

P250: Central Clearing and Cross-market Price Discovery in the Credit Markets

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November 2025

Abstract

We study how central clearing in credit default swap (CDS) markets affects market efficiency and information flow to the underlying corporate bonds. Using staggered difference-in-difference approaches, we analyze the implementation of central clearing under the Dodd-Frank Act. Results show that centrally cleared CDS significantly improves bond return predictability, supporting the hypothesis that central clearing enhances CDS market efficiency by reducing counterparty risk and related costs. Corporate bonds associated with centrally cleared CDS underperform by an annualized alpha of 4.58% as CDS spreads increase even after controlling for risk and bond characteristics.

Keywords: Price discovery, Corporate bond, CDS, Central counterparty

JEL Classification: G12, G14

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1 Introduction

The Dodd-Frank Act introduced central clearing in the single-name CDS market to reduce counterparty risk and promote liquidity. 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.

Since CDS and its underlying asset, corporate bond, share the same credit risk of a firm while the quality of pricing information could be different depending on the relative market efficiency, we study both underlying and derivative market jointly. We hypothesize that 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 counterparty 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 theoretically cancels out, yet the investor B still holds collateral.¹ Panel A of Figure 1 shows that 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 contracts. CCP is a counterparty to every protection buyer and seller, and hence CCP facilitates CDS transactions.

Moreover, CCP can effectively manage 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. Similar to the way the deposit insurance fund operates, the CCP collects funds from members based on the trading volume in the CCP and the additional risk that a member brought to the CCP.

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

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

[Insert Figure 1 here]

On the other hand, there exist other factors that make the bond market inefficient. First, 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 (called naked CDS), and the underlying asset is delivered only when the underlying firm (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.

³See Table 1 in [Bao et al. \(2011\)](#)

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, we utilize the phased 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, we 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, centrally cleared CDS are matched 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.

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

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 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, this paper shows that the performance does not result from risk compensation, and finds 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. \(2005a,b\)](#). We 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 pricing information that is not yet reflected in the corporate bond price, firms with and without CDS are compared and we 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. This suggests that 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 robustness 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 CDS pricing, but the magnitude is small as collateral requirements reduce counterparty risk. The stance of this paper diverges from theirs; We show that the introduction of CCP that reduces the collateral requirement and exposure to counterparty risk affects the cross-market price discovery process rather than focusing on CDS prices. 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 our finding that the effects in the CDS market contributes to the CDS market efficiency and hence the cross-market price discovery.

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

Second, this paper offers insights into return predictability in cross-market analyses. Studies by [An et al. \(2014\)](#) and [Cao et al. \(2023\)](#) have a notable relevance to this paper. 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 it relates 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 margin (Bond with CCP-CDS versus with non-CCP-CDS), but also through extensive margin (Bond with CDS versus without CDS), 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, we 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

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

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. \(2008\)](#), [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 method, first, the issue-level bond returns using the prices of the last trading day of month are computed. The return of the bond i at time t is computed as in Equation (1).

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

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. We 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.

$$\Delta\text{Spread}_t = \text{Spread}_t - \text{Spread}_{t-1} \quad (2)$$

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 $\Delta\text{Spread}_{t-1}$), We 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} .

⁶There 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.

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

3.2.2 CDS Transaction Information

The *Gross Notional* amount represents the total face value of credit protection traded⁸, 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

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

components (Longstaff et al., 2005). The non-default components correlated with ΔSpread might predict bond return, so in the later analysis we 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, we follow 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 inclusion 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, we find counterfactuals by matching samples using the following probit regression.

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

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, we include $Rating_i$, which is average 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, we 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. We 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 mem-

ber 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-treatment 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, the following difference-in-difference regression is estimated to study the effect of CCP inclusion on cross-market price discovery:

$$R_{i,t} = \alpha + \beta_1 \cdot \Delta \text{Spread}_{i,t-1} + \beta_2 \cdot CC_{i,t} + \beta_3 \cdot \text{Spread}_{i,t-1} \cdot CC_{i,t} + X_{i,t-1} + u_i + \nu_t + \epsilon_{i,t} \quad (4)$$

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 relieved 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 CDS market

structure change. 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 2.4 basis points, but the predictability is canceled out (by -3.1 basis points) to near zero 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, zero cost bond portfolios based on sorting ΔSpread are formed and average returns and portfolio alphas are measured to gauge the magnitude of price discovery. Later sections control for variables that might influence cross-market return predictability.

4.2.1 Univariate Sorting

We 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, we use both stock and bond

market risk factors [Fama and French \(2015\)](#) and the bond market factor.⁹ In Table 4, Panel 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 the bond market factor. The alpha measures are divided into two groups: Bonds with centrally cleared CDS (CC group) and without centrally cleared CDS (non-CC group).

First, the alphas decreasing from column (1) to column (5) and indicating negative returns for the zero-cost quintile difference portfolio in column (6) 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. Second, the result shows that the magnitude of price discovery is higher in the centrally cleared group than the traditional bilateral contracts (non-CC group), and the statistical significance of price discovery is weak in the non-CC group. The statistically significant -0.382% alpha (equivalent to -4.584% per year) of zero cost portfolio in panel A (CC group) is consistent with the previous results that the delayed price discovery is more pronounced in the *relatively* inefficient market; Introduction of central counterparty makes the bond market relatively inefficient as CDS market efficiency improves.

[Insert Table 4 here]

Table 5 tests the delayed price discovery horizon. Portfolio formation is same as previous

⁹The stock market factors are from <https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>.

univariate sorting analysis, but the zero-cost quintile difference returns are estimated more than 1-month horizon 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. We 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 Δ Spread and bottom Δ Spread 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 top quintile and relatively low for the bottom quintile 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 relieved 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, and 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, the bond returns are double sorted with bond characteristics and Δ Spread and estimated alphas are reported in Table 7. 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 having 2 by 3 portfolios, and the portfolios are rebalanced following the same procedure every month.

Columns (1) to (6) of Table 7 show alphas from regressing tercile portfolio return difference on the bond market factor. 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 the bond characteristics partially affect the cross-market price discovery process. Specifically, the cross-market price discovery is not evident with good credit (low rating score) and low coupon, which is typically correlated with credit rating as underwriters charge high coupons to non-investment grade bonds. This result suggests that, first, corporate bond returns react to the changes in CDS market implied credit risk more significantly when credit rating is low. The patterns are similar to equally weighted portfolios in panel B.

[Insert Table 7 here]

4.2.3 Panel Regressions

The previous result (Table 7) reveals that there might be some variables affecting the main result of this paper. Therefore, to control these variables and 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, individual firm-level bond returns are regressed 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, an interaction term where its coefficient estimates the effect of central counterparty is included. 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 momentum 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, and the return predictability 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 based on different degrees of innovation in CDS implied

credit risk. As the bond return and changes in CDS spread are significantly correlated, it is important to examine whether CDS provides additional credit information not yet priced in the corporate bond market. To investigate this, we 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, we 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

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

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, we use the next available trading day within 1 week data using the following rule:

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

where $R_{i,t+n}^I$ 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, we run the following regression equation to investigate the effect of CDS on the underpricing:

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

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 5.7 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 underpricing 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 their relative market efficiency, meaning that it is possible to predict asset returns in a relatively less efficient market based on the information from a relatively more efficient market.

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. 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, We 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, 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 the 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, as an extensive margin test, the study explores the extent to which CDS provides additional information not yet reflected in the corporate bond market. The analysis reveals that bonds with traded 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 the cross-market price discovery in the primary and secondary corporate bond markets. 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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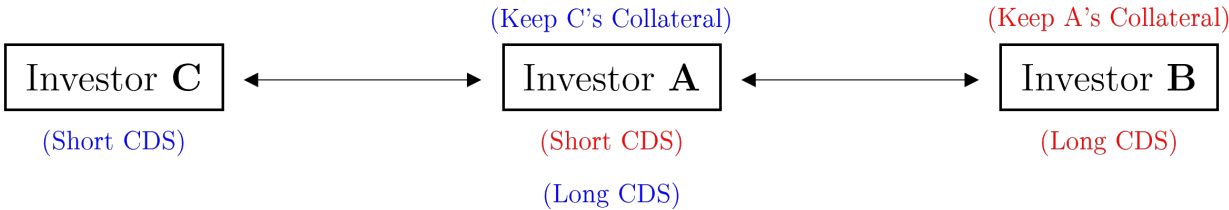
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Figure 1: CDS Transactions with and without Central Counterparty (CCP)

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

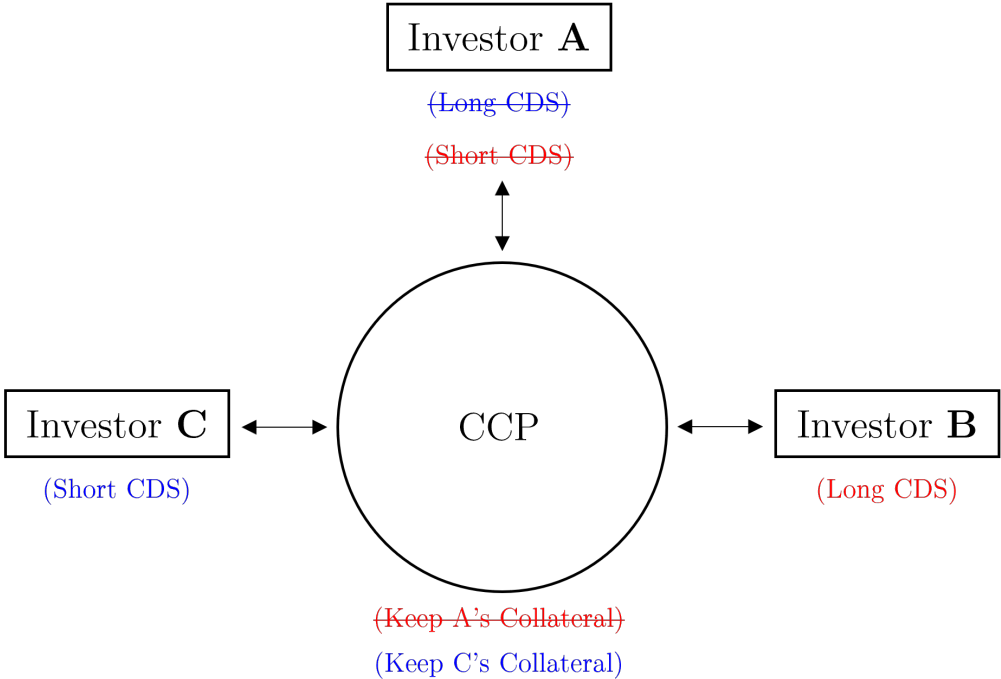


Figure 2: Size of CDS Before and After Central Clearing

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).

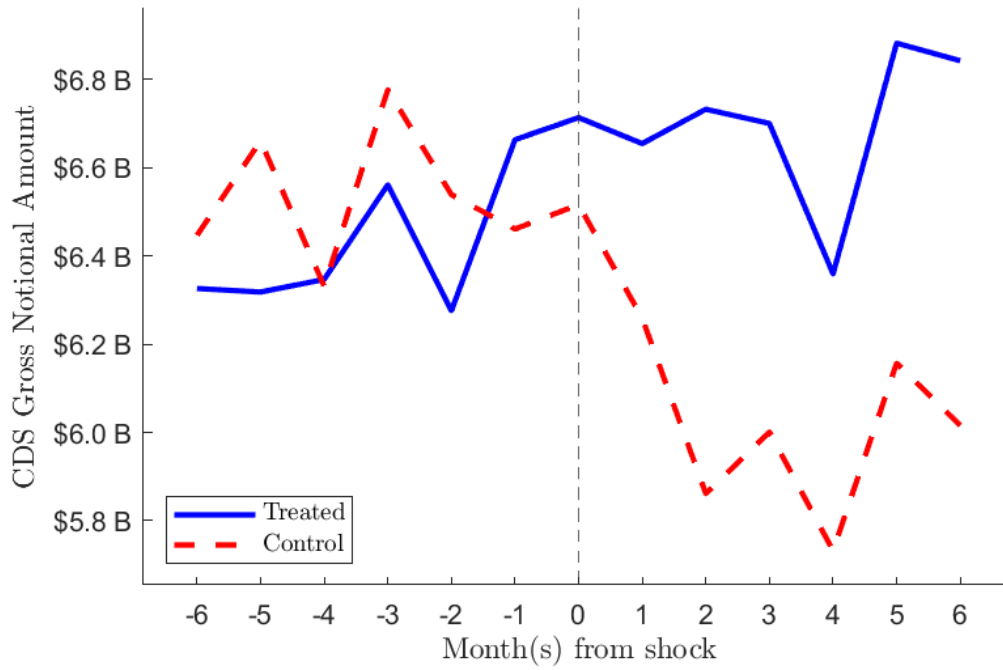


Figure 3: CDS Spread Around Portfolio Formation Month

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 ($\Delta Spread$).

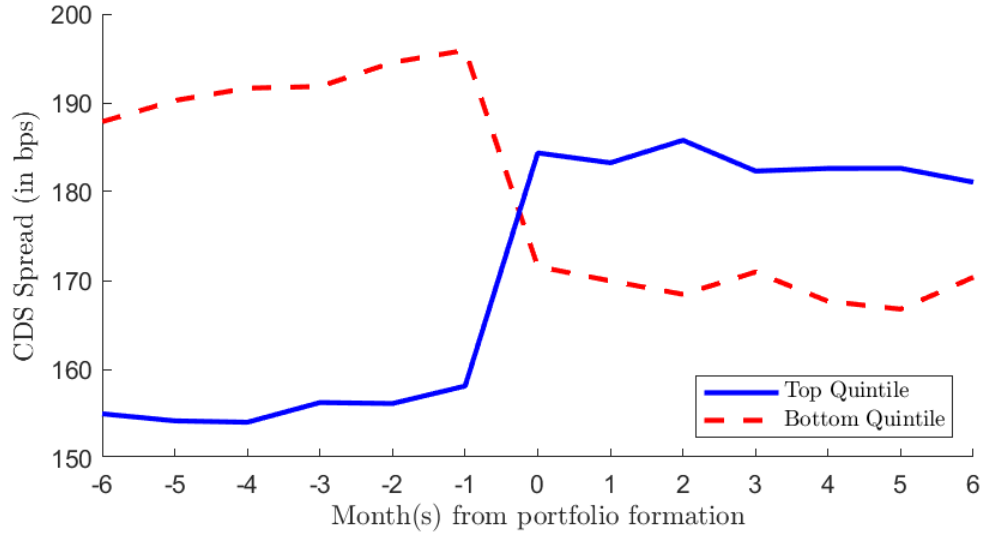


Table 1: Summary Statistics and Correlation Matrix

Panel A shows summary statistics of monthly CDS and issuer-level bond characteristics used for empirical analyses in this paper. *Spread (bps)* is the 5-year spread of CDS in basis points, $\Delta Spread$ (*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
$\Delta Spread$ (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	$\Delta Spread$	Return	Size (Log)	Maturity	Rating	Illiquidity
Spread	1	0.02	-0.03	-0.29	-0.24	0.66	0.19
$\Delta Spread$		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 Return $_{i,t}$		Δ Spread $_{i,t}$	
	Baseline	Placebo	Baseline	Placebo
	(1)	(2)	(3)	(4)
Constant	2.256 (0.67)	2.143 (0.67)	-0.143 (-0.23)	-0.239 (-0.33)
$CC_{i,t}$	0.222 (1.61)	0.127 (0.91)	-0.009 (-0.35)	-0.011 (-0.35)
Δ Spread $_{i,t-1}$	-1.078*** (-6.17)	-0.718*** (-2.90)	0.091*** (3.09)	-0.043 (-1.31)
Δ Spread $_{i,t-1} \times CC_{i,t}$	-0.398** (-2.00)	-0.159 (-0.64)		
Return $_{i,t-1}$	-0.201*** (-5.36)	-0.196*** (-5.62)	-0.024*** (-3.39)	-0.006 (-0.62)
Return $_{t-1} \times CC_{i,t}$			0.031*** (3.92)	-0.018* (-1.79)
Log(Size) $_{i,t-1}$	0.123 (0.59)	0.079 (0.41)	-0.019 (-0.51)	-0.021 (-0.49)
Illiquidity $_{i,t-1}$	-0.241*** (-2.60)	0.056 (0.57)	0.041** (2.33)	0.037* (1.73)
Coupon $_{i,t-1}$	0.073 (0.63)	0.068 (0.55)	-0.004 (-0.21)	-0.005 (-0.18)
Maturity $_{i,t-1}$	-0.018 (-0.50)	0.016 (0.47)	-0.004 (-0.68)	-0.013* (-1.79)

(Continued)

Table 3—*Continued*

	Dependent variable			
	Bond Return _{<i>i,t</i>}		Δ Spread _{<i>i,t</i>}	
	Baseline	Placebo	Baseline	Placebo
	(1)	(2)	(3)	(4)
Rating _{<i>i,t-1</i>}	-0.397*** (-3.18)	-0.334** (-2.51)	0.049** (2.04)	0.068** (2.23)
Obsevation	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 Δ Spread

Panel A (Panel B) reports value-weighted (equally weighted) return and alphas of quintile bond portfolios (in %) sorted by Δ Spread. Columns (1) to (5) represent quintile bond portfolios, bottom to top Δ Spread. The last column of the table, (5)-(1), shows quintile difference portfolios which are zero-cost bond portfolio returns of top Δ Spread minus bottom Δ Spread 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 estimated with the bond market factor. 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 (1.07)	0.191 (1.45)	0.11 (0.77)	-0.01 (-0.08)	-0.112 (-0.62)	-0.278** (-2.03)
	Alpha (Bond)	0.08 (1.11)	0.068 (0.76)	0.03 (0.33)	-0.098 (-1.48)	-0.302* (-1.69)	-0.382** (-2.42)
Non-CC	Alpha (Stock)	0.141 (1.02)	0.078 (0.57)	0.066 (0.52)	0.081 (0.64)	-0.025 (-0.19)	-0.166* (-1.84)
	Alpha (Bond)	0.045 (0.67)	-0.026 (-0.46)	0.003 (0.04)	-0.013 (-0.24)	-0.143 (-1.62)	-0.189** (-2.2)
Panel B: Alpha of Equally Weighted Bond Portfolios							
		Quintile					Difference
		(1)	(2)	(3)	(4)	(5)	(5)-(1)
CC	Alpha (Stock)	0.231 (1.47)	0.163 (1.27)	0.101 (0.76)	-0.005 (-0.04)	-0.087 (-0.51)	-0.318*** (-2.83)
	Alpha (Bond)	0.178* (1.88)	0.044 (0.88)	0.013 (0.22)	-0.107** (-2.13)	-0.193 (-1.22)	-0.370*** (-3.31)
Non-CC	Alpha (Stock)	0.155 (1.21)	0.114 (0.85)	0.045 (0.33)	0.065 (0.51)	-0.063 (-0.45)	-0.218** (-2.51)
	Alpha (Bond)	0.064 (0.76)	0.026 (0.62)	-0.021 (-0.59)	-0.03 (-0.69)	-0.153 (-1.3)	-0.217** (-2.39)

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 (3) show the monthly performance of the quintile difference portfolio after 1 month to 3 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 estimated with the bond market factor. 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)
		t+1	t+2	t+3
CC	Alpha (Stock)	-0.278** (-2.03)	-0.245* (-1.69)	0.014 (0.08)
	Alpha (Bond)	-0.382** (-2.42)	-0.338*** (-2.65)	0.073 (0.24)
Non-CC	Alpha (Stock)	-0.166* (-1.84)	-0.027 (-0.23)	0.077 (0.47)
	Alpha (Bond)	-0.189** (-2.2)	-0.016 (-0.1)	0.116 (0.56)
Panel B: Alpha of Equally Weighted Bond Portfolios				
		(1)	(2)	(3)
		t+1	t+2	t+3
CC	Alpha (Stock)	-0.318*** (-2.83)	-0.271** (-2.36)	-0.01 (-0.08)
	Alpha (Bond)	-0.370*** (-3.31)	-0.345*** (-3.12)	0.074 (0.32)
Non-CC	Alpha (Stock)	-0.218** (-2.51)	-0.057 (-0.49)	-0.025 (-0.16)
	Alpha (Bond)	-0.217** (-2.39)	-0.075 (-0.83)	0.032 (0.15)

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							Panel B: Equally Weighted Characteristics						
		Quintile							Quintile				
		(1)	(2)	(3)	(4)	(5)			(1)	(2)	(3)	(4)	(5)
CC	Return	1.2	0.54	0.27	0.06	-0.53	CC	Return	1.3	0.48	0.27	0.11	-0.55
	Log(Size)	15.69	15.93	16.05	15.97	15.74		Log(Size)	14.82	15.11	15.22	15.12	14.83
	Maturity	10.39	11.53	11.7	11.5	10.55		Maturity	9.03	10.09	10.34	10.09	9.11
	Rating	9.02	7.3	6.85	7.07	8.62		Rating	9.9	8.14	7.77	7.93	9.68
	Illiquidity	0.2	0.19	0.18	0.32	0.24		Illiquidity	0.27	0.23	0.23	0.29	0.39
	Coupon	5.02	4.51	4.37	4.42	4.86		Coupon	5.29	4.58	4.44	4.53	5.19
Non-CC	Return	0.91	0.4	0.29	0.17	-0.22	Non-CC	Return	1.03	0.45	0.31	0.22	-0.28
	Log(Size)	15.42	15.61	15.65	15.66	15.54		Log(Size)	14.45	14.57	14.61	14.6	14.48
	Maturity	9.88	10.57	10.69	10.64	9.86		Maturity	8.69	9.58	9.73	9.5	8.62
	Rating	9.16	6.98	6.4	6.76	8.79		Rating	10.55	8.4	7.76	8.17	10.13
	Illiquidity	0.21	0.2	0.19	0.18	0.23		Illiquidity	0.35	0.3	0.32	0.26	0.39
	Coupon	4.9	4.11	3.9	4.04	4.73		Coupon	5.33	4.54	4.29	4.46	5.16

Table 7: Bivariate Dependent-Sort Portfolio

Panels A (Panel B) shows 2×3 bivariate 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 the bond market factor. 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	-0.202*	-0.136**	-0.187***	-0.174**	-0.246**	-0.141**
ΔSpread	(-1.75)	(-2.54)	(-2.88)	(-2.14)	(-2.41)	(-2.1)
	(4) Rating Score		(5) Illiquidity		(6) Coupon	
	Low	High	Low	High	Low	High
HML	-0.056	-0.277***	-0.169**	-0.191**	-0.078**	-0.255**
ΔSpread	(-1.21)	(-2.62)	(-2.08)	(-2.44)	(-2.01)	(-2.46)

Panel B: Alpha of Equally Weighted Portfolios						
	(1) Return		(2) Log(Size)		(3) Maturity	
	Low	High	Low	High	Low	High
HML	-0.238**	-0.121**	-0.208***	-0.191**	-0.253***	-0.143**
ΔSpread	(-2.19)	(-2.08)	(-2.74)	(-2.14)	(-2.67)	(-2.17)
	(4) Rating Score		(5) Illiquidity		(6) Coupon	
	Low	High	Low	High	Low	High
HML	-0.068	-0.233***	-0.175**	-0.248***	-0.083*	-0.268***
ΔSpread	(-1.53)	(-2.91)	(-2.41)	(-3.57)	(-1.94)	(-3.07)

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 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% (*).

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

(Continued)

Table 8—*Continued*

Dependent variable: Bond Return _{<i>i,t</i>}					
	(1)	(2)	(3)	(4)	(5)
Stock Illiquidity _{<i>i,t</i>}			1.864 (1.20)	5.778*** (2.63)	5.869*** (2.60)
Bond Beta _{<i>i,t</i>}				0.316*** (10.83)	0.323*** (10.97)
Stock Beta _{<i>i,t</i>}				0.001 (0.02)	-0.018 (-0.41)
Stock Short Interest _{<i>i,t</i>}					-1.984*** (-3.80)
Stock DISP _{<i>i,t</i>}					-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. All statistics are computed using data from January 2003 to June 2021.

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 (-1.14)	-0.166 (-0.77)	-0.121 (-0.57)
Bond Coupon	0.466 (0.63)	0.562 (0.66)	0.638 (0.76)
Bond Return		0.634* (1.73)	0.713* (1.96)
Bond Illiquidity		0.528* (1.73)	0.522* (1.72)
Stock Return		0.071 (0.79)	0.071 (0.79)
Stock Illiquidity		14074.264*** (2.72)	10491.074** (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