Bank Private Information in CDS Markets *

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Abstract

Can banks trade credit default swaps (CDSs) referenced on their current corporate clients at competitive prices, or are banks penalized for potentially holding private information? To answer this question we merge CDS trades reported under the European Market Infrastructure Regulation (EMIR) with syndicated loans from Dealscan, and compare the prices on similar CDSs that the same dealer offers to banks and to other investors. We find that banks lending to a corporation purchase CDSs on this corporation at lower prices, and that after trading with banks, dealers can earn higher margins on these CDSs when trading with other investors. Our findings suggest that banks hold valuable private information which is shared in their trades with dealers. Dealers then disseminate this information to financial markets.

Keywords: Credit Derivatives, Banks, Price Discovery, EMIR, Syndicated Loans

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Executive Summary

As banks are likely informed investors, it is conceivable that they have to pay a "lemons premium" when buying default protection on their own borrowers. However, it is also possible that banks enjoy a discount when trading in CDS markets. If bank trades contain private information, derivative dealers could then monetize this information when trading with other investors. Assessing whether dealers price discriminate when selling CDS contracts to banks allows us to better understand whether derivatives function well as a risk management tool.

Using the EMIR dataset on CDS transactions, we first measure whether given similar contracts dealers price discriminate when trading with banks relative to other investors. Second, we examine the price impact of dealer-bank trades. Accordingly, we construct measures of price impact over one-week and one-month horizons. Third, we investigate whether the bank bias affects the actual cost of credit risk, or just the transaction costs of the trades (i.e., the dealer's margins). Are dealers actually willing to incur losses by trading with banks, or do they just forego higher margins? To answer this question, we study the effects on the realized bid-ask spreads. Finally, we also investigate how the effects vary with the ex-ante credit quality of the underlying obligation, by separately estimating the models by rating class.

The results of the pricing analysis suggest that banks indeed are offered different prices relative to other investors when trading credit risk through CDS contracts. The bias is negative, i.e., bank trades carry a discount, suggesting that bank trades are valuable for dealers, plausibly because of their informational content. Our most restrictive estimates suggest that the same dealer selling the same CDS protection contract during the same month to a bank and to another investor, will charge the bank an upfront payment that is lower by 1pp. In monetary terms, this amounts to a net present value of EUR 50,000, calculated over the life of a five-year CDS contract with a standard notional of five million. The effects are smaller in magnitude, but still significant for sell trades. Moreover, we find evidence that trades with banks have a price impact over both one week and one-month horizons. Although they offer banks discounts, dealers are able to extract larger payments from other investors when trading on the same reference firm. Again, this is suggestive of the fact that dealers are learning valuable economic information from their trades with banks. Next, we document that the discount enjoyed by banks is not only due to the reduction in transaction costs, but that the actual cost of CDS protection that they pay is lower. For a standard CDS protection contract, 25% of the bank discount is transmitted through transaction costs, in the form of narrower bid-ask spreads, while the remaining 75% of the discount comes from a lower cost of protection. Finally, when investigating the heterogeneity of the effect across ex-ante credit risk, we find stronger estimates for reference entities with speculative rating, or not rated at all.

Overall, our findings suggest that banks can purchase CDS protection on more affordable terms than other investors. As a result, derivatives can be particularly useful in bank risk management practices and can help price discovery by transmitting valuable information from banks to the rest of the financial market. Efficient and timely risk management practices require that banks are able to trade risks in competitive and liquid derivative markets. CDS contracts appear to offer this possibility.

1 Introduction

Credit derivatives have been subject to intense public and regulatory scrutiny, given their vulnerability to being misused or gamed by market participants. Among the concerns that have been raised are the excessive risk-taking, which led to the bailout of AIG at the start of the great financial crisis, excessive speculation targeting countries in distress, that resulted in the ban on naked sovereign CDS during the European Sovereign Crisis, moral hazard due to "empty creditors" or, as the 2022 Archegos Capital Management case shows, manipulation of the price of the underlying assets. In this paper we analyse another source of economic imperfection that has the potential to hurt the functioning of credit derivatives: the presence of *asymmetric information* between buyside investors and dealers. In particular we focus on one type of participant in credit derivatives, banks, and on one particular type of trade, a credit default swap (CDS) contract taken on a company that that bank is already lending to. Because of this bank-firm credit relationship, banks are the informed traders, likely to hold more (private) information on the underlying than the dealers.

Fully understanding the functioning of the CDS market and increasing its robustness to vulnerabilities is important. While in good times CDS traded volumes tend to be low, in times of perceived credit deterioration, as for example at the start of the COVID-19 pandemic in March-April 2020 and during the global monetary tightening cycle of 2022, CDSs trade again in high volumes. This reflects their utility both in hedging credit risk as well as in active investment strategies.[1]

Our research question is thus the following: do credit default swap markets function well for banks? Can banks purchase credit insurance on equal terms as other investors? It is not a trivial question. As banks are likely informed investors, it is conceivable that they have to pay a 'lemons premium' when buying default protection on their own customers. However, it is also possible that banks enjoy a discount when trading in CDS markets. If bank trades contain private information, derivative dealers could then monetize this information when trading with

[1] Refer to Aldasoro and Ehlers (2018) and Bomfim (2022) for detailed descriptions of the institutional setting in which CDS contracts are traded.

other investors. Assessing whether dealers price discriminate when selling CDS contracts to banks allows us to better understand the functioning of the derivative markets and whether banks can rely on CDS contracts to manage their risks.

The main empirical challenge in studying how private information is discovered in dealer markets is that neither the private information nor the identities of its owners are readily observable. Typically, only aggregated trade volumes and within day prices are observable to researchers. We address this challenge by using data on CDS transactions made available at the European Central Bank, by the European Market Infrastructure Regulation (EMIR). In this data we observe the identity of both the dealer and its customers. Our focus is on bank trades as sources of private information, whereby we rely on insights from the banking literature regarding the unique role of bank relationships.

The dataset contains the universe of CDS transactions on single-name reference entities, with detailed information on the identity of the counterparties to a transaction and of the issuer, the time of the trade, the direction of the trade (a sell or a buy), notional values and currencies, prices, transaction fees, volumes, maturities and settlement dates, as well as the legal definitions that govern the settlement of the contracts in case of default. To all these elements, we add information provided by CMA through Bloomberg on CDS dealer quotes for the most liquid contracts, as well as issuer ratings from the three rating agencies (Fitch, Moody's and S&P). To link the bank to the referenced firm, we merge this CDS transaction-level dataset with bank-firm pairs extracted from the Dealscan syndicated loan database. This provides additional information on whether the bank has given a loan to the firm on which it is purchasing a CDS, as well as on characteristics of this loan (granting date, volume, collateral, number of lenders in the syndicate, etc.)

The identification strategy relies on four elements: (1) the availability of pricing information at trade level in the European CDS market; (2) detailed fixed effects and CDS contract characteristics that account for the heterogeneity of the trades; (3) the identity of the trading parties, and in particular of the dealers and their bank customers; and (4) the existence of a lending relationship between the trader bank and the reference firm on which the CDS contract is traded, as well as characteristics of this lending relationship.

Using the EMIR dataset on CDS transactions, we first measure whether dealers price discriminate when trading with banks relative to other investors, given similar contracts. As we have detailed trade-level data, our estimations can control, both parametrically and non-parametrically, for the main contract characteristics (maturity, coupon, seniority and notional traded). In the most restrictive specifications, we add dealer × reference firm × month fixed effects, effectively measuring whether the same dealer offers a different price to banks versus other investors for a contract on the same reference firm, signed during the same month. While we start by simply using the identity of the buyside trader in order to identify banks, in subsequent analysis we use actual lending relationships from the syndicated loan market, as well as the volume of credit.

Second, we examine the price impact of dealer-bank trades. Accordingly, we construct measures of price impact over one-week and one-month horizons as follows. We use a dummy variable taking value of one in the week or month following a dealer-bank trade, whenever the dealer trades with non-bank investors, on the same reference entity. The dummy takes value zero for the remaining trades.

And, third, we investigate whether the bank bias affects the actual cost of credit risk, or just the transaction costs of the trades (i.e., the dealers' margins). Are dealers actually willing to incur losses by trading with banks, or do they just forego higher margins? To answer this question, we study the effects on the realized bid-ask spreads. We match the contracts in our sample with publicly available information on CDS mid quotes, in order to arrive at estimates of the spreads. For every contract, we then calculate the absolute deviation between the price of the contract (bid or ask), and the quoted mid. This gives us the half spreads, which we use as dependent variables in models where the main explanatory variable is the identity of the investor. We also investigate how the effects vary with the ex-ante credit quality of the underlying obligation, by separately estimating the models by rating class.

The results of the pricing analysis suggest that banks indeed are offered different prices relative to other investors, when trading credit risk through CDS contracts. The bias is negative - that is, bank trades carry a discount -, suggesting that bank trades are valuable for dealers, plausibly because of their informational content. Our most restrictive estimates suggest that the same dealer selling the same CDS protection contract during the same month to a bank and to another investor, will charge the bank an upfront payment lower by 1 percentage point (pp). In monetary terms, this amounts to a net present value of EUR 50,000, calculated over the life of a five-year CDS contract with a standard notional of five million. The effects are smaller in magnitude, but still significant, for sell trades.

Moreover, we find evidence that trades with banks have a price impact over both one week and one month horizons. Although they offer banks discounts, dealers are able to extract larger payments from other investors when trading on the same reference firm. Again, this is suggestive of the fact that dealers are learning valuable economic information from their trades with banks. Next, we document that the discount enjoyed by banks is not only due to the reduction in transaction costs, but that the actual cost of CDS protection that they pay is lower. For a standard CDS protection contract, 25% of the bank discount is transmitted through transaction costs - in the form of narrower bid-ask spreads -, while the remaining 75% of the discount comes from a lower cost of protection. Finally, when investigating the heterogeneity of the effect across ex-ante credit risk, we find stronger estimates for reference entities with speculative rating, or not rated at all.

Overall, our findings suggest that banks can purchase CDS protection on more affordable terms than other investors. As a result, derivatives can be particularly useful in bank risk management practices and can help price discovery by transmitting valuable information from banks to the rest of the financial market. Efficient and timely risk management practices require that banks are able to trade risks in competitive and liquid derivative markets. CDS contracts appear to offer this possibility.

Our first contribution to the literature is to investigate empirically the process of price discovery in over the counter (OTC) markets with adverse selection originating in informed trading. Banks are useful agents in this sense, because they hold private information on their borrowers (Fama 1985; James 1987). Therefore, the order flow that dealers receive from banks can be highly informative about the fundamentals of the reference firms, when the banks also engage in lending relationships with the firms. It could be that such asymmetries raise the premium that banks pay on CDS protection, possibly to prohibitive levels, in line with basic insights from market microstructure. Kyle (1985) and Glosten and Milgrom (1985) suggest that liquidity may dry up and spreads widen in the presence of informed traders. However, it could also be that dealers are able to absorb the private information from banks, and pass it on further in their trades with other investors, therefore facilitating price discovery. Recent theoretical and empirical results (Babus and Kondor 2018; Kondor and Pinter 2021; Kacperczyk and Pagnotta 2019) support the fact that trading in OTC market can be sustained in the presence of private information. Our results indeed suggest that bank trades are special: banks are able to trade CDSs at a discounted price on their customers, and despite the lower price, dealers are willing to make markets for these trades in order to learn the bank private information. The price impact of bank trades is discovered through subsequent trades that dealers conduct with other investors, on the same reference firms.

Our second contribution is to provide new evidence supporting the existence of bank private information, and to measure its value. We show that dealers transact CDSs with banks at a discount, plausibly because they learn banks' privileged information in doing so. Dealers can then earn higher margins on subsequent trades with other investors. This interpretation is consistent with recent empirical evidence suggesting that investors privy to loan information earn abnormal returns when trading in related assets. Ivashina and Sun (2011) combine quarterly stock holdings and information on lending relationships of institutional investors. They find that these investors who attend loan amendments obtain excess returns when trading in the stock of the borrowers. Addoum and Murfin (2020) measure for how long information generated within lending relationships is valuable in the equity market. They show that trading equities based on publicly disseminated loan prices can lead to abnormal returns up to two months following their release. Our results imply that dealers can play an important role in disseminating this information faster. We build on Acharya and Johnson (2007) who look at the CDS market and document how CDS spreads lead equity prices, especially ahead of bad news and for firms with multiple banks. These findings, they argue, are consistent with the presence of informed trading by banks in the CDS market. Using granular data, we shed light on the mechanism driving these findings: when banks trade in the CDS market for risk management purposes, dealers learn their private information.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 overviews our empirical strategy, and the results are discussed in Section 4. Finally, Section 5 concludes.

2 Data Description and Summary Statistics

This section describes the data employed in the analysis, the cleaning procedures, and it presents some summary statistics. We use four different databases: the set of Euro Area CDS transactions available at the European Central Bank through the EMIR, the Dealscan syndicated loan database, daily CDS benchmark prices sourced from Bloomberg and covering the most liquid contract types, as well as rating information from Fitch, Moodys, and S&P.

2.1 EMIR CDS Transactions Database

The EMIR database available at the ECB contains information on derivative transactions, for which at least one counterparty to the trade, or the reference entity on which the trade is written, is headquartered in a Euro Area country.

Reporting to the EMIR dataset has been ongoing on a daily basis since 2014, covering five asset classes: equity, credit, interest rate, commodity, and foreign exchange. The reports include both transactions (the flow of new trades) and positions (the stock), and the reporting obligation is two-sided, which means that both counterparties to the trade have to submit the report. The source data approximately one hundred million observations per day, each containing nearly two hundred and fifty attributes, amounting to about one terabyte of daily information.

Our research focuses on the universe of credit default swap transactions concluded on single-name reference entities. The dataset contains detailed information on the identity of the counterparties to a transaction, the exact time of the trade, the direction of the trade (a sell or a buy), notional values and currencies, prices, transaction fees, volumes, maturities and settlement dates, as well as the legal definitions that govern the settlement of the contracts in case of default.

We were granted access to the CDS transaction data over the period January 2018 to December 2019. The initial CDS transaction dataset covering this time horizon has 3.8 million entries. We keep only single-name trades, that is, those trades written on a single obligation with an underlying ISIN. This results in 1.5 million entries. We further keep only contracts identified as "swap", accounting for 84% of the sample. With this step we drop other contract types such as credit futures, forwards, options, or less standardized trades. We also drop entries marked as compression trades, and restrict the sample to trades with a price expressed in percentage of notional. Finally, we keep trades where the notional is expressed in either euros or US dollars. After applying these filters, our sample comprises about 1.3 million trades.

Because our study is focused on pricing patterns, an important filter we apply to the raw trades is to select the contracts priced according to standard conventions. These are contracts that follow the definitions set in the Big Bang and Small Bang protocols, are fairly homogeneous and priced upfront. In particular, under the fixed legal definitions, the contracts have pre-set maturity dates (the four yearly IMM dates), fixed notional amounts (5 or 10 million), and fixed protection coupons of typically 100bps or 500bps. Because the coupons are fixed, the price of this contract is exchanged upfront, and it amounts to the discounted value of the difference between the market value of the coupon and the fixed rate. When the seller of CDS protection estimates the value of the protection coupon to be higher than the market value, the protection buyer makes an upfront payment to the protection seller. Conversely, when the dealer estimates that the fixed coupon is too high a price for protection, the CDS protection buyer receives an upfront payment from the seller. After keeping only standard contracts with fixed maturities and fixed coupons of 100 or 500 basis points, we are left with 550,000 transactions in the sample.

Finally, we add some additional information on the identities of the parties and reference entities. For this, we first add unique names for the issuers, based on Bloomberg information on the ISIN of the reference entity. CDS transactions typically occur between a dealer and a buyside investor. We identify dealers based on the names of the counterparties to the trades.[2] We only keep trades for which at least one counterparty to the trade is a dealer, restricting the trades to two types: dealer-to-dealer (D2D), and dealer-to-customer (D2C). The sample of CDS transactions we therefore use in the first part of the analysis includes 435,648 individual trades.

[2] We identify the dealers in the sample based on the list of primary dealers provided by the New York Fed, and available at: https://www.newyorkfed.org/markets/primarydealers.

Figures 1-2 and Table 1 offer a descriptive view of this sample, as well as summary statistics. The dataset is composed by 14 dealers sitting on one side of the trade, and trading with 2,698 counterparties on 990 reference firms. Out of the 435,648 trades, 161,833 are dealer-to-dealer (37% of the sample), while 270,017 are dealer-to-buyside (63% of sample). 78 of the buyside investors are banks, and they are counterparties to 69,041 trades (16% of total). Importantly, the dataset is sufficiently rich to allow us to saturate our empirical specifications with fixed effects at the level of dealer *times* issuer *times* month, and to capture differences in trading terms by counterparty type (bank versus non bank). There are 62,597 non-empty groups at the level of dealer-issuer-month-investor type, 40% of which contain trades realized by both bank and non-bank buyside investors.

Most of the analysis focuses on the dealer-to-buyside market. Here we can assume that the dealer-to-buyside trades are initiated by the client, which allows us to sign these trades. Knowing the direction of the trade is indispensable for the price analysis of the upfront fees. For the analysis of the bid-ask spreads we use also the full sample of trades, since we focus on the absolute difference between the upfront payment and the quoted upfront mid.

2.2 Lending Relationships from the Syndicated Market

We augment our dataset with identifiers for lending relationships from the syndicated loan market. For this, we use the WRDS-Reuters Dealscan dataset, and we extract live lending relationships between firms ("Company") and all the members of the syndicate ("Lender"). We then match on relationships with the CDS transaction dataset, in order to identify buyside bank traders that have an underlying credit exposure to the reference entity they are purchasing a CDS on. For every CDS trade, we construct new variables with the underlying credit exposure in the syndicated loan market, as well as characteristics of this exposure: granted date, whether the credit is secured or not, and the number of lenders in the syndicate (the credit exposure is zero where there is no lending relationship). We identify 67 banks and 866 reference firms that are present in both datasets. Finally, 21% of the CDS trades have an underlying lending relationship (this includes both dealers and non-dealer banks).

2.3 CDS Quotes

The final part of our analysis studies the bid-ask spreads realised on the transactions. Because the CDS market is not very liquid to allow us to estimate mid prices directly from daily prices, we calculate half spreads as the absolute difference between the bid or the ask upfront prices and a benchmark mid upfront price. We use daily quoted mid upfronts sourced from CMA through Bloomberg. We match the quotes with our dataset of CDS trades based on reference firm, date, currency, seniority, and tenor. Our matched dataset contains 184,964 trades. 15% of the trades have a bank as a buyside counterparty. In total, there are 14 dealers, trading on 746 reference firms with 2,188 buyside investors, out of which 72 are banks.

We therefore define the absolute half spread on a CDS contract traded on reference entity f entered at time t as follows:

$$
\begin{aligned}
|HalfSpread_{ft,s}| =& (UpfrontAsk_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in selltrade] \\
& - (UpfrontBid_{ft} - UpfrontMid_{ft}) * \mathbf{1}[s \in buytrade]
\end{aligned}
$$

The $UpfrontAsk_{it}$ and the $UpfrontBid_{it}$ are the realised transaction prices. The $UpfrontMid_{it}$ is the daily Bloomberg indicative dealer mid quote, which we calculate as the average of the quoted bid and ask, and s is the direction of the trade. The average half spread is 0.06%.

2.4 Ratings

A third dataset used in the analysis contains ratings information from the S&P, Moodys and Fitch. We build a linear rating score, allocating a number to each rating class. This score function ranges between 1 (prime rated) to 23 (no rating), and we employ it throughout the analysis in order to control for publicly available information on the credit risk of the reference entity.

3 Empirical Strategy

The empirical strategy follows four steps. In the first step, we study whether CDS dealers offer different pricing terms to bank and non bank buyside investors, controlling for contract characteristics and for detailed fixed effects. For this, we use the realized upfront transaction prices that are recorded for every trade. In a second step, we investigate whether there is any meaningful price impact of trades with banks, by looking at any pricing bias that might arise when dealers trade with other investors, *subsequently to trading with a bank, but on the same reference entity*. Third and fourth steps follow the same type of analysis, but we study the impact on realized bid-ask spreads, instead of on the transaction upfront prices.

3.1 Analysis of Upfront Prices Paid by Banks

Using the EMIR dataset on CDS transactions, we measure whether there is any bias in the trading terms CDS market makers offer to bank relative to non-bank investors, for equal contracts. For this, we estimate the following specification:

$$\begin{aligned} Upfront_{idft} =& \beta * \mathbf{1}[buyside_i \in bank] + \alpha_d + \theta X_c + \sum_k \gamma_k * \mathbf{1}[maturity_i \in k] + \\ &+ \sum_p \gamma_p * \mathbf{1}[coupon_i \in p] + \sum_r \gamma_r * \mathbf{1}[seniority_i \in r] + \epsilon_{idft} \end{aligned}$$

In this model, the dependent variable, $Upfront_{idft}$, captures the upfront price realized on contract i, sold by dealer d, on reference entity f, at time t. The term $\mathbf{1}[buyside_i \in bank]$ takes value one when the CDS contracts are sold to banks and the estimate β picks up any pricing bias incurred by banks. In a series of estimations, the model includes fixed effects at the level of the *dealer*, *industry* and *month*, as well as *dealer x reference entity* and *dealer x reference entity x time.* In the latter case, β measures whether the same dealer offers banks and non-bank investors different terms on contracts written on the same reference entities, for trades concluded within the same month. Finally, because CDS contracts mostly trade with standardized maturities and fixed rates, we can control non-parametrically for the composition of contracts. The term $\sum_k \gamma_k * \mathbf{1}[maturity_i \in k]$ includes a full set of dummies for standardized CDS maturities, while the term $\sum_p \gamma p * \mathbf{1}[rate_i \in p]$ includes dummies for standardized fixed rates. $\sum_r \gamma_r * \mathbf{1}[seniority_i \in r]$ accounts for the seniority of the reference obligation, while X_c are additional controls at contract and firm level, such as the logarithm of the notional amount and the rating score of the reference entity.

For the model explaining upfront prices, it is important to separate trades according to their direction (whether the buyside investor sells or buy the CDS). This is the reason why we can only carry out this analysis on the dealer-to-customer market. In fact, for client buy trades, the lower the upfront fee, the more advantageous the trade is for the buyer. For client sell trades, the higher the upfront fee the more advantageous the trade. Therefore, when a bank buys a CDS contract, and the β coefficient is negative (positive) then the bank is paying a lower (higher) price than non-bank investors, for similar contracts. In contrast, when a bank sells the CDS contract, and the β coefficient is positive (negative) then the bank is paying a lower (higher) price than non-bank investors, for similar contracts.

In a second specification, we interact the dummy variable $\mathbf{1}[buyside_i \in bank]$ with a second dummy, $\mathbb{1}_{\text{Lending Relationship}}$, that identifies whether the trader in the CDS is part of a lending syndicate. The interaction of the two variables allows us to identify the buyside bank investors that trade CDS and have a contemporaneous lending relationship on the same reference firm.

For robustness we use two alternative specifications. First, we saturate the regressions with both dealer and buyside fixed effects. Thus this includes bank fixed effects, and it allows us to study the effect within bank, i.e., whether a bank gets a better price on the CDS of the firms with which it has a lending relationship, relative to the price it has to pay on other trades, while controlling for contract and issuer characteristics. And, finally, instead of using a dummy variable for the syndicated lending relationship, we also use the log of the lending volumes.

3.1.1 Price Impact

Next, we study whether there is any price impact following trades that dealers conclude with banks. We measure the price impact of bank privileged information at two different horizons: one week and one month. For this, we investigate whether there is any pricing bias on trades dealers conclude with non-bank investors, after trading with a bank, and on the same reference entity on which the transaction with the bank was concluded. If the dealer learned valuable private information after trading with the bank and if it compensated the bank for it, then we would expect the dealer to charge its subsequent clients less favourable prices. In this way, the dealer recovers the losses they made by trading with banks, and extracts higher information rents by trading with other non informed dealers or investors.

For this, we identify the trades that dealers conclude with non bank clients on reference entities on which their previously concluded a trade with a bank, over the following week or month. We then compare their prices to those trades entered into with clients on reference entities on which the same dealer did not trade with a bank, over the past week of month. We again restrict the sample of transactions to the dealer to customer set, and in particular to dealer versus non-bank investors, and we separate the estimations for buy and sell trades.

3.2 Analysis of Bid-Ask Spreads Paid by Banks

Next, we study the impact of trading with banks on transaction costs in the CDS market. For this, we use as dependent variable the half bid ask spreads defined above. This estimation seeks to identify whether the spreads that dealers set when trading with banks are different (narrower or wider) than the spreads that they charge with non-bank investors.

$$
\begin{aligned}
|HalfSpread_{idft}| = & \beta * \mathbf{1}[buyside_i \in bank] + \alpha_d + \theta X_c + \sum_k \gamma_k * \mathbf{1}[maturity_i \in k] + \\
& + \sum_p \gamma_p * \mathbf{1}[coupon_i \in p] + \sum_r \gamma_r * \mathbf{1}[seniority_i \in r] + \epsilon_{idft}
\end{aligned}
$$

In this model, the dependent variable, $|HalfSpread_{idft}|$, captures the absolute value of the realized half spread sold by dealer d to investor i, on reference entity f, at time t. As before, we control non-parametrically for the main contract features, parametrically for notionals trades and rating scores, and we add different fixed effects. Crucially, because we work with deviations from the upfront fees quoted by CDS dealers for the same contract, on the same day, our measure of pricing impact is robust with respect to daily changes in characteristics and risk profile of the underlying entities. In the most restricted specification, we add dealer $\times$ reference entity fixed effects to study whether spreads charged to banks are different from spreads charged to non-bank investors, when then same dealer transacts on the same reference with the two investor types.

Finally, because we work with deviations from the mid in absolute terms, there is no need to separate buy and sell trades for this estimations. As a result, we can employ the full sample of trades, that is, both dealer-to-dealer and dealer-to-customer. A negative β would indicate that bid-ask spreads paid by banks are narrower than for the remaining investors, thus suggesting that banks are treated relatively more favourably by their dealers in terms of transaction costs. Conversely, a positive β would indicate that banks pay higher transaction costs relatively, and are thus penalized on the CDS market.

3.2.1 Price Impact

If dealers learn any private information from their trades with banks, then this information might be also reflected in the bid-ask spreads that they set on subsequent trades. We therefore also study whether there is any bias in transaction costs following trades with banks. Again, we identify trades that a dealer concludes with non-bank counterparties over a one-week and one-month horizon. In this case, we can see whether any information appears to be transmitted to the spreads in the dealer market, as well as in the dealer to customer market. Plausibly, if dealers trade with banks in order to learn their private information and compensate these banks with narrower bid-ask spreads, then they might charge larger spreads on subsequent trades, in order to monetize this information.

4 Results

4.1 On the Overall Cost of Credit Risk

Table 1 already shows that, on average, banks pay relatively lower CDS upfront fees whenever they purchase CDS protection from dealers, and they receive relatively higher upfront fees whenever they sell CDS protection. The average upfront payment is 0.2% of notional for trades where the buyside is a bank purchasing protection, whereas the average upfront in dealer-to-non bank trades is as high as 2.4%. Banks also receive higher payments whenever they are selling protection. A bank investor receives on average 3.2% of notional, compared to 1.6% that non-bank protection sellers receive from their dealers. While these averages are also driven by compositional effects, regressions with comprehensive controls and fixed effects uphold a pricing wedge.

Tables 2 and 3 confirm that there is indeed a pricing bias in dealer-to-bank trades. Across the different specifications, banks are charged lower upfront payments when they purchase protection, and are rewarded with higher payments when they sell protection. Because we need to sign the trades in order to observe these effects, the sample underlying these estimations is composed of dealer-to-buyside trades. On average and controlling for the main contract characteristics, banks pay upfront amounts lower by 2pp when purchasing protection, relative to non bank investors. The most restricted specification in Column (6), including dealer x issuer x month fixed effects, suggests that the same dealer selling the same CDS protection contract during the same month to a bank and a non-bank investor, will charge the bank an upfront lower by 1pp. The effects are weaker in magnitude, but still significant, for sell trades. A dealer buying the same CDS protection contract during the same month from a bank and from a non-bank investor, will pay the bank an upfront higher by 0.7pp. This suggests that banks are consistently better informed than dealers about changes in credit risk, and that dealers learn valuable information when trading with banks. In exchange, they reward banks for this information.

Tables 4 and 5 support this conclusion. When we confirm that the bank has indeed an underlying credit exposure to the reference entity it is trading CDS on, the results continue to be economically and statistically significant. Crucially, a bank trade seems to be valuable for a dealer, regardless of whether the dealer is part of the credit syndicate, or not.[3] What matters is that the bank is in the syndicate.

But is the private information then incorporated into transaction prices? Do dealers monetize this information? Table 6 and Table 7 show that dealers that become informed after trading with a bank then use this information when offering quotes to non-bank buyside investors. After selling CDS protection to a bank, a dealer will increase its price and sell protection more expensively to other investors, on the same reference entity. After purchasing CDS protection from a bank, a

[3]One explanation for this might be the existence of Chinese walls between the market making and lending businesses at large dealer banks.

dealer will be buying protection at more favourable fees from non-bank investors. Thus non-bank protection sellers get paid less, relatively to banks. These effects are economically significant and broadly unchanged in specifications with dealer and dealer x industry fixed effects, when controlling for contract and reference entity characteristics, and they hold both a one week and one month horizons.

4.2 On Transaction Costs

Tables 8 and 9 focus on the transaction costs that banks pay when trading CDS. We measure transaction costs as the absolute half spreads (upfront payment on the contract minus benchmark quote). We find that banks enjoy a discount also in terms of the bid-ask spreads they pay. The analysis of the full sample of trades in Table 8 and of the D2C segment in Table 9 both reveal that bid-ask spreads are narrower by around 0.2 - 0.4 pp when the buyside investor is a bank. In fact, when banks purchase credit protection and therefore potentially reveal negative information about the underlying firm, they pay about 1.6% of notional less in total upfront payments, 25% of which amounts to savings in transaction costs.

Finally, Table 10 investigate how these effects vary with the credit quality of the reference entity. We group issuers in three categories, depending on their rating: prime or highly rated, medium grade, and speculative or without rating. We find that the effect is concentrated in the last group, which suggests that bank information is more important whenever the underlying firm is riskier.

5 Conclusion

We use the CDS transaction-level dataset made available at the European Central Bank by the European Market Infrastructure Regulation (EMIR) to study whether banks are able to trade derivatives on corporate borrowers at the same prices as non-bank buyside investors. Overall, our findings suggest that banks can indeed purchase CDS protection on more affordable terms than non-bank investors. This is consistent with banks holding and monetizing private borrower information. Thus, derivatives can be particularly useful in bank risk management practices, and the liquid derivative markets can help transmitting valuable information from banks to the rest of the financial market.

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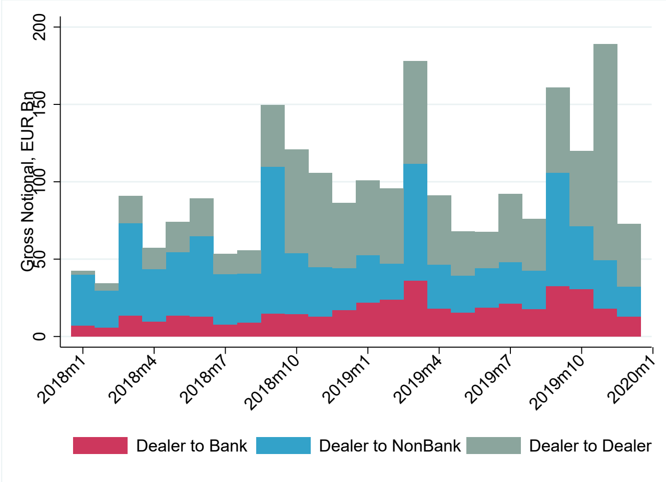
A. FIGURES

Panel A. CDS Trading by Market Segment - Volumes



Panel B. CDS Trading by Market Segment - Number of Trades

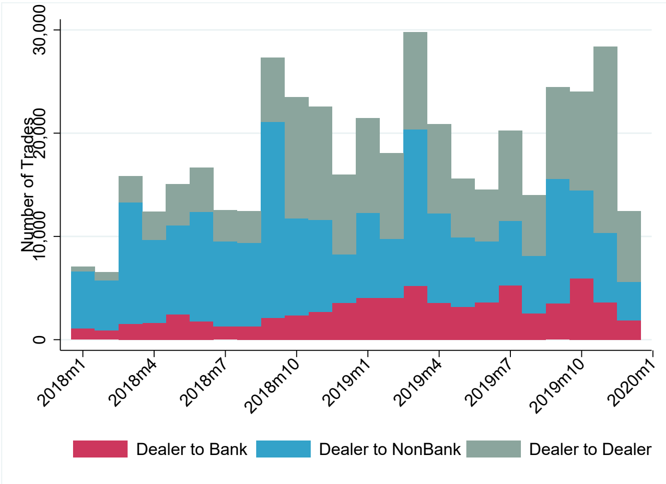
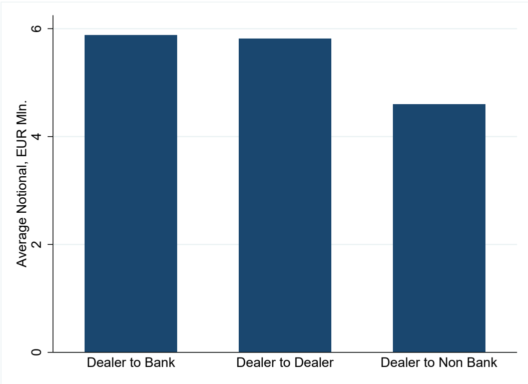
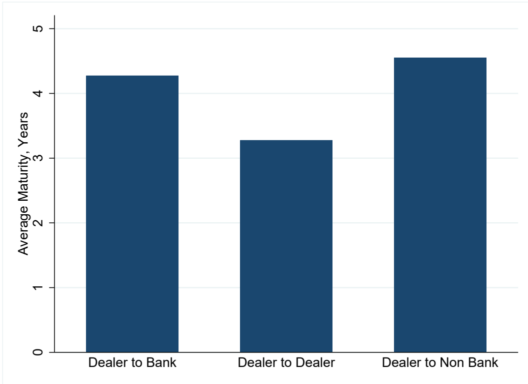


Figure 1: Total CDS Notional

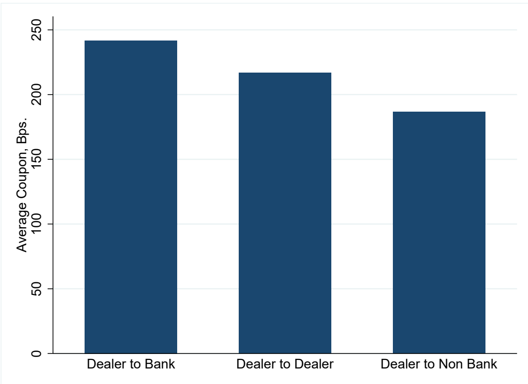
This figure shows total CDS trading across our final sample of 435,648 trades. Panel A shows monthly volumes by market segment: dealer-to-dealer, dealer-to-bank investor, and dealer-to-non bank investor. Panel B shows the same decomposition for the number of trades.



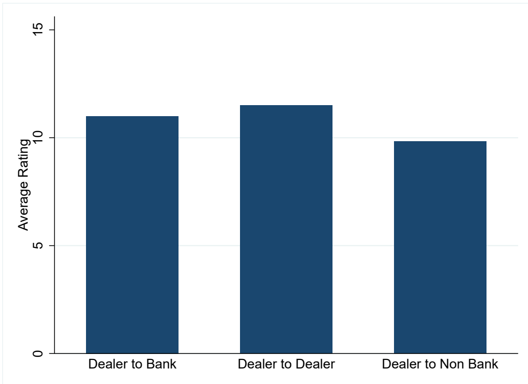
(a) Average Notional



(b) Average Tenor



(c) Average Coupon



(d) Average Rating

Figure 2: Main CDS Contract Characteristics by Market Segment

The four figures compare average characteristics of CDS contracts (notional, tenor, coupons and issuer rating) across market segments: dealer-to-dealer, dealer-to-bank investor, and dealer-to-non bank investor.

B. TABLES

Table 1: Summary Statistics: Trade Characteristics

	N (1)	Mean (2)	SD (3)	P25 (4)	P50 (5)	P75 (6)
Intradealer Market						
Upfront Fee (=Upfront Payment/Notional, in %)	161,833	1.81	7.12	-0.89	0.93	3.28
Notional (EUR Million)	161,833	5.82	10.30	1.40	3.60	5.96
Coupon	161,833	216.72	181.84	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	161,833	1.00	0.02	1.00	1.00	1.00
Tenor (in Years)	161,833	3.27	2.06	1.00	4.00	5.00
Rating Score	161,833	11.49	5.55	8.00	10.00	14.00
Dealer-to-Customer Market - Buy Trades - Dealer to Bank						
Upfront Fee (=Upfront Payment/Notional, in %)	33,880	0.21	8.46	-2.75	0.15	2.74
Notional (EUR Million)	33,880	6.06	12.90	2.00	4.00	5.50
Coupon	33,880	243.99	192.00	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	33,880	1.36	0.48	1.00	1.00	2.00
Tenor (in Years)	33,880	4.10	1.63	3.00	5.00	5.00
Rating Score	33,880	11.06	5.12	7.00	10.00	14.00
Dealer-to-Customer Market - Buy Trades - Dealer to Non Bank						
Upfront Fee (=Upfront Payment/Notional, in %)	106,515	2.46	7.61	-0.01	1.57	3.74
Notional (EUR Million)	106,515	4.65	28.60	0.48	1.72	5.00
Coupon	106,515	189.60	166.77	100.00	100.00	100.00
Seniority (1=Senior; 2=Subordinate)	106,515	1.43	0.49	1.00	1.00	2.00
Tenor (in Years)	106,515	4.59	1.19	5.00	5.00	5.00
Rating Score	106,515	9.82	3.93	8.00	9.00	11.00
Dealer-to-Customer Market - Sell Trades - Dealer to Bank						
Upfront Fee (=Upfront Payment/Notional, in %)	35,161	3.23	7.63	0.27	1.99	4.90
Notional (EUR Million)	35,161	5.71	14.00	2.00	3.00	4.90
Coupon	35,161	239.62	190.67	100.00	100.00	500.00
Seniority (1=Senior; 2=Subordinate)	35,161	1.33	0.47	1.00	1.00	2.00
Tenor (in Years)	35,161	4.45	1.68	4.00	5.00	5.00
Rating Score	35,161	10.94	5.19	7.00	9.00	14.00
Dealer-to-Customer Market - Sell Trades - Dealer to Non Bank						
Upfront Fee (=Upfront Payment/Notional, in %)	94,461	1.64	7.66	-1.37	1.24	3.30
Notional (EUR Million)	94,461	4.54	12.20	0.48	1.81	5.00
Coupon	94,461	183.22	162.36	100.00	100.00	100.00
Seniority (1=Senior; 2=Subordinate)	94,461	1.48	0.50	1.00	1.00	2.00
Tenor (in Years)	94,461	4.49	1.36	5.00	5.00	5.00
Rating Score	94,461	9.85	3.93	8.00	9.00	11.00

This table reports summary statistics for the 435,648 CDS contracts in the final sample, over the period January 2018 to December 2019. The sample is split into different market segments: dealer - to - dealer and dealer - to - customer trades, as well as, for the latter category, based on trade direction and on whether the buyside investor is a bank or not.

Table 2: Analysis of Upfront Prices Paid by Banks (I)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**Dealer to Customer Market - Buy Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0246*** (0.0005)	-0.0218*** (0.0006)	-0.0189*** (0.0006)	-0.0125*** (0.0006)	-0.0157*** (0.0005)	-0.0100*** (0.0006)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry × Month FE	-	-	Yes	-	-	-
Issuer × Month FE	-	-	-	Yes	-	-
Dealer × Issuer FE	-	-	-	-	Yes	-
Dealer × Issuer × Month FE	-	-	-	-	-	Yes
Observations	140,395	140,395	140,395	140,395	140,395	140,395
R^2	0.079	0.095	0.143	0.423	0.430	0.629

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to December 2019, the segment is the dealer-to-customer market, and the trades are all buy (i.e., the buyside investor buys CDS protection). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10,^{\star\star} p < 0.05,^{\star\star\star} p < 0.01$

Table 3: Analysis of Upfront Prices Paid by Banks (II)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**Dealer to Customer Market - Sell Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	0.0085***	0.0113***	0.0079***	0.0114***	0.0092***	0.0074**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry × Month FE	-	-	Yes	-	-	-
Issuer × Month FE	-	-	-	Yes	-	-
Dealer × Issuer FE	-	-	-	-	Yes	-
Dealer × Issuer × Month FE	-	-	-	-	-	Yes
Observations	129,622	129,622	129,622	129,622	129,622	129,622
R^2	0.118	0.134	0.421	0.169	0.467	0.635

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to December 2019, the segment is the dealer-to-customer market, and the trades are all sell (i.e., the buyside investor sells CDS protection). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10, ^{\star\star}p < 0.05, ^{\star\star\star}p < 0.01$

Table 4: Upfront Price Analysis: Banks in the Lending Syndicate

Dependent Variable	Upfront Price Points = Upfront Payment/Notional				
Sample	**Dealer to Customer Market - Buy Trades**				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{\text{Trader is Bank}} \times \mathbb{1}_{\text{Lending Relationship}}$	-0.0209***	-0.0204***	-0.0064***	-0.0034***	-0.0226***
	(0.0004)	(0.0009)	(0.0009)	(0.0012)	(0.0010)
$\mathbb{1}_{\text{Trader is Bank}}$	-0.0171***	-0.0145***	-0.0163***	-0.0089***	
	(0.0006)	(0.0006)	(0.0006)	(0.0008)	
$\mathbb{1}_{\text{Lending Relationship}}$	0.0044***	0.0027***	0.0040***	0.0012***	0.0018***
	(0.0004)	(0.0005)	(0.0006)	(0.0029)	(0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	-	Yes
Buyside FE	-	-	-	-	Yes
Issuer FE	-	-	Yes	-	-
Dealer × Issuer × Month FE	-	-	-	Yes	-
Observations	140,395	140,395	140,395	140,395	140,395
R^2	0.082	0.098	0.239	0.565	0.172
Sample	**Dealer to Customer - Sell Trades**				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{\text{Trader is Bank}} \times \mathbb{1}_{\text{Lending Relationship}}$	0.0069***	0.0074***	0.0030***	0.0057***	0.0126***
	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0009)
$\mathbb{1}_{\text{Trader is Bank}}$	0.0059***	0.0087***	0.0038***	0.0005***	
	(0.0005)	(0.0006)	(0.0006)	(0.0007)	
$\mathbb{1}_{\text{Lending Relationship}}$	0.0040***	0.0024***	0.0002	-0.0026	0.0021***
	(0.0005)	(0.0004)	(0.0007)	(0.0028)	(0.0004)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	-	Yes
Buyside FE	-	-	-	-	Yes
Issuer FE	-	-	Yes	-	-
Dealer × Issuer × Month FE	-	-	-	Yes	-
Observations	129,622	129,622	129,622	129,622	129,622
R^2	0.120	0.134	0.260	0.568	0.204

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to December 2019, the segment is the dealer-to-customer market, and the trades are split in buy (first table) and sell (second table). The explanatory variable, $\mathbb{1}_{\text{Trader is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. The variable $\mathbb{1}_{\text{Lending Relationship}}$ takes value 1 when the trader and the reference firm are in a (syndicated) lending relationship. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 5: Upfront Price Analysis: Credit Volumes

Dependent Variable	Upfront Price Points = Upfront Payment/Notional			
Sample	**Buy Trades**		**Sell Trades**	
	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{Trader is Bank}} \times$ Log Loan Volume	-0.0024***	-0.0028***	0.0009***	0.0017***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\mathbb{1}_{\text{Trader is Bank}}$	-0.0147**	-0.0038	0.0086***	-0.0093***
	(0.0006)	(0.0027)	(0.0006)	(0.0021)
Log Loan Volume	0.0002***	0.0001**	0.0002***	0.0001**
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Contract Characteristics	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes
Buyside FE	-	Yes	-	Yes
Observations	140,395	140,395	129,622	129,622
R^2	0.098	0.172	0.134	0.204

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to December 2019, the segment is the dealer-to-customer market. The first two columns cover buy trades, while the following two cover sell trades. The explanatory variable, $\mathbb{1}_{\text{Trader is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. The variable *Log Loan Volume* is a continuous variable with the log of the syndicated credit volume. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10, ^{\star\star} p < 0.05, ^{\star\star\star} p < 0.01$

Table 6: Price Impact on Non Bank Investors (I)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Buy Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
1-Week Impact	0.0028***		0.0022***		0.0006	
	(0.0006)		(0.0006)		(0.0006)	
1-Month Impact		0.0046***		0.0044***		0.0030***
		(0.0005)		(0.0005)		(0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	-	Yes	Yes	Yes	Yes
Industry × Month FE	-	-	-	-	Yes	Yes
Observations	106,515	106,515	106,515	106,515	106,515	106,515
R^2	0.098	0.097	0.120	0.120	0.167	0.167

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is January 2018 to December 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all buy (i.e., the buyside investor buys CDS protection). The sample only includes trades with non-bank buyside investors. The main explanatory variables, 1-Week Impact and 1-Month Impact, take value 1 when the trade follows a trade that the same dealer conducts with a bank within the last week (respectively, month), and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table 7: Price Impact on Non Bank Investors (II)

Dependent Variable	Upfront Price Points = Upfront Payment/Notional					
Sample	**D2C Market - Sell Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
1-Week Impact	-0.0060***		-0.0064***		-0.0044***	
	(0.0006)		(0.0006)		(0.0006)	
1-Month Impact		-0.0037***		-0.0039***		-0.0014***
		(0.0005)		(0.0005)		(0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	-	Yes	Yes	Yes	Yes
Industry × Month FE	-	-	-	-	Yes	Yes
Observations	94,461	94,461	94,461	94,461	94,461	94,461
R^2	0.119	0.119	0.140	0.139	0.178	0.178

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the transaction price, expressed as the ratio between the upfront payment exchanged by the two parties, and the traded notional. The period of analysis is April 2018 to June 2019, the segment is the dealer-to-customer (D2C) market, and the trades are all sell (i.e., the buyside investor sells CDS protection). The sample only includes trades with non-bank buyside investors. The main explanatory variables, 1-Week Impact and 1-Month Impact, take value 1 when the trade follows a trade that the same dealer enters with a bank within the last week (respectively, month), and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10,^{\star\star} p < 0.05,^{\star\star\star} p < 0.01$

Table 8: Analysis of Bid-Ask Spreads Paid by Banks (I)

Dependent Variable	Absolute Half Spreads					
Sample	**D2D + D2C Market, All Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0002 (0.0005)	-0.0012*** (0.0005)	-0.0018*** (0.0005)	-0.0020*** (0.0005)	-0.0029*** (0.0005)	-0.0008* (0.0004)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry FE	-	-	Yes	-	-	-
Month FE	-	-	Yes	-	Yes	-
Industry × Month FE	-	-	-	Yes	-	-
Dealer × Industry FE	-	-	-	-	Yes	-
Dealer × Issuer FE	-	-	-	-	-	Yes
Observations	184,955	184,955	184,955	184,955	184,955	184,955
R^2	0.35	0.36	0.38	0.38	0.38	0.77

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is April 2018 to June 2019, and the sample includes all trades for which there was a matching mid (D2D and D2C segments, as well as both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table 9: Analysis of Bid-Ask Spreads Paid by Banks (II)

Dependent Variable	Absolute Half Spreads					
Sample	**D2C Market, All Trades**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	-0.0028*** (0.0006)	-0.0024*** (0.0006)	-0.0045*** (0.0006)	-0.0049*** (0.0006)	-0.0053*** (0.0006)	-0.0040*** (0.0005)
Contract Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	-	Yes	Yes	Yes	-	-
Industry FE	-	-	Yes	-	-	-
Month FE	-	-	Yes	-	Yes	-
Industry × Month FE	-	-	-	Yes	-	-
Dealer × Industry FE	-	-	-	-	Yes	-
Dealer × Issuer FE	-	-	-	-	-	Yes
Observations	101,677	101,677	101,677	101,677	101,677	101,677
R^2	0.38	0.39	0.40	0.42	0.42	0.72

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is April 2018 to June 2019, and the sample includes all D2C trades for which there was a matching mid, thus including both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Issuer rating is a linear function of the rating of the reference firm, as classified by one of the top three rating agencies. $^{\star}p < 0.10,^{\star\star} p < 0.05,^{\star\star\star} p < 0.01$

Table 10: Effects by Rating Group

Dependent Variable	Absolute Half Spreads		
Sample	**D2D + D2C Market, All Trades**		
	High Grade	Medium Grade	Speculative and No Rating
	(1)	(2)	(3)
$\mathbb{1}_{\text{Buyside Investor is Bank}}$	0.0001 (0.0007)	0.0006 (0.0004)	-0.0048*** (0.0012)
Contract Characteristics	Yes	Yes	Yes
Issuer Rating	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Dealer × Industry FE	Yes	Yes	Yes
Observations	6,622	111,834	60,494
R^2	0.32	0.49	0.35

This table reports the coefficients of OLS estimations where the unit of observation is a trade, at dealer - counterparty - reference entity level. The dependent variable is the absolute value of the half-bid ask spread, expressed as the difference between the transaction price of the contract, and the quote mid for the same reference firm, maturity, coupon, and seniority. The period of analysis is April 2018 to June 2019, and the sample includes all trades for which there was a matching mid (D2D and D2C segments, including both buy and sell trades). The main explanatory variable, $\mathbb{1}_{\text{Buyside Investor is Bank}}$, takes value 1 when the buyside investor is a bank, and 0 otherwise. Contract characteristics include standardized maturities and coupons, the seniority of the reference obligation (senior or subordinate), and the logarithm of the traded notional. Column (1) restricts the sample to reference entities with a "high grade" or "prime" rating, column (2) captures reference entities rated "upper medium grade" or "lower medium grade", whiles column (3) shows the effects on references rated "speculative", "highly speculative", or without rating. Issuer ratings follow the classification of the top three rating agencies. $^{\star}p < 0.10,^{\star\star} p < 0.05,^{\star\star\star} p < 0.01$