Counterparty Risk and Cross-market Price Discovery: Evidence from a Quasi-natural Experiment

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Abstract

Over the past decade, the Credit Default Swap (CDS) market structure has changed from a traditional bilateral contract environment to central clearing after the Dodd-Frank Act. This study examines the impact of central clearing on the information quality of single-name CDS. Using the gradual introduction of the central counterparty as market efficiency shocks under the staggered difference-in-difference framework, I provide causal evidence that the predictability of corporate bond return via CDS spread innovations is significantly enhanced when the CDS is included in the central counterparty. Consistent with a hypothesis that the central clearing counterparty improves CDS market efficiency by reducing counterparty risk and associated costs, delayed price discovery is evident in the relatively inefficient market. An ensuing analysis examines the overall economic significance of cross-market price discovery based on trading strategies. For corporate bonds with centrally cleared CDS, an increase in CDS spread significantly underperforms those with a decrease in CDS spread by 4.33% per year, which is not explained by risk compensations.

Keywords: Price discovery, Corporate bond, CDS, Counterparty Risk

JEL Classification: G12, G14

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1 Introduction

Central clearing has been introduced in the single-name CDS market to reduce counterparty risk and increase liquidity after the Dodd-Frank Act. Several studies have shown that central clearing improves the CDS market in terms of liquidity, trading volume, bid-ask spread, and transaction costs, but it has not been studied whether the information quality of CDS is improved. CDS and bond share the same credit risk of a firm, but the information quality could be different depending on the relative market efficiency. If one market has better information about a firm's credit risk than another market, delayed price discovery would be evident in the relatively inefficient market. Therefore, this study examines the impact of central clearing on the cross-market price discovery process.

Cross-market studies have shown that investors prefer to trade in the derivative market over the underlying market. However, one impediment that could prevent investors from entering the CDS market is the counterparty risk inherent in a CDS contract. This is because both parties to a CDS contract face the risk that the other might default on their obligations. A stark example of this occurred during the global financial crisis in late 2008. Lehman Brothers, a major financial institution, was both a buyer and seller of numerous CDS contracts. When Lehman defaulted, institutions that had purchased CDS protection from Lehman found themselves exposed to credit risk because the protection vanished overnight. Similarly, institutions that had sold Lehman CDS protection to neutralize their position faced potential payouts to other contracts as their position was no longer netted out. This mutual uncertainty around the reliability of the counterparty became widespread in the credit market, exacerbating financial turmoil (Augustin et al., 2014). Subsequently, collateral requirements have increased and even led to over-collateralization (Arora et al., 2012). The counterparty risk and collateral requirement are implicit costs in entering the CDS market.

Recognizing the systemic risks posed by such counterparty vulnerabilities, policymakers introduced the central clearinghouse, which is part of the Dodd-Frank Act, to mitigate and efficiently control counterparty risk and to increase market transparency and liquidity. The central counterparty (CCP) efficiently nets out exposure to credit risk. Panel A of Figure 1 shows an example case in which investor A purchases credit protection from investor C to cancel out its existing position with investor B. Its position is theoretically canceled out, but the collateral is still held by investor B.[1] Panel A of Figure 1 shows that even if the underlying firm defaults and investor C is unable to provide credit protection, investor A has to provide credit protection to investor B, and investor A realizes a loss. In contrast, Panel B of Figure 1 illustrates that investor A can walk out of the contract and that CCP deals with counterparty risk by netting CDS. CCP is a counterparty to every protection buyer and seller, and hence CCP facilitates CDS transactions. Moreover, CCP effectively manages counterparty risk by mandating initial margins and subsequent additional margins. The CCP oversees its overall CDS position and collateral value and conducts daily stress tests on its aggregate positions under various scenarios to impose additional margins.[2] In addition to the collected margin, CCP maintains guaranty funds to provide additional protection for CCP members against the possibility of a clearing member's default. As the deposit insurance fund works, the CCP collects funds from members based on the trading volume in the CCP and the additional risk that a member brought to CCP.

[Insert Figure 1 here]

On the other hand, there are other factors that makes the bond market inefficient. First,

[1]Instead of purchasing the credit protection from investor C, A could make a termination agreement with B, but B can refuse to do so.

[2]See https://www.ice.com/publicdocs/ICE_CDS_Clearing_Margin_Calculator_Overview.pdf for more details.

the nature of both assets is different in that the bond is a security, and the CDS is a contract. Trading in the corporate bond market involves the delivery of bonds between the buyer and the seller in which the supply of the bond is fixed. On the other hand, CDS can be created to meet investor demand (Longstaff et al., 2005), neither the buyer nor the seller is required to hold the corporate bond (naked CDS), and the underlying asset is delivered only when the reference entity defaults.

Second, both markets are different in terms of participating investor types and liquidity. One of the major investor groups in the corporate bond market is insurance companies which buy and hold bonds to meet their needs. In contrast, various types of investors utilize CDS to alter their credit risk exposure (e.g. reaching for yield, speculation, or hedging purposes), and they can unwind their position by entering the offsetting contract, through novation, or by writing a termination agreement with their counterparty. Overall, the CDS market is a more liquid market than the bond market (Bessembinder et al., 2008).

Last, it is cheaper to enter the CDS market than the bond market. The transaction cost of trading a CDS is approximately 15 basis points regardless of the size of the trade, but for corporate bonds, transaction cost decreases from 50 basis points to 15 points as the trading size rises from approximately $100,000 to $2 million (Biswas et al., 2015). Therefore, trading corporate bonds is cheaper than CDS only when the trading size is greater than $2 million which is rarely observed.[3] Furthermore, entering a short position is more convenient with selling CDS than with short-selling corporate bonds as the latter requires lending fees.

So far, we have explored the pros and cons of trading in the CDS and corporate bond market, and it is unclear whether central clearing in the CDS market improves the information quality of CDS and the price discovery process. To address this, I utilize the phased

[3]See Table 1 in Bao et al. (2011) and also Table 1.

introduction of CCPs as a series of microstructure shocks aimed at reducing counterparty risks and collateral requirements and explore cross-market price discovery in this context. Campbell (2014) shows that shifting CDS trading from non-CCP to CCP reduces notional exposures and collateral requirements by approximately 60%. Given that not all single-name CDS are included in CCP, this setting provides a unique opportunity to examine the effect of shocks alongside counterfactual scenarios.[4] If central clearing improves market efficiency and information quality of CDS, we expect to see *delayed* price discovery in the bond market (Blanco et al., 2005). Specifically, recent changes in the CDS spread would forecast future bond returns, but the predictability is weaker for non-CCP CDS. Furthermore, the predictability horizon would be proportional to the relative degree of market friction in the bond market.

For the analysis, I employ a staggered difference-in-difference model with centrally cleared CDS groups and control groups. Since the inclusion of CCP is not randomized but depends on the liquidity of CDS, I match centrally cleared CDS to non-centrally cleared CDS using the propensity score method. Empirical findings suggest that when samples from the treated group are centrally cleared, the influence of CDS spread innovations on future bond returns becomes notably significant relative to the control group, even after accounting for bond characteristics. This causal relationship suggests that a relatively less restricted market microstructure (reduced counterparty risk and collateral requirement) makes investors engage more actively in the CDS market.

This paper also evaluates the overall economic magnitude of price discovery using wide panel samples. Forming a zero-cost corporate bond portfolio based on the previous month's CDS spread change results in significantly negative corporate bond returns, implying that

[4] All multi-name CDS such as CDS index are included in CCP after Dodd-Frank Act.

the increased credit risk observed in the CDS market predicts negative bond returns in the next month. Using conventional stock and bond market research factors, I show that the performance does not result from risk compensation. I also find that the return predictability is short-lived. The corporate bond market takes only a few months to reflect the new information from the CDS market.

Previous studies have indicated that characteristics of bonds, such as credit rating, coupon rate, and outstanding amount, explain the cross-section of corporate bond returns Gebhardt et al. (2005a,b). I employ a bivariate dependent sorting method to show that the delayed price discovery in the bond market is affected by the characteristics related to the bond's trading costs. Consistent with the hypothesis that relative market efficiency affects cross-market price discovery, bonds with low transaction costs like liquid bonds with good credit ratings show weak delayed price discovery. Furthermore, the predictability of CDS spread innovation in bond return is still statistically significant when the additional bond characteristics and stock market characteristics are all considered in panel regressions, and the predictability is pronounced for bonds with centrally cleared CDS.

To assess whether CDS has additional information that is not yet reflected in the corporate bond price, I compare firms with and without CDS and find that the seasonal bond offering price for firms without CDS is underpriced by 6 basis points on the first day of secondary market transaction compared to the firms with CDS. Hence, primary market brokers have more bargaining power and make larger profits when the CDS market does not monitor a firm's credit risk externally. The result is consistent with the hypothesis that the CDS market's assessment of credit risk partially resolves information asymmetry not only in the secondary market but also in the primary market.

The remainder of this paper proceeds as follows. Section 2 reviews the literature related to this study, and Section 3 describes the data and explains the variables used in this paper. Section 4 explores cross-market price discovery, Section 5 provides additional evidence as a robust ness check, and Section 6 concludes the paper.

2 Related Literature

The main contribution of this paper is to connect two different strands of literature. First, this paper contributes to the growing literature on the effect of central clearing. Duffie and Zhu (2011) provide a framework that explains how central clearing increases the efficiency of netting and reduces counterparty risk as the number of CCP decreases. Their argument supports this paper because there are only two CCP in the sample period which eventually merged to one.[5] Arora et al. (2012) hypothesizes that counterparty risk is factored into the pricing CDS market, but the magnitude is small as collateral requirements reduce counterparty risk. The stance of this paper diverges from theirs; I show that not only does counterparty risk influence investors' selection of credit markets, but the associated costs to offset this risk also play a pivotal role because collateral requirements convert investors' liquid cash-equivalent assets into less liquid forms of collateral. I show that the introduction of CCP that reduces the collateral requirement and exposure to counterparty risk affects the cross-market price discovery process.

Loon and Zhong (2014) study the effects of CCP introduction in the CDS market and find that the central clearing house improves the liquidity and transparency of the CDS market. Also, Wang et al. (2021) show that reduced cost of trading CDS improves liquidity in the cross-section. This is consistent with my finding that the event of CDS inclusion in CCP increases liquidity and reduces implicit trading cost.

[5] See https://www.cmegroup.com/notices/clearing/2018/03/Chadv18-115.html

Second, I offer insights into return predictability in cross-market analyses. Studies by An et al. (2014) and Cao et al. (2023) have a notable relevance to my work. Specifically, An et al. (2014) demonstrate that the information embedded in the implied volatility of the options possesses significant predictive power for future stock returns. They further contend that informed trading in one market facilitates price discovery in the other market. Similarly, Cao et al. (2023) studies cross-section of corporate bond returns using a measure based on the implied volatility of the options. They show that frictions in the bond market prevent informed traders from trading in the bond market and make them choose the option market. In contrast to studying frictions in the underlying market, this paper adds to the existing literature in that I relate price discovery to market frictions in the derivative market by providing causal evidence. Furthermore, this study not only uncovers the price discovery of CDS through intensive margins, but also through extensive margins, shedding light on underpricing in the primary market (also related to Cai et al. (2007); Nikolova et al. (2020)).

3 Data and Variable Definitions

The primary data source for the price and trade information is TRACE, which reports secondary market transactions. The details of the primary market bonds issue are from Mergent FISD. CDS data including spread quote, CDS characteristics, and quote quality are from Markit CDS. The price and characteristics of stocks are from CRSP and Compustat, respectively. Using the link table provided by Markit CDS that matches CUSIP 6-digit with the CDS identifier, I merge the firm-level bond data to single-name CDS. The merged samples cover from August 2010 to June 2022 and include 465 unique firms. The final sample results in 29,303 firm-month samples.

3.1 Corporate Bond Data

I use Mergent FISD to obtain the characteristics of the issue-level bonds such as maturity, coupon, credit rating, and information about the issuer. Corporate bond intraday transaction data is gathered from the Enhanced TRACE. Bond prices are cleaned for cancellations, corrections, reversals, and double counting following Dick-Nielsen (2014). Additional filters are applied to the cleaned price data as follows:

1. I remove bonds with floating-rate coupons and convertible bonds for accuracy of bond return measure
2. I exclude asset, agency or mortgage-backed bonds, foreign currency-denominated bonds, bonds issued under the 144A rule, private placement bonds, and perpetuities.
3. To match the CDS data, I filter out bonds with lower seniority: subordinated, junior, and missing security level information.
4. I eliminate bonds with maturity less than 1 year as these bonds are excluded from major bond indices and hence affect index tracking investors' bond holdings and distort return measure (Bai et al., 2019).
5. To eliminate non-institutional trades and minimize pricing errors, I remove small trades (trade volume $< \$100,000$) (Bessembinder et al., 2008), and trades with prices under \$5 and over \$1000.

Finally, the filtered intraday prices are weighted by trade volumes to compute the daily bond prices.

3.1.1 Issue-level Bond Return

As opposed to stocks, fixed income securities are not traded frequently, and many bond returns are excluded if we only include end-of-month prices to compute bond returns. To mitigate this problem, the fixed income literature (including Bessembinder et al. (2008), Bai et al. (2019), and Cao et al. (2023), and many others) has suggested including bond prices close to the end of month date if the end-of-month price is not available. Following this methodology, first, I compute the issue-level bond return using the prices of the last trading day of month. The return of the bond i' at time t is computed as in Equation (1).

$$R_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{1}$$

where $P_{i,t}$ is end of month bond price, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is coupon payment, if any. Finally, for bonds that do not have a transaction record on the last trading day of the month, the transaction prices whose trading day is close to the last trading day of the month in the last five trading days are used.

3.1.2 Bond Characteristics

log(Size) is the logarithm of the bond outstanding amount, *Maturity* is the years left to maturity of the bond, and *Rating* is the average rating score based on three different rating agencies (Standard & Poor's, Moody's, and Fitch) where 1 is the highest letter rating (e.g., AAA or Aaa) and increases by one as the letter rating grade goes down. Investment grade and non-investment grade are below and above 10, respectively.

3.1.3 Firm-level Bond Return and Characteristics

To compute the firm-level (CUSIP 6-digit) bond return and characteristics, all variables in the previous section are weighted by the outstanding bond amount, and the weighted average variables are computed. I use firm-level (issuer-level) bond variables instead of bond-level (issue-level) variables for the analyses to better detect changes in valuation of bond and to avoid excessive weights on firms with multiple bond issues in regression analysis (Bessembinder et al., 2008).

3.2 Credit Default Swap Data

Markit CDS aggregates CDS quotes from various dealers and reports average CDS quotes and details, including tenure, document clauses, implied rating, Markit's 10-industry classification, and reference entity identifier (called REDCODE). Markit CDS data also includes some of transaction details from Depository Trust and Clearing Corporation (DTCC), which reports weekly summaries of trading volume such as gross and net notional outstanding and the number of outstanding contracts. The transaction details are only available after 2010 and do not cover all CDS.

3.2.1 CDS Spread

CDS spread refers to the periodical payment amount (like a coupon), usually quoted in basis points, that the protection buyer pays to the protection seller throughout the contract's life. This spread acts as the "price" or "premium" of the CDS and represents the credit risk associated with the underlying reference entity (firm or sovereign). On the other hand, in case of default, the protection buyer receives a notional amount from the protection seller and the protection seller gets the defaulted bond. Therefore, the CDS spread is a price that both parties agreed on and that equalizes the present value of future cash flows for both parties. The CDS spread reflects the perceived credit risk of the reference entity. A higher CDS spread indicates that the market sees a greater risk of default for the reference entity, meaning that it costs more to insure against that default. On the contrary, a lower CDS spread means that the market views the entity as having a lower risk of default.

The main source of CDS spread data is Markit CDS. Markit collects CDS spread bid-ask quotes from various dealers, and reports median bid-ask spread with varying maturity profiles and seniorities, and document clauses. Standard CDS contracts can differ based on their "document clause" related to deliverable obligations in the event of a credit event.[6]

In order to maintain consistent time series and sample size, CDS spreads with different document clauses are averaged and 5-year CDS for senior unsecured debt are used in this study, which are the most liquid contract in the CDS market.[7] The CDS implied credit risk change is measured by monthly CDS spread change (ΔSpread) in the following equation where s_t is the CDS spread on the last trading date of the month.

$$\Delta \text{Spread}_t = \text{Spread}_t - \text{Spread}_{t-1} \tag{2}$$

It is very important to note that for any empirical analysis that involves bond returns and previous CDS spread change (i.e. R_t and $\Delta \text{Spread}_{t-1}$), I use CDS spread on the day before the last bond trading day of the month used to compute bond return to avoid forward-looking bias, that is, there is one trading day gap between P_{t-1} and Spread_{t-1}.

[6]There are four main restructuring clauses. First, Full Restructuring (CR) allows the protection buyer to deliver bonds of any maturity after any restructuring event. Second, Modified Restructuring (MR) restricts deliverable obligations to those maturing in less than 30 months. Third, Modified-Modified Restructuring (MM) confines deliverable obligations to those with less than 60 months to maturity. Finally, No Restructuring (XR) excludes restructuring events from the CDS contract's coverage.

[7]If CDS implied rating is not available from Markit, I remove them to eliminate pricing errors.

3.2.2 CDS Transaction Information

The *Gross Notional* amount represents the total face value of credit protection traded[8], and measures CDS trading volume and liquidity. However, changes in gross notional amount do not necessarily represent credit risk exposure because one could find a counterparty to offset the current position. In contrast, *Net Notional* amount is net position of all buy-side participants for single-name CDS, better measuring credit exposure. *Composite Depth* is number of dealers whose contributions were included in estimating CDS spread quotes. *Contracts* is the number of open contracts for the reference entity.

3.2.3 Descriptive Statistics

Panel A of Table 1 demonstrates summary statistics for the full sample data used in this section. There are 465 unique firms and 29,303 firm-level bond-month observations from August 2010 to June 2022. On average, CDS spread is 157 basis points and the distribution is skewed to right. The changes in CDS spread is close to zero on average but vary from -18 basis points to 16 basis points within deciles. The average firm-level bond has a BBB credit rating (rating score=8.96) and 9.3 years of maturity. Investment grade is credit rating score less than or equal to 10, which is 75% of the sample, and bonds with a credit rating score greater than 10 are non-investment grade bonds, which is 25% of the sample. The size of an average firm-level bond is \$2.4 million. Panel B shows the time-series average of cross-sectional correlation among the CDS and bond characteristics. Bond return and changes in CDS spread are negatively correlated, but the magnitude (-0.25) is low. This suggests that the bond price reflects not only the default components, but also non-default components

[8]Because CDS has zero net supply, the gross notional amount purchased is equal to the gross notional amount sold.

(Longstaff et al., 2005). The non-default components correlated with ΔSpread might predict bond return, so in the later analysis I control for possible bond and stock characteristics that affect future bond returns.

[Insert Table 1 here]

4 Empirical Analysis

4.1 Introduction of Central Counterparty (CCP)

As shown in Campbell (2014), the CCP reduces counterparty risk exposure and the cost to mitigate the risk. Alleviated counterparty risk and implicit trading cost in trading CDS should further incentivize institutional traders to trade in the CDS market. To test this hypothesis, I adopt an event study suggested by Loon and Zhong (2014) using the introduction of central clearing to identify the counterfactuals for single-name CDS.

4.1.1 Propensity Score Matching

The introduction of central clearing is not random. Loon and Zhong (2014) report that liquidity and open interest are the primary criteria used in selecting obligors for central clearing. To address this problem, I find counterfactuals by matching samples using the following probit regression.

$$\begin{aligned} CCP_i = &\beta_1 \cdot \text{Relative quoted spread}_i + \beta_2 \cdot \text{Coposite depth}_i + \beta_3 \cdot Log(\text{Net Notional}_i) \\ &+ \beta_4 \cdot Log(\text{Contracts}_i) + \beta_5 \cdot \text{Rating}_i + \beta_6 \cdot \text{Illiquidity}_i + \beta_7 \cdot \text{Log(Size)}_i \\ &+ \beta_8 \cdot \text{Nonfincl}_i \times \text{Leverage}_i + \beta_9 \cdot \text{Nonfincl}_i \times \text{Leverage}_i^2 + \beta_{10} \cdot \text{MB}_i \\ &+ u_I + \epsilon_i \end{aligned} \tag{3}$$

CCP_i is 1 if centrally cleared and 0 otherwise. All variables are averaged over the past 12 months prior to the central clearing event. *Relative quoted spread* (quoted CDS bid-ask spread over spread midpoint), *composite depth* (number of contributors in the CDS market to compute CDS spread), CDS *net notional* amount outstanding, and number of open CDS *contracts* are used to find the counterfactuals that resemble CDS liquidity of treated group.

In order to control for default risk, I include an $Rating_i$, which is bond rating score where 1 is the best credit quality and higher is the worse credit quality; financial ratios such as the leverage ratio ($Leverage_i$) and Market-to-Book ratio (MB_i); and the squared value of leverage ratio to account for any non-linear impacts of financial leverage on default. Although these ratios are valid default risk indicators for industrial companies, they can be challenging to interpret for financial firms. To account for this variation, I use an interaction term with the dummy variable '*Nonfincl*' (set to one for non-financial firms and zero for financial firms) to ensure that both types of firms from our sample are appropriately considered. In addition, to control for liquidity of the underlying asset, illiquidity and size of bond are included. I match samples based on selecting the control observation with the closest propensity score for each treated sample with a 0.25 caliper.

Finally, the introduction of central clearing is not a one-time event rather gradual. Therefore, the propensity score matching is done for each event. For unbiased analysis, any member of the treated group including 'to-be-treated' firms is not eligible for the candidate for a matched sample in propensity score matching.

Panel A of Table 2 compares the characteristics between the treated and control groups. There are 81 treated and 81 matched samples, and the sample period covers November 2010 to June 2022. Each treated and matched sample includes 12 months before and after the CCP inclusion month. The result shows that there are no significant differences between the two groups. The standardized mean difference between the treated and control groups for each variable is within one standard deviation (not reported in the table). Panel B of Table 2 compares the other characteristics not used for propensity score matching, and the results are similar to panel A in that there are no noticeable differences between the two groups.

[Insert Table 2 here]

To visualize how well the propensity score matching method addresses the sample selection, Figure 2 shows the liquidity trend of the treated and control groups in terms of the gross notional amount of CDS. The trend of the matched sample group (dashed red line) shows that there is a decreasing trend of CDS liquidity, meaning that total transactions (in dollar terms) and maximum aggregate credit exposure have decreased throughout the sample period. On the other hand, the post-treatement trend of the treated group (solid blue line) suggests that the liquidity of CDS had improved since the CDS was included in CCP.

[Insert Figure 2 here]

4.1.2 Staggered Difference-in-Difference

Using the propensity score matched samples, I run the following difference-in-difference regression to study the effect of CCP inclusion on cross-market price discovery:

$$
\begin{aligned}
R_{i,t} =& \alpha + \beta_1 \cdot \Delta\text{Spread}_{i,t-1} + \beta_2 \cdot CC_{i,t} + \beta_3 \cdot \text{Spread}_{i,t-1} \cdot CC_{i,t} \\
& + X_{i,t-1} + u_i + \nu_t + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

where the CC is the dummy variable equal to 1 if the firm i's CDS is included in the CCP and 0 otherwise. Control variables (X) include lagged bond characteristics such as return, size (amount outstanding), illiquidity, coupon rate, maturity and credit rating score.

Column (1) of Table 3 shows that a hundred-basis point increase in CDS spread predicts the bond return of -1.078% with a t-statistic of -6, and additional -0.398% return predictability when the CDS is included in the central counterparty. This is consistent with the view that relived market friction improves the information quality of CDS in terms of the predictability of bond returns. The result confirms that the reduced implicit cost of trading CDS and counterparty risk improve the cross-market price discovery.

Column (2) of Table 3 show the results of placebo tests for Column (1). The placebo tests shift the sample period to 12 months before the CCP inclusion date so that all samples in the placebo test are not treated. The coefficients on ΔSpread show that the cross-market price discovery is evident throughout the sample period, but the statistically insignificant coefficients on the interaction term show that the introduction of CCP (placebo) does not add the effect as expected.

Since both CDS and bond share the same default risk, they are co-integrated. Column (3) of Table 3 tests whether the cross-autocorrelation structure is affected by the market structure changed in the CDS market. First of all, the past bond return predicts the CDS spread changes but with very small magnitude, that is, a 1% increase in bond return predicts CDS spread to increase by 2.5 basis points. Furthermore, the predictability is canceled out when the CDS is included in the central counterparty. Column (4) of Table 3 shows the result of placebo test and it confirms that the bond has no return predictability on CDS spread innovation. The result suggests that the pricing information flows from CDS to bond market.

[Insert Table 3 here]

4.2 Price Discovery of CDS Spread Innovation in the Bond Market

This section explores the overall economic significance of cross-market price discovery with extended sample. Specifically, I form zero cost bond portfolios based on sorting ΔSpread and measure average returns and portfolio alphas to gauge the magnitude of price discovery. Later sections control for variables that might influence cross-market return predictability.

4.2.1 Univariate Sorting

I form quintile portfolios based on size of ΔSpread and rebalance them monthly and estimate average performance and Newey and West (1987) standard errors with 6 months lags. In order to investigate risk-adjusted return performance, I use both stock and bond market risk factors provided by Fama and French (2015) and Bai et al. (2019).[9] In Table 4, Panel

[9]The stock market factors are from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ and the bond market factors from https://sites.google.com/a/georgetown.edu/turan-bali/.

A (Panel B) uses value-weighted (equally weighted) return and shows alphas of quintile bond portfolios (in %) sorted by ΔSpread. The first and third rows demonstrate the alphas of regressing bond returns on conventional stock market factors (FF5) of Fama and French (2015) plus stock market momentum (MOM), and the second and third rows show the alphas of regressing bond returns on bond market factors of Bai et al. (2019). The alpha measures are divided into two groups: Bonds with centrally cleared CDS (CC) and without centrally cleared CDS (non-CC).

First, the alphas decreasing from column (1) to column (5) and indicating negative returns for the zero-cost quintile difference portfolio in the 6th column support that, on average, corporate bonds with a decrease in CDS spread significantly outperform those with an increase in CDS spread. The magnitude is reduced for equally weighted portfolios and it suggests that the price discovery is somewhat related to the size of bond. Seocnd, the result shows that the price discovery comes from centrally cleared groups, and the statistical significance of price discovery is weaker for the non-CC group. The statistically significant -0.361% alpha (equivalent to 4.33% per year) of zero cost portfolio in panel A (CC group) is consistent with the previous results that the delayed price discovery is significant in the relatively inefficient market (Bond market).

[Insert Table 4 here]

Table 5 tests the delayed price discovery horizon. Portfolio formation is same as previous univariate sorting analysis, but zero-cost quintile difference returns are estimated from 1 month to 6 months, columns (1) to (6) respectively, and estimated alphas are reported. Column (1) is the same as column (6) in Table 4 and reported for convenience. The results show that the alphas are statistically significant up to two months after the portfolio formation for the CC group and one month for the non-CC group. This suggests that the predictability horizon is longer for centrally cleared CDS. These results are consistent with An et al. (2014); Cao et al. (2023) in that the predictability of returns across markets disappears in the first few months.

[Insert Table 5 here]

Table 6 reports the bond characteristics of the quintile portfolio in the rebalancing month. Both panel A (Value-weighted) and B (Eqaul-weighted) show similar patterns, and both centrally cleared CDS and non-centrally cleared CDS group have approximately same values, suggesting that bond characateristics are not much different from each other. Bond return is linearly related to the ΔSpread, and size and maturity are relatively constant across the quintiles. However, other characteristics have a V-shape, non-linear, relationship with ΔSpread, that is, the bottom quintile (column (1)) and the top quitile (column (1)) have similar characteristics, but the middle quintile (column (3)) has the lowest magnitude than the two extreme quintiles. This is because bond return and CDS spread change are difference variables whereas the other variables are levels. As long as the top and bottom portfolios share similar characteristics, the bond characteristics are less likely to affect the performance of zero-cost quintile difference portfolio based on single sorts. I explore the confounding variables in subsequent analyses.

[Insert Table 6 here]

Figure 3 illustrates the average CDS spread of the top and bottom quintile portfolio from 6 months before the portfolio formation to 6 months after the portfolio formation (including both CC and non-CC groups), repeating the same exercise for top ΔSpread and bottom ΔSpread quintiles. Besides the changes in the portfolio formation month, no significant shifts in CDS spread for the pre- and post-formation month. This suggests that the CDS implied credit risk remains fairly high for quintile 5 and relatively low for quintile 1, following the disturbance in the portfolio formation month. This is consistent with that investors in the CDS market adjust the CDS spread and then investors in the bond market subsequently adjust the bond price in the next month.

[Insert Figure 3 here]

4.2.2 Bivariate Dependent Sorting

The previous results show that the relieved market friction improves the predictability of CDS in bond returns, emphasizing cross-sectional differences in relived counterparty risk and associated costs in the CDS market. The corporate bond market also has cross-sectional differences in trading frictions such as transaction cost and illiquidity. In general, firms with poor credit quality have bonds with high coupon rates as the underwriters require higher coupon rates. Transaction costs are higher for non-investment grade bonds. Large firms typically have better credit ratings, long maturity bonds, and liquid bonds. To examine whether the trading friction in the bond market affects the cross-market price discovery process, I sequentially double-sort the bond characteristics with ΔSpread. The dependent sorting method controls for the first sorting variable and estimates the effect of the second sorting variable on portfolio returns. In this way, we have the same number of firm-level bonds in each bucket in contrast to independent sorting. Specifically, bond portfolios are sorted by bond characteristic into high and low groups first and then each group is sorted by ΔSpread into tercile groups thereby we have 2 by 3 portfolios, and the portfolios are rebalanced using the same procedure every month.

Columns (1) to (6) of Table 7 show alphas from regressing tercile portfolio return difference on bond market factors of Bai et al. (2019). Panel A of the Table 7 shows that the alphas of tercile difference portfolio in low and high groups are different in terms of magnitude and statistical significance, suggesting that all bond characteristics affect the cross-market price discovery process. The cross-market price discovery is not evident with high liquid bonds (low illiquidity), good credit bonds (low rating score), and low coupon bonds. Investors prefer to trade CDS over bonds having opposite characteristics (i.e. illiquid and non-investment grade). This is consistent with the idea that the transaction cost of trading in the underlying market makes investors choose the derivative market as shown in Cao et al. (2023). The patterns are similar to equally weighted portfolios in panel B.

[Insert Table 7 here]

4.2.3 Panel Regressions

To study the overall cross-sectional relationship between variations in CDS spread and future bond returns and the impact of central clearing on the price discovery process, I regress individual firm-level bond returns on ΔSpread and various bond and stock characteristics for each month throughout the sample period. Similar to the difference-in-difference regression in Table 3, I include an interaction term whose coefficient estimates the effect of central counterpaty. A key difference between this panel regression and the difference-in-difference regression in Table 3 is that the panel regression includes more samples (including excluded samples in the previous set-up due to propensity score matching with narrow caliper) and time-series data (samples are not limited to the 12 months rule).

Column (1) of Table 8 shows the baseline result that an increase in the CDS spread predicts negative bond returns in the next month. Specifically, an increase of 100 basis points in CDS spread predicts a decrease in the return of 0.235% in the next month, and additional predictability is added by 0.373% if the CDS is included in the central counterparty.

Column (2) of Table 8 adds bond characteristics and controls for issuer-level bond characteristics. The magnitude of the average coefficient on ΔSpread is reduced, but the additional predictability due to central clearing is increased. The model is improved in that the intercept is close to zero and is insignificant, and the adjusted R^2 is significantly improved. The lagged bond return has a negative coefficient, meaning that corporate bonds are overpriced and the price is adjusted in the next period or that investors initially overreact to changes in default risk.

Column (3) of Table 8 adds stock characteristics. Stock market capitalization controls firm characteristics, and stock illiquidity, after Amihud (2002), controls the liquidity of the stock market that could affect price discovery as the illiquidity of bonds works. Lagged bond and stock return controls for momemtum in corporate bond market Gebhardt et al. (2005b). The result shows that lagged stock return is also related to the bond return as lagged bond return confounds. The positive coefficient on firm size suggests that big firms outperform small firms throughout the sample period. Nonetheless, the cross-market predictability is still significant.

Column (4) of Table 8 adds bond and stock beta. Bond (stock) beta is the regression coefficient of bond (stock) returns on bond (stock) market return and is estimated using the past 36 months of data on a monthly rolling basis. The result is consistent with the previous estimates as to the coefficient of change in CDS spread and its interaction term.

Lastly, Column (5) in Table 8 adds information from institutional investors. Stock short interest ratio is the short interest on the number of outstanding shares. *Stock DISP* is the dispersion of analysts' EPS forecast after Diether et al. (2002). These variables control shorting demand related to CDS and institutional investors' disagreement on uncertainty about the firm. However, the result is qualitatively indifferent from the column (4). The coefficient on ΔSpread and its interaction term are still statistically significant.

Overall, Table 8 shows that lagged bond and stock returns, credit rating, and firm size are related to bond returns in the cross-section. However, the return predictability of ΔSpread and the effect of central clearing are robust to controlling these variables.

[Insert Table 8 here]

5 Robustness Check

5.1 Does CDS provide additional information?

The previous analyses focus on the intensive margin of the change in CDS spread, that is, comparing future bond returns with different degrees of innovation in CDS implied credit risk. As the bond return and CDS spread are significantly correlated, it is important to examine whether CDS provides additional credit information not yet priced in the corporate bond. To investigate this, I test the extensive margin effect of single-name CDS. Although we cannot observe the CDS spread of a bond that does not have CDS, we can compare whether the existence of CDS affects the price discovery of bond return.

The bond underpricing literature has shown that, in general, bonds are underpriced in the primary market. The underpricing is more severe for private firms and initial bond offerings due to information asymmetry (Cai et al. (2007) and Nikolova et al. (2020)). If CDS spreads have additional information that is not yet reflected in the bond market, bonds with CDS should be less underpriced than those without CDS.

5.1.1 Extensive Margin Test

In order to examine the extensive margin, I collect the bond issue information from FISD and the first trading day and price from enhanced TRACE and then apply the filtering rule described in section 3.1. To rule out the other source of information asymmetry that might be correlated with the existence of CDS, only public firms' seasoned bond offerings are included in the analyses. Following Cai et al. (2007) and Nikolova et al. (2020), The first-day bond return in the secondary market is computed as

$$R_{i,t+n} = \frac{P_{i,t+n} + AI_{i,t+n}}{OP_{i,t}} - 1 \tag{5}$$

where $P_{i,t}$ is the end of daily bond price from the secondary market, $AI_{i,t+n}$ is accrued interest from time t to $t+n$, and $OP_{i,t}$ is offering price from the primary market. If the bond price is not available on the first trading day in the secondary market, I use the next available trading day within 1 week data using the following rule:

$$UP_{i,t} = \begin{cases} R_{i,t+n} & \text{if } n = 0 \\ R_{i,t+n} - R^{I}_{i,t+n} & \text{if } 1 \leq n \leq 6 \end{cases} \tag{6}$$

where $R^I_{i,t+n}$ is the cumulative return for the Bloomberg Barclays aggregate bond index over n days beginning on day t matched with the letter credit rating of bond issue i. UP_i, t is the bond underpricing measure on the first traded day in the secondary market. Finally, I run the following regression equation to investigate the effect of CDS on the underpricing:

$$UP_{i,j,t} = \alpha + \beta \cdot \text{CDS Dummy}_{i,t} + \theta X_{i,j,t-1} + \phi u_i + \tau \nu_t + \epsilon_{i,t} \tag{7}$$

where *CDS Dummy* is 1 if the firm i's bond issue, j, has corresponding CDS and 0 otherwise. Control variables $X_{i,j,t-1}$ are comprised of three groups. Firm characteristics are a logarithm of market capitalization, market-to-book ratio, leverage ratio, current ratio, the logarithm of firm age, firm-level bond portfolio's credit rating, size, maturity, and coupon. The market characteristic group includes lagged bond portfolio and stock return, bond portfolio illiquidity, Amihud's stock liquidity, stock short interest, and option dummy variable that is 1 if the firm has equity options traded in the derivative market and 0 otherwise. The new bond issue information group has a logarithm of offering amount, coupon, and logarithm of maturity.

Table 9 shows the result of two-way fixed-effects models in Equation (7). The dependent variable is the underpricing of the bond issue level (in basis points) in Equation (6), and fixed effects are CUSIP 6-digits and months. Column (1) of Table 9 controls the characteristics of the firm that include firm size, market-to-book ratio, leverage ratio, current ratio, and firm age, and controls characteristics of the firm-level bond such as credit rating, bond size, maturity and coupon rate. These characteristics are included to control investors' demand for certain characteristics. The result shows that bonds with CDS are less underpriced by 5.6 basis points compared to the bond without CDS. The magnitude is quite significant given that average underpricing for seasoned bond offering is 15 basis points for non-investment grade bonds reported in the literature (Cai et al., 2007). This suggests that CDS provides additional information on the pricing of new bonds.

There are other characteristics that might affect the valuation of bonds in the primary market. Option implied volatility has information about firm's credit risk and other information relevant to value firms. Furthermore, bonds with no hedging instruments could be discounted more than those without shorting availability, and hence, it is important to control such hedging availability. Column (2) of Table 9 controls the options and stock short interest ratio. *Dummy(Option)* is dummy variable that is 1 if the firm's equity option is traded on the option market and 0 otherwise. Stock short interest ratio is short interest over the number of shares outstanding. Furthermore, the model controls market characteristics such as past performance and illiquidity of stock and firm-level bond. The result still holds that CDS provides additional information about the firm so that primary market brokers cannot greatly deviate valuation from what market values.

Column (3) of Table 9 controls the characteristics of the new bond issue, including size, coupon, and maturity. The result is not qualitatively different from the result of other models. Overall, the coefficient of CDS dummy variable survives after controlling various characteristics that could affect underpicing in the primary market. This suggests that CDS has additional information about the firm's credit risk that is not yet reflected in the bond price.

[Insert Table 9 here]

6 Conclusion

A corporate bond and its credit default swap contract share the same credit risk of a firm, but the information quality could be different depending on the relative market efficiency. Using the phased introduction of central clearing in the CDS market as market efficiency shocks, the effect of central clearing in the CDS market on the information quality of CDS is examined. If one market has better information about a firm's credit risk than another market, delayed price discovery would be evident in the relatively inefficient market.

The introduction of the central counterparty (CCP) after the Dodd-Frank Act has played a significant role in enhancing cross-market price discovery. The reduction in counterparty risk and collateral requirements associated with CCP has incentivized investors to engage more actively in the CDS market. This has led to a stronger relationship between past CDS spread innovations and future bond returns, enhancing cross-market price discovery. Using the gradual introduction of the central counterparty as market efficiency shocks under the staggered difference-in-difference framework, I provide causal evidence that the predictability of corporate bond return via CDS spread innovations is significantly enhanced when the CDS is included in the central counterparty.

The economic significance of cross-market return predictability is also examined. The results show that, for corporate bonds with centrally cleared CDS, an increase in CDS spread significantly underperforms those with a decrease in CDS spread by 4.33% per year, even after controlling for conventional risk factors. However, the predictability is reduced for bonds without centrally cleared CDS. This is consistent with the hypothesis that the central clearing counterparty improves information quality of CDS and market efficiency by reducing counterparty risk and associated costs. The effect of central clearing on the cross-market price discovery is still robust when the additional bond characteristics and stock market characteristics are all considered in panel regressions.

Furthermore, the study explores the extent to which CDS provides additional information that is not yet reflected in the corporate bond market as an extensive margin test. The analysis reveals that bonds with CDS are less underpriced in the primary market compared to bonds without CDS. This suggests that the CDS market's assessment of credit risk partially resolves information asymmetry not only in the secondary market but also in the primary market.

Overall, this study contributes to understanding market frictions and cross-market price discovery in the corporate credit market. The findings highlight the importance of the central clearing in providing valuable information for investors and its role in shaping the pricing of corporate bonds.

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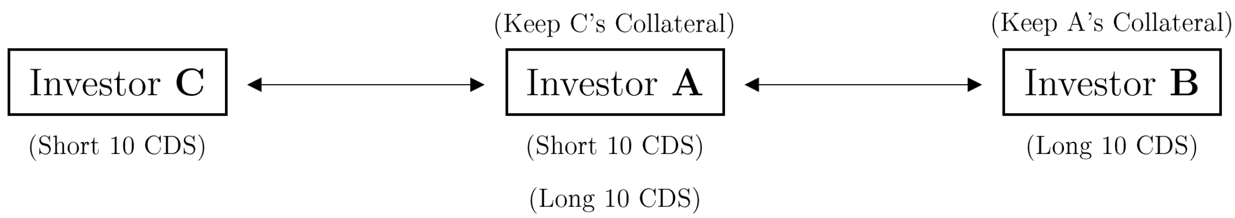
Figure 1: CDS Transactions with and without Central Counterparty

This figure compares the CDS transactions with and without the central counterparty. Panel A shows the CDS market without CCP where investor A's theoretical position is neutralized but the collateral is kept by investor B. Panel B shows the CDS market with CCP which nets out investor A's position.

Panel A: Bilateral CDS Contracts



Panel B: Multilateral Netting with CCP

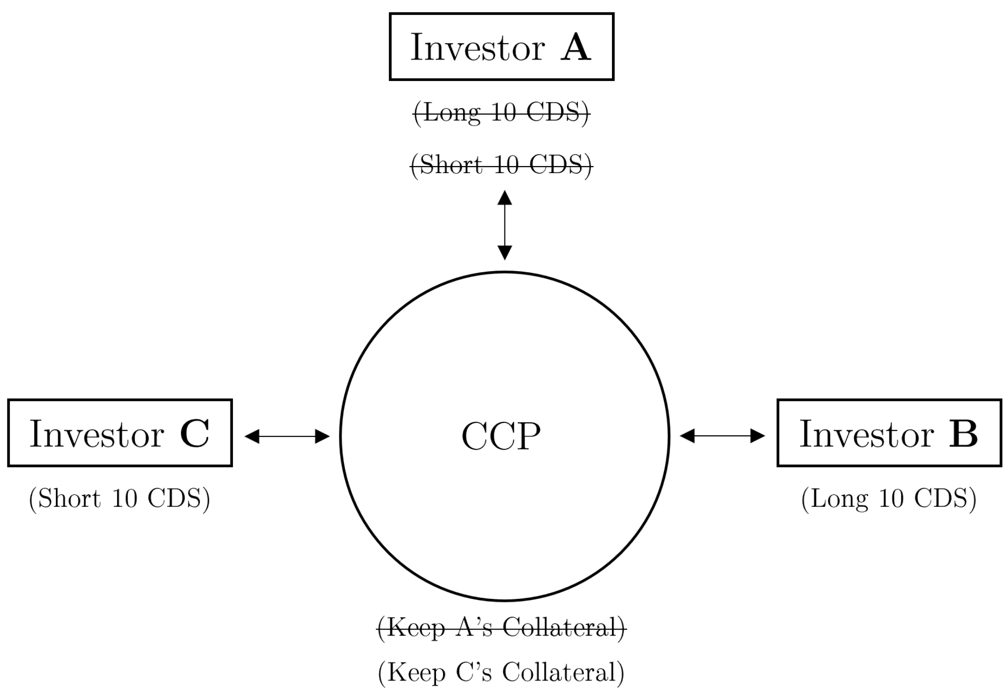


Figure 2: Size of CDS Before and After Central Clearing

This figure compares the cross-sectional average size of CDS contracts of treated and control groups 6 months before and after the introduction of central clearing. The vertical axis shows the average gross notional amount (in billions). The solid blue line represents the centrally cleared CDS group (treated group) and the dashed red line shows the propensity score matched sample group (control group).

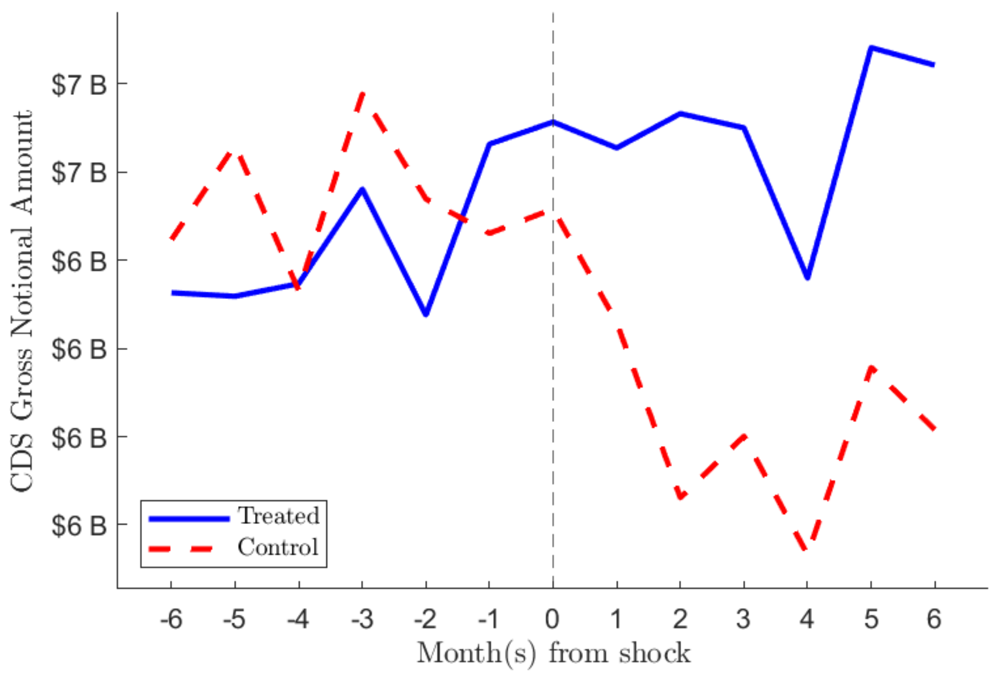


Figure 3: CDS Spread Around Portfolio Formation Month

This figure plots average CDS spread 6 months before and after the portfolio formation. The bottom (Dashed red line) and top (Solid blue line) quintile groups are formed by sorting CDS spread changes ($\Delta Spread$).

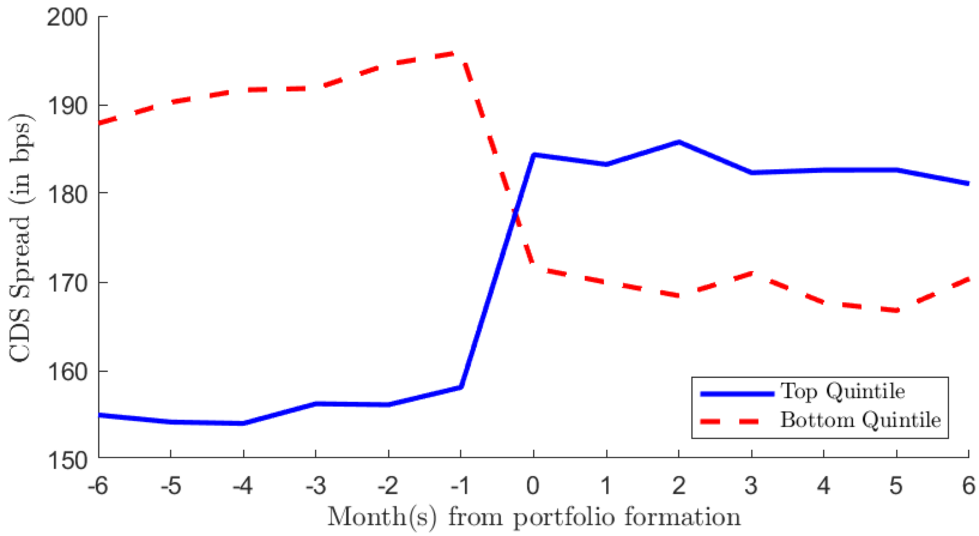


Table 1: Summary Statistics and Correlation Matrix

Panel A shows summary statistics of monthly CDS and bond characteristics used for empirical analyses in this paper. *Spread (bps)* is the 5-year spread of CDS in basis points, Δ*Spread (bps)* is the change in the spread of CDS for 1 month. The following variables are corporate bond variables. *Return* is corporate bond return (in %), *Log(Size)* is logarithm of bond outstanding amount, and *Maturity* is remaining years to maturity. *Rating* is average credit rating based on three credit rating agency (Standard & Poor's, Moody's, and Fitch) where 1 is the highest rating and decreases by one as the rating grade goes down. Investment and non-investment grade are below and above 10, respectively. *Illiquidity* is the measure of illiquidity after Bao et al. (2011). Panel B shows the time-series average of cross-sectional correlation among the variables. All variables are firm-level average variables weighted by the outstanding amount of the bond. The sample period covers from August 2010 to June 2022, and excludes firms in financial and utility industry (SIC 4-digit 6000-6999 and 4000-4999 respectively).

Panel A: Descriptive Statistics

Variable	N	Mean	10%	25%	Median	75%	90%
Spread (bps)	28,875	157.48	33.54	52.18	88.81	166.47	341.36
ΔSpread (bps)	28,875	-1.95	-18.10	-5.02	-0.06	3.41	15.56
Return	29,303	0.31	-1.80	-0.47	0.33	1.22	2.37
Log(Size)	29,303	14.70	13.17	13.89	14.73	15.48	16.21
Maturity	29,303	9.33	4.09	5.68	8.10	12.43	15.89
Rating	29,303	8.96	5.50	7.00	9.00	10.00	13.33
Illiquidity	29,302	0.31	0.01	0.03	0.08	0.21	0.51

Panel B: Correlation Matrix

	Spread	ΔSpread	Return	Size (Log)	Maturity	Rating	Illiquidity
Spread	1	0.02	-0.03	-0.29	-0.24	0.66	0.19
ΔSpread		1	-0.25	0.03	0.02	-0.06	0.13
Return			1	-0.03	0	0.04	-0.23
Log(Size)				1	0.32	-0.43	-0.07
Maturity					1	-0.31	0.05
Rating						1	0.06
Illiquidity							1

Table 2: Comparison of Pre-treatment Sample Characteristics

This table compares the average characteristics of the centrally cleared samples (treated group) and their matched samples (control group), prior to the treatment date (CCP inclusion date). Panel A shows the CDS, bond, and firm characteristics used for propensity score matching in Equation (3). *Relative quoted spread* is the CDS bid-ask spread over spread midpoint, and *Composite depth* is the number of contributors in the CDS market to compute CDS spread. *Log(Net Notional)* is the logarithm of the CDS net notional outstanding, and *Log(Contracts)* is number of open CDS contracts. Panel B shows the bond and firm characteristics that are not included for the propensity score matching. *Return*, *Rating*, *Maturity*, *Coupon*, *Illiquidity*, and *Log(Size)* are bond characteristics described in Section 3.1. *Short Interest* is stock short interest ratio calculated by short interest divided by the number of outstanding shares.

Panel A: Characteristics Used for Propensity Score Matching

Variable	Matched sample	Treated
Relative quoted spread	0.11	0.1
Composite depth	5.29	5.88
Log(Net Notional)	19.86	20
Log(Contracts)	6.85	6.97
Leverage Ratio	4.5	2.43
Market-to-Book Ratio	2.09	3.34
Rating	10.69	10.53
Illiquidity	0.49	0.42
Log(Size)	14.69	14.49

Panel B: Characteristics Not Included for Propensity Score Matching

Variable	Matched sample	Treated
Return	0.38	0.38
Maturity	8.65	9.34
Coupon	5.66	5.79
Short Interest	0.04	0.05

Table 3: Does CCP Inclusion Enhance Cross-market Price Discovery?

The sample period covers November 2010 to June 2022, and matched samples include 12 months before and after the CCP inclusion month. *CC* is the dummy variable equal to 1 if the firm *i*'s CDS is included in the CCP and 0 otherwise. Columns (1) and (3) demonstrate the effect of CCP introduction on the cross-market price discovery. Columns (2) and (4) show the results of the placebo test. All samples from the placebo test are not treated as the sample period is shifted one year prior to the central counterparty inclusion date. The treated (CCP CDS) and control groups (non-CCP CDS) are selected following the propensity score matching method in Equation (3). CUISP 6-digit (firm) and month (time) fixed effects are included, t-statistics are reported in parentheses, and significance levels are 1% (***), 5% (**), and 10% (*).

	Dependent variable			
	Bond $\text{Return}_{i,t}$		$\Delta\text{Spread}_{i,t}$	
	Baseline	Placebo	Baseline	Placebo
	(1)	(2)	(3)	(4)
Constant	2.256	2.143	-0.143	-0.239
	(0.67)	(0.67)	(-0.23)	(-0.33)
$\text{CC}_{i,t}$	0.222	0.127	-0.009	-0.011
	(1.61)	(0.91)	(-0.35)	(-0.35)
$\Delta\text{Spread}_{i,t-1}$	-1.078***	-0.718***	0.091***	-0.043
	(-6.17)	(-2.90)	(3.09)	(-1.31)
$\Delta\text{Spread}_{i,t-1} \times \text{CC}_{i,t}$	-0.398**	-0.159		
	(-2.00)	(-0.64)		
$\text{Return}_{i,t-1}$	-0.201***	-0.196***	-0.024***	-0.006
	(-5.36)	(-5.62)	(-3.39)	(-0.62)
$\text{Return}_{t-1} \times \text{CC}_{i,t}$			0.031***	-0.018*
			(3.92)	(-1.79)
$\text{Log(Size)}_{i,t-1}$	0.123	0.079	-0.019	-0.021
	(0.59)	(0.41)	(-0.51)	(-0.49)
$\text{Illiquidity}_{i,t-1}$	-0.241***	0.056	0.041**	0.037*
	(-2.60)	(0.57)	(2.33)	(1.73)
$\text{Coupon}_{i,t-1}$	0.073	0.068	-0.004	-0.005
	(0.63)	(0.55)	(-0.21)	(-0.18)
$\text{Maturity}_{i,t-1}$	-0.018	0.016	-0.004	-0.013*
	(-0.50)	(0.47)	(-0.68)	(-1.79)

(*Continued*)

Table 3—*Continued*

	Dependent variable			
	Bond $\text{Return}_{i,t}$		$\Delta\text{Spread}_{i,t}$	
	Baseline	Placebo	Baseline	Placebo
	(1)	(2)	(3)	(4)
$\text{Rating}_{i,t-1}$	-0.397***	-0.334**	0.049**	0.068**
	(-3.18)	(-2.51)	(2.04)	(2.23)
Obsevations	1,976	2,065	1,917	2,016
Adjusted R^2	0.40	0.37	0.18	0.19
Fixed Effects	Yes	Yes	Yes	Yes

Table 4: Quintile Portfolios of Bonds Sorted by ΔSpread

Panel A (Panel B) reports value-weighted (equally weighted) return and alphas of quintile bond portfolios (in %) sorted by ΔSpread. Columns (1) to (5) represent quintile bond portfolios, bottom to top ΔSpread. The last column of the table, (5)-(1), shows quintile difference portfolios which are zero-cost bond portfolio returns of top ΔSpread minus bottom ΔSpread quintile bond portfolio return. The samples are divided into two groups: CC and Non-CC. CC group is bonds with centrally cleared CDS, and Non-CC group is bonds with non-centrally cleared CDS. *Alpha (Stock)* shows the alphas of regressing bond returns on conventional stock market factors (FF5) of Fama and French (2015) plus stock market momentum (MOM), and *Alpha (Bond)* shows the alphas of estimated with the bond market factors of Bai et al. (2019). The sample excludes firms in the financial and utility industry and covers from August 2010 to June 2022. Standard errors are estimated after Newey and West (1987) with 6 lags, t-statistics are reported in parentheses, and significance levels are 1% (***), 5% (**), and 10% (*).

Panel A: Alpha of Value-Weighted Bond Portfolios

		Quintile					Difference
		(1)	(2)	(3)	(4)	(5)	(5)-(1)
CC	Alpha (Stock)	0.166	0.191	0.11	-0.01	-0.112	-0.278**
		(1.07)	(1.45)	(0.77)	(-0.08)	(-0.62)	(-2.03)
	Alpha (Bond)	0.048	0.037	0.034	-0.077***	-0.313**	-0.361**
		(0.7)	(0.84)	(1.08)	(-2.66)	(-2.23)	(-2.48)
Non-CC	Alpha (Stock)	0.141	0.078	0.066	0.081	-0.025	-0.166*
		(1.02)	(0.57)	(0.52)	(0.64)	(-0.19)	(-1.84)
	Alpha (Bond)	0.031	-0.04	0.022	-0.016	-0.127	-0.158
		(0.55)	(-1.17)	(0.68)	(-0.51)	(-1.54)	(-1.59)

Panel B: Alpha of Equally Weighted Bond Portfolios

		Quintile					Difference
		(1)	(2)	(3)	(4)	(5)	(5)-(1)
CC	Alpha (Stock)	0.231	0.163	0.101	-0.005	-0.087	-0.318***
		(1.47)	(1.27)	(0.76)	(-0.04)	(-0.51)	(-2.83)
	Alpha (Bond)	0.123	0.015	-0.007	-0.111**	-0.217*	-0.340***
		(1.53)	(0.35)	(-0.24)	(-2.59)	(-1.83)	(-3.12)
Non-CC	Alpha (Stock)	0.155	0.114	0.045	0.065	-0.063	-0.218**
		(1.21)	(0.85)	(0.33)	(0.51)	(-0.45)	(-2.51)
	Alpha (Bond)	0.017	0.006	-0.035	-0.046	-0.176**	-0.193**
		(0.33)	(0.15)	(-1.22)	(-1.38)	(-2.43)	(-2.11)

Table 5: Predictability Horizon

Panel A (Panel B) reports value-weighted (equally weighted) alphas of quintile difference bond portfolios (in %) sorted by ΔSpread. Portfolios are sorted in time t. Columns (1) to (6) show the monthly performance of the quintile difference portfolio after 1 month to 6 months from the portfolio formation month. The samples are divided into two groups: CC and Non-CC. CC group is bonds with centrally cleared CDS, and Non-CC group is bonds with non-centrally cleared CDS. *Alpha (Stock)* shows the alphas of regressing bond returns on conventional stock market factors (FF5) of Fama and French (2015) plus stock market momentum (MOM), and *Alpha (Bond)* shows the alphas of estimated with the bond market factors of Bai et al. (2019). The sample excludes firms in the financial and utility industry and covers from August 2010 to June 2022. Standard errors are estimated after Newey and West (1987) with 6 lags, t-statistics are reported in parentheses, and significance levels are 1% (***), 5% (**), and 10% (*).

Panel A: Alpha of Value-Weighted Bond Portfolios

		(1)	(2)	(3)	(4)	(5)
		t+1	t+2	t+3	t+4	t+5
CC	Alpha (Stock)	-0.278**	-0.245*	0.014	0.142	-0.202
		(-2.03)	(-1.69)	(0.08)	(0.77)	(-1.22)
	Alpha (Bond)	-0.361**	-0.419***	0.186	0.345	-0.156
		(-2.48)	(-3.39)	(0.74)	(1.33)	(-0.88)
Non-CC	Alpha (Stock)	-0.166*	-0.027	0.077	0.133	-0.179*
		(-1.84)	(-0.23)	(0.47)	(1.43)	(-1.82)
	Alpha (Bond)	-0.158	-0.001	0.163	0.184	-0.132
		(-1.59)	(0)	(0.76)	(1.47)	(-1.2)

Panel B: Alpha of Equally Weighted Bond Portfolios

		(1)	(2)	(3)	(4)	(5)
		t+1	t+2	t+3	t+4	t+5
CC	Alpha (Stock)	-0.318***	-0.271**	-0.01	0.049	-0.163
		(-2.83)	(-2.36)	(-0.08)	(0.31)	(-1.11)
	Alpha (Bond)	-0.340***	-0.349***	0.196	0.27	-0.105
		(-3.12)	(-3.52)	(0.92)	(1.14)	(-0.7)
Non-CC	Alpha (Stock)	-0.218**	-0.057	-0.025	0.122	-0.213*
		(-2.51)	(-0.49)	(-0.16)	(1.49)	(-1.84)
	Alpha (Bond)	-0.193**	-0.087	0.053	0.186	-0.137
		(-2.11)	(-0.88)	(0.25)	(1.61)	(-1.01)

Table 6: Bond Characteristics on Portfolio Formation Month

Panel A (Panel B) reports value-weighted (equally weighted) bond characteristics of quintile bond portfolios in portfolio formation months. Bond portfolios are sorted by ΔSpread. Columns (1) to (5) represent characteristics of quintile bond portfolios, bottom (1) to top (5) ΔSpread. The samples are divided into two groups: CC and Non-CC. CC group is bonds with centrally cleared CDS, and Non-CC group is bonds with non-centrally cleared CDS. *Return* is corporate bond return (in %), *Log(Size)* is logarithm of bond outstanding amount, and *Maturity* is remaining years to maturity. *Rating* is average credit rating based on three credit rating agency (Standard & Poor's, Moody's, and Fitch) where 1 is the highest rating and decreases by one as the letter rating grade decreases. Investment grade and non-investment grade are below and above 10, respectively. *Illiquidity* is the measure of illiquidity after Bao et al. (2011). The sample excludes firms in financial and utility industry are excluded (SIC 4-digit 6000-6999 and 4000-4999, respectively). All statistics are computed using the Bond-CDS merged data from August 2010 to June 2022.

Panel A: Value-Weighted Characteristics

		Quintile				
		(1)	(2)	(3)	(4)	(5)
CC	Return	1.2	0.54	0.27	0.06	-0.53
	Log(Size)	15.69	15.93	16.05	15.97	15.74
	Maturity	10.39	11.53	11.7	11.5	10.55
	Rating	9.02	7.3	6.85	7.07	8.62
	Illiquidity	0.2	0.19	0.18	0.32	0.24
	Coupon	5.02	4.51	4.37	4.42	4.86
Non-CC	Return	0.91	0.4	0.29	0.17	-0.22
	Log(Size)	15.42	15.61	15.65	15.66	15.54
	Maturity	9.88	10.57	10.69	10.64	9.86
	Rating	9.16	6.98	6.4	6.76	8.79
	Illiquidity	0.21	0.2	0.19	0.18	0.23
	Coupon	4.9	4.11	3.9	4.04	4.73

Panel B: Equally Weighted Characteristics

		Quintile				
		(1)	(2)	(3)	(4)	(5)
CC	Return	1.3	0.48	0.27	0.11	-0.55
	Log(Size)	14.82	15.11	15.22	15.12	14.83
	Maturity	9.03	10.09	10.34	10.09	9.11
	Rating	9.9	8.14	7.77	7.93	9.68
	Illiquidity	0.27	0.23	0.23	0.29	0.39
	Coupon	5.29	4.58	4.44	4.53	5.19
Non-CC	Return	1.03	0.45	0.31	0.22	-0.28
	Log(Size)	14.45	14.57	14.61	14.6	14.48
	Maturity	8.69	9.58	9.73	9.5	8.62
	Rating	10.55	8.4	7.76	8.17	10.13
	Illiquidity	0.35	0.3	0.32	0.26	0.39
	Coupon	5.33	4.54	4.29	4.46	5.16

Table 7: Bivariate Dependent-Sort Portfolio

Panels A (Panel B) shows 2×3 bivaraite dependent-sort portfolio results. Bond portfolios are sorted by bond characteristic into *High* and *Low* groups and then each group is sorted by ΔSpread into tercile groups. Hence, the number of issuer level bonds are equally divided. Columns (1) to (6) show alphas (in %) from regressing tercile portfolio return difference on bond market factors of Bai et al. (2019). The sample excludes firms in financial and utility industry are excluded (SIC 4-digit 6000-6999 and 4000-4999 respectively). All statistics are computed using data from August 2010 to June 2022. Standard errors are estimated after Newey and West (1987) with 6 lags, the t-statistics are reported in parentheses, and significance levels are 1% (***), 5% (**), and 10% (*).

Panel A: Alpha of Value-Weighted Portfolios

	(1) Return		(2) Log(Size)		(3) Maturity	
	Low	High	Low	High	Low	High
HML	-0.161*	-0.113**	-0.193***	-0.139*	-0.208**	-0.130*
ΔSpread	(-1.7)	(-2.08)	(-3.05)	(-1.69)	(-2.18)	(-1.84)
	(4) Rating Score		(5) Illiquidity		(6) Coupon	
	Low	High	Low	High	Low	High
HML	-0.037	-0.251**	-0.164**	-0.149*	-0.062	-0.249**
ΔSpread	(-0.76)	(-2.58)	(-1.99)	(-1.82)	(-1.62)	(-2.39)

Panel B: Alpha of Equally Weighted Portfolios

	(1) Return		(2) Log(Size)		(3) Maturity	
	Low	High	Low	High	Low	High
HML	-0.207**	-0.085	-0.189***	-0.161*	-0.225***	-0.135**
ΔSpread	(-2.41)	(-1.62)	(-2.81)	(-1.76)	(-2.67)	(-2.01)
	(4) Rating Score		(5) Illiquidity		(6) Coupon	
	Low	High	Low	High	Low	High
HML	-0.06	-0.194**	-0.158**	-0.225***	-0.077*	-0.231***
ΔSpread	(-1.35)	(-2.38)	(-2.32)	(-3.09)	(-1.85)	(-2.64)

Table 8: Panel Regressions for Bond Returns

Columns (1) to (5) show panel regression results with firm and time fixed effects. The dependent variable is individual firm-level bond return (in %) from Equation (1). *CC* is the dummy variable equal to 1 if the firm i's CDS is included in the CCP and 0 otherwise. Column (2) controls for issuer-level bond characteristics in Section 3.1. Column (3) adds the stock characteristics in which *Stock Illiquidity* is after Amihud (2002). Column (4) adds bond and stock market beta. Column (5) adds the short interest ratio and the dispersion of the EPS forecast after Diether et al. (2002). The sample excludes firms in the financial and utility industry are excluded (SIC 4-digit 6000-6999 and 4000-4999, respectively). All statistics are computed using data from August 2002 to December 2022. Standard errors are estimated after Newey and West (1987) with 6 lags, t-statistics are reported in parentheses, and significance levels are 1% (***), 5% (**), and 10% (*).

	Dependent variable: Bond Return$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Constant	0.334***	-0.497	-1.795**	-4.370***	-3.614***
	(11.85)	(-1.13)	(-2.56)	(-4.78)	(-3.83)
CC$_{i,t}$	-0.016	0.035	0.036	-0.091	-0.115
	(-0.25)	(0.53)	(0.53)	(-1.06)	(-1.33)
ΔSpread$_{i,t-1}$	-0.235***	-0.188***	-0.242***	-0.238***	-0.228***
	(-6.33)	(-4.49)	(-5.77)	(-4.24)	(-4.03)
ΔSpread$_{i,t-1}$ $\times$ CC$_{i,t}$	-0.373***	-0.415***	-0.349***	-0.461***	-0.472***
	(-6.51)	(-7.26)	(-6.22)	(-6.95)	(-7.05)
Bond Return$_{i,t-1}$		-0.018***	-0.013*	-0.052***	-0.051***
		(-2.67)	(-1.91)	(-6.52)	(-6.37)
Bond Rating$_{i,t}$		0.159***	0.148***	0.127***	0.139***
		(10.71)	(8.79)	(5.54)	(5.96)
Bond Maturity$_{i,t}$		0.014***	0.017***	0.008	0.006
		(3.08)	(3.58)	(1.22)	(0.91)
Bond Illiquidity$_{i,t}$		-0.284***	-0.278***	-0.370***	-0.367***
		(-38.71)	(-36.75)	(-41.35)	(-40.82)
Bond Log(Size)$_{i,t}$		-0.049*	-0.015	0.050	0.055
		(-1.83)	(-0.54)	(1.32)	(1.44)
Bond Coupon$_{i,t}$		0.013	-0.025	-0.029	-0.039
		(0.61)	(-1.18)	(-0.99)	(-1.31)
Stock Return$_{i,t-1}$			0.101***	0.106***	0.108***
			(68.60)	(61.67)	(61.43)
Stock Log(Size)$_{i,t}$			0.057*	0.152***	0.107**
			(1.74)	(3.77)	(2.52)

(*Continued*)

Table 8—*Continued*

Dependent variable: Bond Return$_{i,t}$					
	(1)	(2)	(3)	(4)	(5)
Stock Illiquidity$_{i,t}$			1.864	5.778***	5.869***
			(1.20)	(2.63)	(2.60)
Bond Beta$_{i,t}$				0.316***	0.323***
				(10.83)	(10.97)
Stock Beta$_{i,t}$				0.001	-0.018
				(0.02)	(-0.41)
Stock Short Interest$_{i,t}$					-1.984***
					(-3.80)
Stock DISP$_{i,t}$					-0.024**
					(-2.32)
Observations	28,783	27,273	22,639	15,951	15,661
Adjusted R^2	0.37	0.41	0.51	0.55	0.56
Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 9: Does CDS Provide Additional Information? (Extensive Margin Test)

This table shows the result of two-way fixed effect models in Equation (7). The dependent variable is the underpricing at the bond issue level (in basis points, positive value means underpricing) in Equation (6) that calculates the first day return in the secondary market when an issue is transferred from the primary market to the secondary market. The samples include seasoned bond offerings only; private firms and initial bond offerings are excluded. *Dummy(CDS)* is 1 if a firm's CDS is traded and 0 otherwise. *Dummy(Option)* is 1 if a firm's equity option is traded and 0 otherwise. Column (1) controls for firm characteristics and issuer-level bond characteristics. Column (2) controls for market characteristics such as past month return, illiquidity, and short interest. *Dummy(Option)* is a dummy variable equal to 1 if the option is traded and 0 otherwise. Lastly, column (3) controls for the characteristics of the new bond issue. t-statistics are reported in parentheses.

Dependent variable: Bond Underpricing			
	(1)	(2)	(3)
Constant	105.732** (2.16)	45.673 (0.74)	23.620 (0.37)
Dummy(CDS)	-5.676** (-1.98)	-6.762** (-2.28)	-6.065** (-2.07)
Dummy(Option)		5.231 (0.33)	2.000 (0.13)
Stock Short Interest		31.443 (0.87)	15.516 (0.43)
Stock Log(Size)	-6.626*** (-3.33)	-5.991** (-2.57)	-4.453* (-1.87)
MB	-0.005 (-0.19)	-0.011 (-0.41)	-0.013 (-0.50)
Leverage	0.132 (0.75)	0.139 (0.79)	0.151 (0.87)
Current	0.410 (0.27)	-0.216 (-0.13)	-0.498 (-0.29)
Log(Firm Age)	13.235 (1.16)	28.696** (2.10)	26.511* (1.95)
Bond Rating	-0.632 (-0.96)	-1.319* (-1.76)	-1.843** (-2.44)
Bond Log(Size)	-0.473 (-0.62)	-0.078 (-0.07)	-0.214 (-0.21)

(*Continued*)

Table 9—*Continued*

Dependent variable: Bond Underpricing			
	(1)	(2)	(3)
Bond Maturity	-0.211	-0.166	-0.121
	(-1.14)	(-0.77)	(-0.57)
Bond Coupon	0.466	0.562	0.638
	(0.63)	(0.66)	(0.76)
Bond Return		0.634*	0.713*
		(1.73)	(1.96)
Bond Illiquidity		0.528*	0.522*
		(1.73)	(1.72)
Stock Return		0.071	0.071
		(0.79)	(0.79)
Stock Illiquidity		14074.264***	10491.074**
		(2.72)	(2.02)
Issue Log(Size)			-0.335
			(-0.23)
Issue Coupon			3.702***
			(4.15)
Issue Maturity			0.043
			(0.49)
Observations	3,027	2,765	2,764
Adjusted R^2	0.41	0.41	0.43