Information Chasing or Adverse Selection: Evidence from Bank CDS Trades *

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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? 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 position better their prices when trading with other investors. This suggests that dealers do not fear being adversely selected, but rather chase banks' private information. This information gets incorporated into market prices, helping price discovery.

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

JEL Classification: G14, G21, G23

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1 Introduction

Do informed traders receive better or worse prices in over-the-counter (OTC) financial markets relative to less informed traders? Theories of *adverse selection* dating back to Ackerloff (1970) imply that in the presence of adverse selection sellers increase their prices to privately informed clients to protect themselves from the winner's curse. In the OTC market, that would translate into dealers offering higher bid-ask spreads to buyside customers they perceive as informed. There is however a competing dealer incentive that plays in the opposite direction: dealers may chase information from the informed trader. Under this mechanism dealers can learn the information from their informed clients, use it to better position their spreads in future trades with non-informed clients, and thus pass on the winner's curse to the latter. The main prediction of the theories of *information chasing* is that the informed trades receive better pricing terms, i.e. tighter bid-ask spreads.

We test empirically whether adverse selection or information chasing prevails in the credit default swap (CDS) market by using non-anonymised transaction-level data for the European CDS market. For identification we use bank trades as sources of client private information. A large theoretical and empirical literature has shown that through their screening and continuous monitoring, banks collect and hold useful private information on their borrowers.[1] Banks are often active in lending to companies on which credit derivatives are traded. But they will also hold CDS themselves, either to hedge their loans of bonds, in which case they buy CDS protection, or to take on additional credit exposure, by selling CDS protection. Smaller banks will trade with dealers CDS on their own customers, a trade that implies some exchange of private information. We are in the unique position to observe the terms of these trades, and in particular, how dealers price trades to banks relative to other investors.

For the mechanism we follow closely Pinter et al. (2022) and adapt it to the

[1]E.g., Diamond (1984); Fama (1985); James (1987); Freixas and Rochet (2008); Degryse et al. (2009)) have focused on banks existing for and being proficient in bridging the information asymmetry that exists between financiers and borrowers.

CDS market: A bank that purchases CDS protection might have received a negative signal on the credit worthiness of the underlying. If the dealer chases that information, it will sell to the bank CDS protection relatively cheaper, accepting to be adversely selected on that trade. The dealer can subsequently use the information gleaned from the customer transaction to better position its quotes on future trades and gain from trading with the non-informed traders. On the contrary if the dealer seeks to avoid being adversely selected, it will charge the bank initially seeking CDS protection a relatively higher price than to other uninformed traders. Conversely, a bank that initially sells CDS protection may reveal positive news about the underlying.

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 Credit Market Analytics (CMA) through Bloomberg on CDS dealer quotes for the most 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 LPC DealScan syndicated loan database.[2] 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 all relevant characteristics of this loan (granting date, volume, collateral, number of lenders in the syndicate, etc.). For the two-year period we focus on, i.e., from January 2018 to December 2019, there are almost half a million CDS contracts in the resultant dataset.

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.

To set up the analysis, we start by confirming that bank trades anticipate the CDS spreads of the underlying firms. Using the EMIR dataset on CDS transactions as well as the complete set of daily CDS quotes over the span of two years, we first show that bank trades on corporates are indeed useful to predict CDS spreads. In line with Acharya and Johnson (2007), we find this to be the case when the credit quality of the underlying worsens: following a trade in which a bank purchases CDS protection on a firm, credit spreads on this firm tend to increase.

We then turn to the analysis of the transaction prices in the CDS market, in order to understand the price discovery mechanism. Here we first study 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

[2] Syndicated loans constitute an important type of bank lending to medium- and large-sized enterprises, both domestically and cross-border, in which mainly one or more lead arrangers aim to reduce the information asymmetry with the borrower. DealScan has been widely used to study the syndicated loan market (e.g., Sufi (2007); De Haas and Van Horen (2013)).

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 $\times$ reference firm $\times$ 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. After selling protection to a bank, dealers increase their prices for selling CDS protection in subsequent trades. This is consistent with dealers using the private information gained in the bank bank trade to avoid being adversely selected in future trades, and 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, because dealers "chase" bank trades in order to learn and monetize their information. 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 by banks. 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 (Pinter et al. 2022; 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.

Finally, our work contributes to a better understanding the functioning of the CDS market, and in particular of how the CDS market is useful to discover information generated within the bank-client credit relationship. Saretto and Tookes (2013) look first at the link between CDS and credit markets, but emphasize the liquidity benefit of CDS. They show that lenders appear more willing to extend credit to firms with traded CDS because they can hedge the exposures. Closer to our idea of studying the interaction of bank monitoring and CDS trading are Subrahmanyam et al. (2014) and Amiram et al. (2017). They however focus on the potential problem of "empty creditors", or banks that stop monitoring the firm they had lent to, once they can hedge their credit exposure. The former paper finds that, after the inception of CDS trading, the probabilities of credit rating downgrades or of bankruptcy increase substantially. Amiram et al. (2017) show that after the inception of CDS trading the share of loans retained by the loan syndicate lead arrangers increases, in order to reinforce their commitment to monitoring, and so counteract the negative effect on the value of the firm.[3]

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.

[3]For detailed descriptions of the institutional setting in which CDS contracts are traded see for example Aldasoro and Ehlers (2018) and Bomfim (2022).

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 access 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 (because of our research focus to link trades to lending to specific firms), 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 so-called International Money Market IMM dates), fixed notional amounts (Euro 5 or 10 million), and fixed protection coupons of typically 100 or 500 basis points (bps). 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 bps, 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.[4] 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.

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.

[4]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.

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 active 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:

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

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

3.1 Bank Trades and CDS Spreads

We start out by confirming that bank trades in the CDS market predict corporate CDS spreads. For this, we analyse how the CDS spreads change in the aftermath of bank trades. We estimate the following set of regressions:

$$UpfrontQuote_{i,f,t+h} = \beta_h * BankTrade_{ft} + \alpha_i + \gamma_{t+h} + \epsilon_{i,f,t+h}$$

where $h = 1..30$ captures an horizon of up to 30 days after a bank trade. Therefore we measure how the quoted CDS prices on contract i change over the 30-day window following a bank trade. For precision, we work with granular CDS contracts, which are at the level of a reference entity f, seniority, currency, maturity and restructuring type: in general, there are several contracts quoted on a given

Reference Entity f. α_i are thus contract fixed effects, and γ_t are day fixed effects. We study in turn the effect of trades where banks are CDS protection buyers, or when banks are CDS protection sellers. We use the entire sample of CDS quotes available and estimate the regressions separately on corporate reference entities and on sovereign reference entities. In principle, we expect that any price discovery from bank trades should only occur for corporates.

3.2 Analysis of Upfront Prices Paid by Banks

The remaining of our 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 various, and sequentially more comprehensive, sets of fixed effects. In this first step, 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.* In the third and fourth steps, we follow the same type of analysis, but we study the impact on realized bid-ask spreads, instead of on the upfront transaction prices.

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 purpose, we estimate the following specification:

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

In this model, the dependent variable, $UpfrontPrice_{idft}$, 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 zero otherwise, 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.

The flow of information occurs as follows: A bank that purchases CDS protection might have received a negative signal on the credit worthiness of the underlying. If the dealer chases that information, it will sell to the bank CDS protection relatively cheaper, accepting to be adversely selected on that trade. The dealer can subsequently use the information gleaned from the customer transaction to better position its quotes on future trades and gain from trading with the non-informed traders. On the contrary if the dealer seeks to avoid being adversely selected, it will charge the bank initially seeking CDS protection relatively more than to other uninformed traders. Conversely a bank that is looking to sell CDS protection may reveal positive news about the underlying. Under adverse information the price on this trade should be relatively higher, while under information chasing there would be a discount on the informed bank trade, which the dealer would recoup by entering more profitable future trades.

For the model explaining upfront prices, it is important to separate trades according to their direction (whether the buyside investor sells or buys 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 is for the seller. 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 with 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.

3.2.1 Price Impact

Next, we study whether there is any price impact following the 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.

3.3 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 sets of 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.

3.3.1 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

Figure 3 confirms the earlier result by Acharya and Johnson (2007) that there is information discovery from bank trades into the CDS market, in particular when the credit quality worsens. The first figure in the panel shows that credit spreads of the average firm increases after a bank buys CDS protection on it. The average effect is economically and statistically significant: in the 30 days after a bank buys CDS protection CDS spreads increase by 0.30% of par. Two thirds of the effect occurs instantaneously (within a day), while the remaining one third occurs over the following 15 days. However, there does not seem to be a significant effect of trades where a bank is selling CDS protection (second figure). The second panel replicates the regressions for sovereigns. Here again we do not observe any significant effect.

Consistent with bank trades being valuable, Table 1 already showed that, on average, banks pay relatively lower CDS upfront fees whenever they purchase CDS protection from dealers. The average upfront payment is 21 bps of notional for trades where the buyside is a bank purchasing protection, whereas the average upfront in dealer-to-non bank trades equals 246 bps. Banks also receive higher payments whenever they are selling protection. A bank investor receives on average 323 bps of notional, compared to 164 bps that non-bank protection sellers receive from their dealers. While these averages are also driven by compositional effects, estimates from regressions (reported below) that are saturated with with comprehensive controls and fixed effects uphold the finding of this 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 between 100 and 246 bps when purchasing protection, relative to non bank investors. Indeed, even in the most restrictive 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 100 bps. 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 74 bps. 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 extend this result. In both tables we differentiate between banks according to whether they are in a current syndicated lending relationship with the firm, and how much syndicated lending was taking place. From Table 4 Column (4), we glean that the same dealer selling the same CDS protection contract during the same month to a non-lending relationship bank versus a non-bank investor, will charge the bank an upfront that is lower by 89 bps.[5] When the bank is also in a lending relationship, the upfront drops by an additional 34 bps. In contrast, for a non-bank with a recent syndicated lending relationship the upfront increases by 12 bps! On the other hand, a dealer buying the same CDS protection contract during the same month from a bank and from a non-bank investor, will pay a non-lending bank an upfront higher by only 5 bps, while a lending lending captures an addition 57 bps. This once more suggests that banks are better informed than dealers about changes in credit risk of their borrowers, and that dealers learn valuable information when trading with banks. Table 5 then shows these findings to hold also for lending volumes.

But is the private information then incorporated into transaction prices? Do

[5]One explanation for this estimate likely is that the bank may not only have lent recently to the firm in the syndicated loan market, but has a comprehensive history of lending and dealings with the firm and its competitors that gives the bank a information edge.

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 adjust its price and sell protection more expensively to other investors, on the same reference entity. After purchasing CDS protection from a bank, a 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 160 bps 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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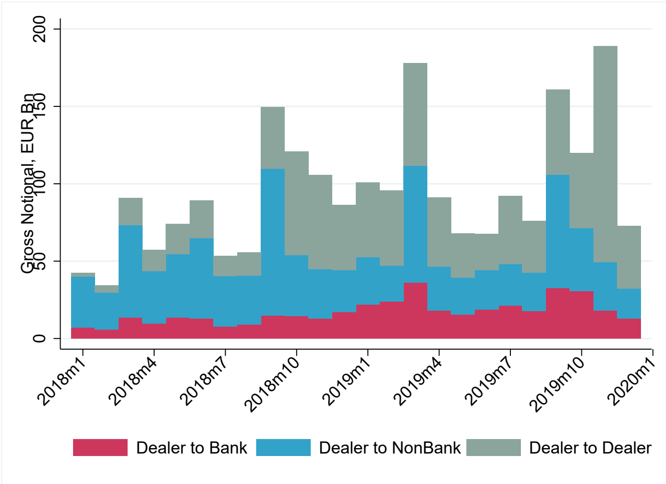
A. DATA DESCRIPTION

Panel A. CDS Trading by Market Segment - Volumes



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

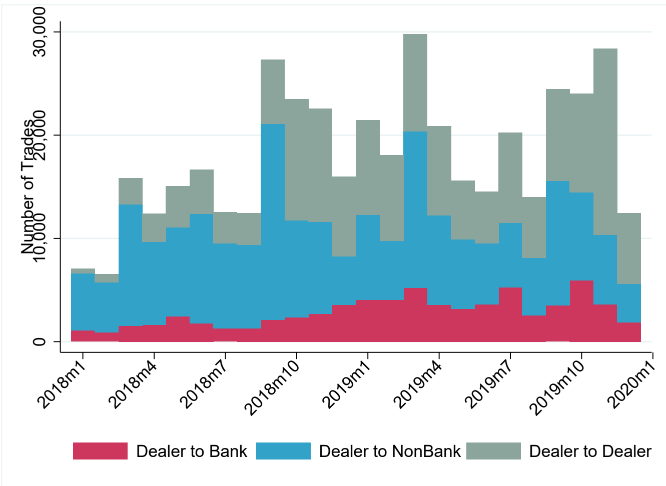
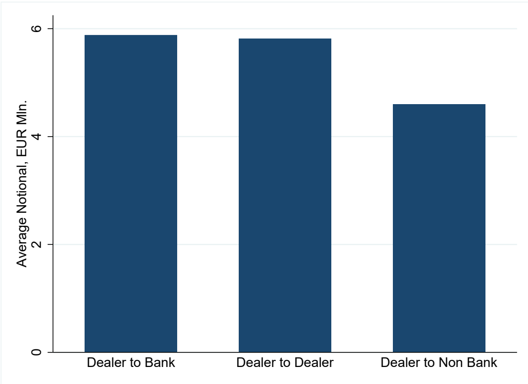
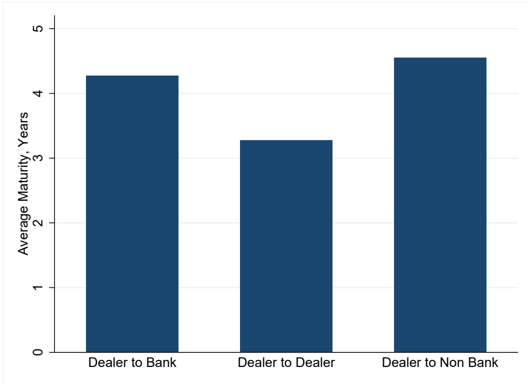


Figure 1: Total CDS Notional

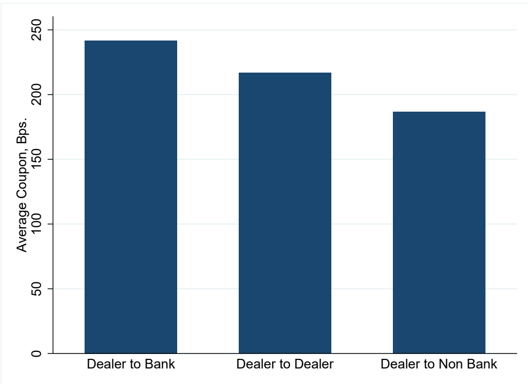
This figure shows total CDS trading across our final sample of 435,648 trades. Panel A shows monthly volumes by market segment: dealer-to-dealer, dealer-to-bank investor, and dealer-to-non bank investor. Panel B shows the same decomposition for the number of trades.



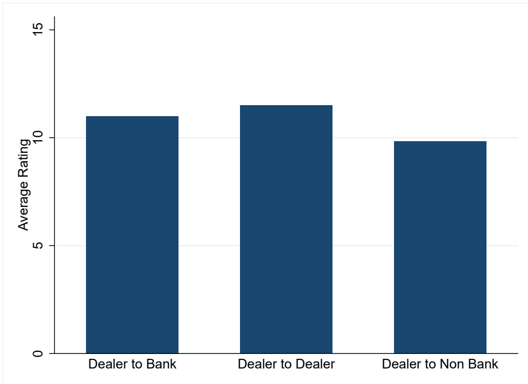
(a) Average Notional



(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.

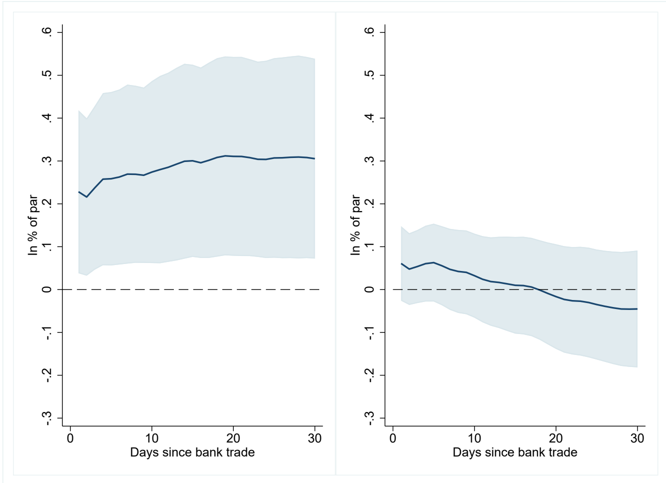
Table 1: Summary Statistics: Trade Characteristics

	N	Mean	SD	P25	P50	P75
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(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

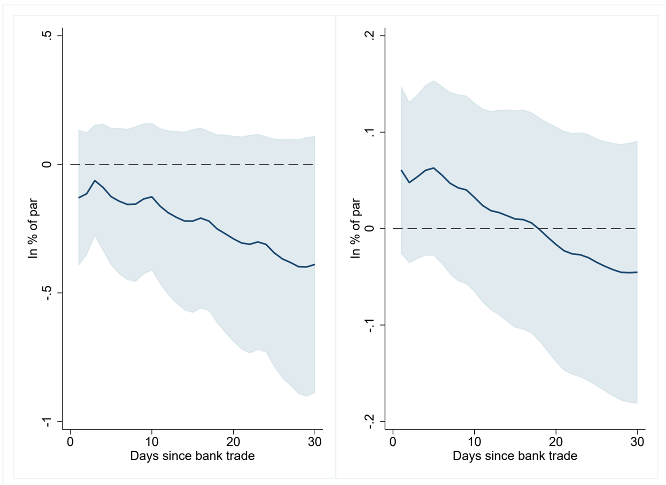
This table reports summary statistics for the 435,648 CDS contracts in the final sample, over the period January 2018 to December 2019. The sample is split into different market segments: dealer - to - dealer and dealer - to - customer trades, as well as, for the latter category, based on trade direction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

B. Results

Panel A. Price Impact of Bank Trades on Corporate CDS Spreads



Panel B. Price Impact of Bank Trades on Sovereign CDS Spreads



This graph shows the price impact of bank trades on the CDS spreads of the underlying Reference Entities. The graphs on the right hand side measure the impact of trades where the bank purchases CDS protection, while the graphs on the left hand side measure the impact of trades in which the bank sells credit protection. Panel A focuses on quotes on corporate CDS, excluding Sovereigns and Financials. Panel B focuses on Sovereigns. The blue lines are estimates from the following set of regressions: $UpfrontQuote_{i,f,t+h} = \beta_h * BankTrade_{ft} + \alpha_i + \gamma_{t+h} + \epsilon_{i,f,t+h}$, while the light blue areas are 90% confidence intervals. Standard errors are clustered at contract and day.

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***	-0.0218***	-0.0189***	-0.0125***	-0.0157***	-0.0100***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(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	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. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

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 $\times$ 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	-0.0012***	-0.0018***	-0.0020***	-0.0029***	-0.0008*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(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 $\times$ Month FE	-	-	-	Yes	-	-
Dealer $\times$ Industry FE	-	-	-	-	Yes	-
Dealer $\times$ 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 $\times$ Month FE	-	-	-	Yes	-	-
Dealer $\times$ Industry FE	-	-	-	-	Yes	-
Dealer $\times$ 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. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

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	0.0006	-0.0048***
	(0.0007)	(0.0004)	(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. ${}^{\star}p < 0.10, {}^{\star\star}p < 0.05, {}^{\star\star\star}p < 0.01$