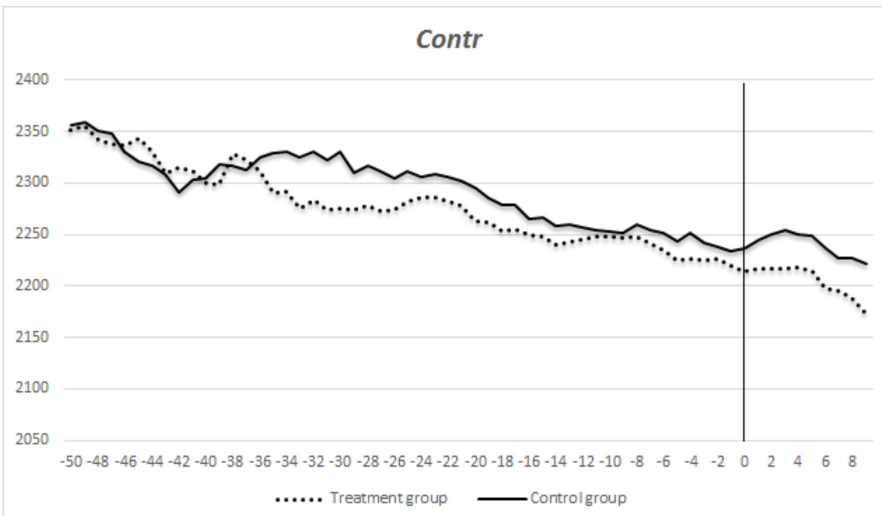


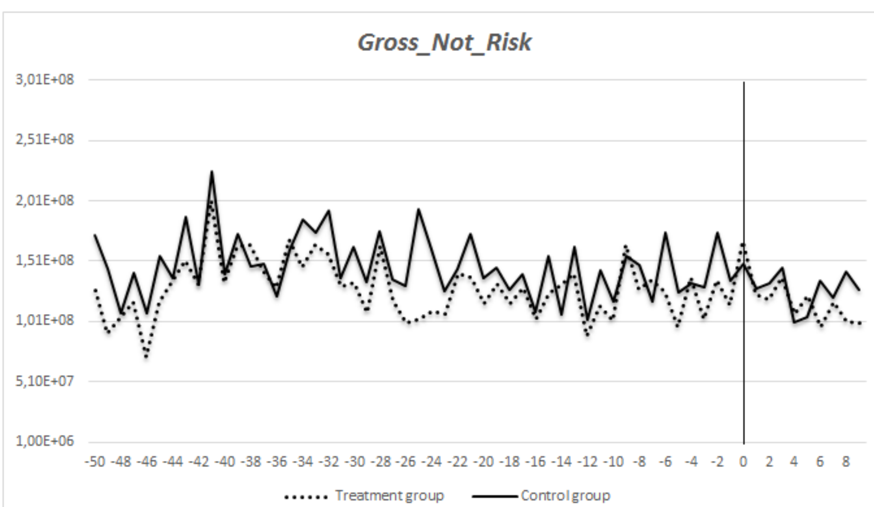
Figure B.2: Comparison of other trading activity measures

This figure compares other trading activity measures of cleared and non-cleared entities, obtained from DTCC. *Contr* is the number of contracts outstanding for each CDS contract. *Gross_Not_Risk* is the sum of all notional CDS contracts bought (or equivalently sold) for each reference entity. It captures transaction types that result in a change in the market risk position. *Contr_Risk* is the number of contracts outstanding for each CDS contract of cleared and non-cleared entities. It captures contracts involved in a market risk transfer activity. The horizontal axis represents time in weeks where date 0 denotes the clearing event date. The dotted and solid lines represent the weekly average number of the trading activity measure of the treatment group and the control group respectively. Both groups are constructed using dynamic propensity score matching.

Panel A : Comparison of the number of contracts.



Panel B : Comparison of Gross notional amounts - Risk transfer.



Panel C : Comparison of the number of contracts - Risk transfer.