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Abstract

Using granular transaction-level data, this paper investigates the characteristics and implications of dealer-client trading relationships in the over-the-counter FX derivatives market. We first document that dealer-client trading relationships are persistent over time. Then, to shed light on the role of relationship strength for client access to these instruments during times of dealer stress, we examine the collapse of Credit Suisse in March 2023. Our analysis reveals that clients with greater exposure to Credit Suisse experienced a larger increase in spreads at the client level relative to unexposed clients by about 16 basis points per notional dollar traded on average across maturities, although their trading activity remained unchanged. The greater spread increases paid by clients who relied more heavily on Credit Suisse occurred through their trades with non-Credit Suisse dealers. While more exposed clients continued to trade with Credit Suisse in the post-period, less exposed clients reduced their trading activity with Credit Suisse, but increased their trading activity elsewhere, indicating an ability to substitute counterparties. These findings underscore the critical role of search and bargaining frictions in this market, particularly when a relationship dealer encounters adverse shocks.

Key words: Foreign exchange, derivatives, trading relationships.

JEL classification: G14, G15, G12.

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1 Introduction

The over-the-counter (OTC) foreign exchange (FX) derivatives market is one of the largest financial markets globally and is accessed by a variety of institutions for a wide array of purposes. FX derivatives are used by hedge funds, non-financial corporates, asset managers, and banks, among others, to hedge currency risk, borrow synthetically in foreign currency, and speculate (Hacioğlu-Hoke et al. 2024). According to the BIS OTC Derivatives Statistics, only about 6.8 percent of FX outright forwards and swaps are centrally cleared, \$4.944 trillion USD of the \$72.827 trillion USD total notional outstanding in the second half of 2024.[1] Therefore, even though this market is very large and is accessed by a broad set of institutions, it is a decentralized OTC market where most trades are cleared bilaterally. Thus, the market is opaque and subject to search and bargaining frictions.

Although previous work documents significant price dispersion in OTC markets, including the FX derivatives market (Hau et al. 2021), there is limited empirical evidence documenting the characteristics of bilateral trading relationships in the OTC FX derivatives market and the importance of relationships for client trading outcomes in times of dealer stress. This paper provides new insight into the characteristics of bilateral trading relationships in this major global financial market and investigates how the reliance of clients on a dealer shapes client trading outcomes after that dealer is adversely shocked. Thus, we examine how trading relationship persistence matters for clients' trading outcomes in a market with search frictions and costs to relationship creation.

Frictions in counterparty search and relationship creation can make pre-existing bilateral dealer-client relationships important for clients' ability to access the OTC FX derivatives market. First, fixed costs to new relationship creation, such as the creation of an International Swaps and Derivatives Association (ISDA) master agreement, exist in this market. In fact, according to Figure E.5 of FSB (2018), clients expect relationship negotiations and contract completion for new clearing relationships to take on average 2–6 months. Clients with existing dealer relationships do not need to pay this fixed cost to access these instruments. However, this fixed cost can make it difficult to substitute in the short run, and clients with fewer established relationships may be charged higher markups on their trading activity.

Second, even across established dealer relationships, clients may trade more persistently with some dealers based on bilateral relationship characteristics. This trading persistence can affect clients' trading outcomes, especially when one of their dealers is adversely shocked. For example, if bilateral trading persistence reflects the client's underlying search technology,

1. BIS OTC Derivatives Statistics, Table D6, 2024S2. Accessed on June 14, 2025, https://data.bis.org/topics/OTC_DER/tables-and-dashboards/BIS,DER_D6,1.0.

then the allocation of the client's trading portfolio reflects their propensity to trade across dealers and, therefore, their set of outside trading options. When a dealer is adversely shocked, the dealer may pass through higher costs to clients via larger spreads, and this pass through may be heterogeneous depending on the elasticity of client demand. Since this elasticity depends critically on search frictions and client bargaining power, the persistence of a client's trading activity with a dealer may matter for their trading outcomes at that dealer. Additionally, non-shocked dealers may charge higher markups to exposed clients to take advantage of any increase in their bargaining power post-shock, which may be greater for exposed clients that rely on them more heavily.

To shed light on the role of dealer-client relationships in this market for client trading outcomes, we first document new facts about dealer-client relationships in the OTC FX derivatives market. Using granular transaction-level data with counterparty identifiers, we show that there is cross-client heterogeneity in the count of dealers that clients trade with within-client sector, even after controlling for client trading volume. In addition, for the same count of dealer trading relationships, there is cross-client dispersion in the concentration of clients' trading portfolios across dealers. Thus, we provide greater insight into the degree of client segmentation and the heterogeneity of bilateral trading relationships in this market.

Next, we examine clients' choices of dealer counterparties, based on bilateral dealer-client relationship characteristics. Using weekly panel regressions with dealer–client sector–week fixed effects, we show that trading relationships are persistent. In weeks when a client trades, clients have a higher probability of trading with dealers with which they (i) had a relationship with more recently, especially if it was their only recent dealer relationship, (ii) relied on more heavily, and (iii) had an outstanding position in the same currency pair. In our baseline specification, which focuses on a client's recent reliance on a dealer, we find that, in weeks when a client trades, clients have a 0.4% higher probability of trading with a dealer that accounts for a 1 percentage point larger share of the client's trading portfolio in the last 4 weeks. Our results are robust to including client or client–week fixed effects. To our knowledge, these results are the first to characterize bilateral dealer-client trading relationships in this market.

Additionally, using a granular panel of spreads at the dealer–client–currency pair–maturity–date level, which measure the cost the client paid as the notional weighted average across trades of the log-difference between the transaction price and a benchmark reference price, we provide evidence that clients pay higher average spreads at dealers that compose a larger share of the client's trading portfolio. This is consistent with dealers charging larger markups to clients that search less intensely. However, the relationship between client reliance on a dealer and spreads in this analysis is endogenous. To address this issue, we exploit an adverse shock to a dealer to more causally identify the role of pre-existing relationship strength on spreads paid by clients and clients' trading activity. In particular, we study the role that dealer-client relationship strength plays for client trading outcomes in times of dealer stress in the context of the March 2023 shock to Credit Suisse.

To our knowledge, we are the first to examine the shock to Credit Suisse in March 2023, which ultimately led to its acquisition by UBS, in this market. We implement difference-in-differences and triple difference regression analyses using this shock to study trading activity in the EURUSD. We exploit that the shock to Credit Suisse is exogenous to pre-existing bilateral trading relationships, but affects exposed clients' trading options as long as relationships are persistent. Using this shock, we study how trading conditions changed for clients from the pre- to the post-period depending on their relationships, thus, more causally identifying how client reliance on a dealer affects spreads relative to our granular panel analysis.

Our results show that clients that relied more heavily on Credit Suisse do not face a reduction in total trading volume, but pay a 16 basis point larger increase in spread per notional dollar traded on average across maturities in the post-period relative to untreated clients. Clients that were more exposed to Credit Suisse paid a larger differential increase in spreads at non-Credit Suisse dealers relative to unexposed clients. In addition, our results suggest that clients that were more exposed to Credit Suisse pay a 24 basis point differential increase in spreads per notional dollar traded on average across maturities at their main non-Credit Suisse dealer in the post-period relative to the change in spread paid by unexposed clients at their main non-Credit Suisse dealer.

Overall, our results have implications for client relationship decisions in this market and for policymakers. We document that bilateral relationships exhibit strong persistence and, when a relationship dealer is adversely shocked, clients who were more reliant on that dealer face significantly higher trading costs, suggesting that relationship persistence can amplify the impact of dealer distress on client outcomes. This is informative for clients that wish to develop additional dealer relationships to prevent facing additional costs in these states of the world. For policymakers, we provide insight into the segmentation of client trading portfolios across dealers. Reducing search costs for clients that rely heavily on particular dealers or increasing outside trading options in times of dealer stress may help increase competition for client activity and prevent alternative dealers from charging greater markups to the most exposed clients in these periods. In addition, FX derivative trading costs could affect client risk mitigation or investment decisions. Since our results inform which clients will be most adversely affected in the face of adverse dealer conditions, they may help guide further research into how such shocks may propagate through the financial sector or economy.

2 Related Literature

Our paper contributes most directly to the literature that studies OTC markets and the role of trading relationships within them. Theoretical literature on OTC markets emphasizes search and bargaining frictions and limited transparency as drivers of price dispersion. Specifically, Duffie, Gârleanu, and Pedersen (2005) and Duffie, Gârleanu, and Pedersen (2007) theoretically model markets with sequential search and bargaining, and argue that less sophisticated clients pay larger spreads due to lower search efficiency and worse bargaining power. A natural prediction that arises is that a client will pay higher spreads when their set of outside options worsens, leading to a reduction in bargaining power. We exploit an adverse shock to Credit Suisse in March 2023 to provide causal empirical support for the importance of search and bargaining frictions in the OTC FX derivatives market. In addition, these theories assume that clients search across all counterparties and differences in search intensity generate price dispersion. We document that clients trade persistently with dealers that they previously relied on, which highlights that clients do not necessarily search across all dealers.

In the empirical literature studying OTC markets, there has been evidence of price dispersion that is consistent with price discrimination (Cenedese, Ranaldo, and Vasios 2020; Cocco, Gomes, and Martins 2009; Hau et al. 2021; Hendershott et al. 2020; Osler, Bjonnes, and Kathitziotis 2016). Hendershott et al. (2020) show that insurers in the corporate bond market pay smaller execution prices when they have more dealer relationships, but this is non-monotonic because clients can better substitute but have weaker bilateral relationships as dealer relationship count increases. Our paper particularly emphasizes bilateral relationship strength in the OTC FX derivatives market and studies a broader set of client sectors, including asset managers and hedge funds, among others. Also, we show that even conditional on the count of dealer relationships, there is cross-client heterogeneity in the concentration of a client's trading activity across dealers.

We specifically extend the work of Hau et al. (2021), which finds that less sophisticated clients pay larger transaction costs in the OTC FX derivatives market for the EURUSD. Hau et al. (2021) interact client sophistication with dealer-client relationships and find that sophisticated non-financial clients receive a trading discount from their relationship dealer while unsophisticated clients pay a premium. Unlike their paper, we focus on trading persistence due to bilateral dealer-client trading relationships, particularly the client's reliance on the dealer, for a client's trading outcomes. In addition, a client's count of dealer relationships and measures of client sophistication are endogenous. We exploit a shock to a dealer as a shock to exposed clients' bargaining power or set of outside options, and thus their ability to prevent price discrimination, to document how spreads for exposed clients change post-shock. Our trade-level data set is similar to that used by Hau et al. (2021), but is restricted to trades where at least one counterparty is a UK legal entity. However, we include a larger set of currencies, a more recent time period, and a broader set of client sectors.

A growing strand of empirical literature studying OTC markets examines the implications of trading relationships for pricing. This literature has primarily focused on the corporate bond and other markets, instead of the OTC FX derivatives market, and finds that stronger trading relationships are associated with smaller transaction costs (Afonso, Kovner, and Schoar 2013; Bernhardt et al. 2005; Di Maggio, Kermani, and Song 2017; Hendershott et al. 2020; Jurkatis et al. 2023). Closely related to our paper is Jurkatis et al. (2023), which studies bilateral dealer-client trading relationships in the corporate bond market. They find that dealers give discounts to clients that provide liquidity to the dealer or account for a large share of the dealers profits. We also emphasize the importance of bilateral dealer-client relationships, focusing specifically on the importance of the relationship from the client's perspective. Hence, our focus is on price discrimination due to persistence in a client's search process and the importance of these persistent relationships for a client's bargaining power.

Our examination of the Credit Suisse shock enhances the existing literature that studies the effects of dealer shocks in OTC markets (Cenedese, Della Corte, and Wang 2021; Di Maggio, Kermani, and Song 2017; Eisfeldt et al. 2023). Eisfeldt et al. (2023) study the role of network incompleteness and bilateral trading costs for pricing in the OTC CDS market and the implications when a dealer is removed. However, they do not focus on cross-client heterogeneity in trading outcomes. Di Maggio, Kermani, and Song (2017) focus on inter-dealer trading in the corporate bond market. They document that dealers with stronger previous relationships pay lower spreads, relationships are more important in times of dealer stress, and dealers charge more to clients than dealers. However, they also do not examine the differences across clients. We extend their analyses by focusing on dealer-client trading activity in the OTC FX derivatives market and emphasizing heterogeneity in client trading outcomes, particularly in the context of the March 2023 shock to Credit Suisse.

Cenedese, Della Corte, and Wang (2021) most closely relates to our paper, as we use the same source of trade repository data to study shocks to dealers in the OTC FX derivatives market. Although they include supplementary evidence that highly exposed clients substituted to untreated and existing dealer relationships, their focus is to show that a shock to the UK leverage ratio framework generated deviations from covered-interest-parity (CIP). Instead, we focus in detail on the role of dealer-client relationship strength for heterogeneous trading outcomes across clients and examine a different dealer shock. Moreover, our analysis is not specific to CIP, but provides insight into whether dealers may heterogeneously pass through costs to client-level CIP deviations based on previous relationship strength.

Thus, we contribute to the growing literature studying dealer bank constraints and the role they play in asset pricing, particularly for CIP deviations (Augustin et al. 2024; Cenedese, Della Corte, and Wang 2021; Du, Tepper, and Verdelhan 2018; Kloks, Mattille, and Ranaldo 2023; Moskowitz et al. 2024; Wallen 2022). This literature has documented that CIP deviations widen when dealer banks become constrained (Du, Tepper, and Verdelhan 2018) and the role of segmentation and market power for FX prices (Moskowitz et al. 2024; Siriwardane, Sunderam, and Wallen 2025; Wallen 2022). However, these papers primarily focus on prices at the currency–maturity–date level. Cenedese, Della Corte, and Wang (2021) use trade-level price data to document that the leverage ratio affects CIP deviations at this granular level. We provide additional insight into the types of clients that bear more of the costs of dealer balance sheet shocks, specifically based on bilateral dealer-client relationship characteristics.

Finally, we also contribute to literature that uses trade repository data, associated with the European Market Infrastructure Regulation, to study the OTC FX derivatives market (Abad et al. 2016; Bardoscia, Bianconi, and Ferrara 2019; Cenedese, Della Corte, and Wang 2021; Hacioğlu-Hoke et al. 2024; Hau et al. 2021) and to literature that studies counterparty choice (Di Maggio, Egan, and Franzoni 2022; Du et al. 2024; Ferrara et al. 2021). We extend this literature by providing new stylized facts on dealer-client relationships and the segmentation of client activity across dealers in this major global financial market, and documenting dealer-client relationship characteristics that affect counterparty choice.

The rest of the paper is organized as follows. In Section 3, we describe the data used for analysis, outline our measurement of spreads, and provide descriptive statistics. We empirically categorize bilateral trading relationships and their relationship to spreads in the OTC FX derivatives market in Section 4. In Section 5, we study the shock to Credit Suisse in March 2023 to address how client reliance on a dealer shapes client trading outcomes after an adverse dealer shock. Section 6 concludes.

3 Data Description

This section describes the granular trade repository data used in our analyses, which contain counterparty identifiers and trade-level information, including prices. This is ideal for studying the characteristics of dealer-client trading relationships and trading activity at the counterparty pair level. Then, we outline our computation of spreads, which measure the costs that clients pay on their trades, and provide descriptive information about our sample.

3.1 UK European Market Infrastructure Regulation (UK EMIR)

Our main dataset consists of trade repository data, collected under UK EMIR, from the Bank of England covering all trades of OTC FX outright forwards or forward legs of FX swaps where at least one counterparty is a UK legal entity. This is the same source of FX derivative trade repository data as Cenedese, Della Corte, and Wang (2021), but our sample is more recent, covering trades executed from January 1, 2022 through December 31, 2023.

UK EMIR requires UK legal entities to report details of all their derivatives trades, including interest rate and FX, among others, to a trade repository that is registered with the Financial Conduct Authority.[2] There exist two types of reports, activity and state reports. The state reports give trade-level information for all trades that are outstanding each day, while the activity reports cover all trades that were reported each day. We use data from the state reports, since the set of outstanding positions allows us to more correctly identify dealer-client relationships.[3] We focus on data for currency forwards (i.e., outright FX forwards and forward legs of FX swaps). So, our data consist of all OTC forward trades where at least one counterparty is a UK legal entity and the trade is outstanding at the end of each date in our sample period.

For each transaction, we observe information about counterparties (i.e., legal entity identifier (LEI) and corporate sector) and contract characteristics (e.g., price, notional amount, maturity date, execution date, execution time). We are able to identify counterparty sectors including, but not limited to, dealer, bank, non-financial, hedge fund, asset manager, pension fund, insurer, and others.[4] Since there exist internal capital market connections between subsidiaries of the same parent company, we aggregate dealers and banks of the same parent institution into a single dealer entity for analysis.[5] When aggregating, we drop any trades that are between a dealer and bank of the same parent institution. So, a dealer-client relationship captures trading activity between a client and the set of dealers and banks that we identify as belonging to the same parent institution.[6]

2. For information on UK EMIR, see www.bankofengland.co.uk/financial-stability/trade-repository-data.

3. The state reports contain trade-level information on trades that are outstanding at the end of the day. From this, we can identify trades executed each day, not just the outstanding positions.

4. The sector mapping that we use is internal to the Bank of England and is generated from public and regulatory information. We identify dealer identities from this mapping.

5. It has been documented by Gupta (2021) that internal capital markets of holding companies are important and dealers rely heavily on internal capital markets with sibling subsidiaries of the same parent institution. In addition, although there is some limitation for non-bank subsidiaries to be financed by commercial deposits of sibling banks, for example due to Section 23A of the Federal Reserve Act, there are exceptions. For Section 23A of the Federal Reserve Act, see https://www.federalreserve.gov/aboutthefed/section23a.htm.

6. For example, JP Morgan Chase Bank LEIs will be aggregated with JP Morgan Chase Dealer LEIs as a single JP Morgan Chase Dealer Bank. The trades between JP Morgan Chase banks and dealers will be dropped, as will those between JP Morgan Chase banks and those between JP Morgan Chase dealers. See Appendix A.2 for more information on this process.

We restrict our sample to trades and outstanding positions for seven major currencies relative to the USD and keep a maturity panel that contains standard maturities and a maturity bucket that aggregates all maturities less than or equal to 1 year. Specifically, we retrieve data for AUDUSD, CADUSD, CHFUSD, EURUSD, GBPUSD, JPYUSD, and NZDUSD for the following maturities: 1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 7m, 8m, 9m, 10m, 11m, 1y, all $\leq$ 1y.[7] When we refer to the "maturity panel" going forward, we refer to the set of observations with maturity not given by the all $\leq$ 1y maturity. In our maturity panel, a larger share of activity is in shorter maturities, consistent with the fact that trading in FX OTC derivatives is dominated by short maturities.[8]

The all $\leq$ 1y maturity contains all trades (outstanding positions) with maturity (residual maturity) less than or equal to 1 year. We define this bucket to keep activity and positions that exist in non-standard maturities, since these are important for measuring dealer-client relationship strength and existence. For example, a dealer and client may have a relationship in a non-standard maturity contract, but this would not appear when we only look at activity in standard maturities.

We merge our trade data with a currency pair–maturity–date panel of forward rates and settlement dates from Bloomberg to include benchmark prices, which we use to compute spreads, and identify the trades to include in each maturity bucket.[9] A trade is included in a maturity bucket if it matched with the Bloomberg panel for that maturity on execution date, currency pair, and days to maturity.[10] We use the maturity panel for any analysis related to spreads, the measurement of which is discussed in Section 3.2.

The trade-level dataset is very large, so we aggregate our panel across trades to the dealer–client–currency pair–maturity–date–direction (d, i, c, m, t, dir) level, where direction indicates whether the client in the counterparty pair is buying or selling USD. After aggregation, our dataset contains trading and outstanding positions, and spreads, for all dealer-client pairs at a daily frequency in the currencies and maturities listed above. Only maturity panel

7. Appendix A.1 includes a description of how we identify trades to include in each maturity bucket. In summary, we match the variables (execution date, currency pair, maturity date) in our trade-level data on the variables (date, currency pair, settlement date) in a currency–maturity–date level panel of forward rates and settlement dates from Bloomberg with the maturities listed.

8. See the box plots of daily activity totals by maturity over our 2-year sample in Appendix D.3 Figure 3.

9. See Appendix A.1 for information on identifying maturity buckets.

10. For example, for the 1-week maturity, we keep trades that match the maturity date and currency pair on date t for the 1-week Bloomberg observations, and drop those that do not exactly match the 1-week Bloomberg characteristics. So, for notional trading activity, suppose that the maturity for a EURUSD 1-week trade in Bloomberg executed on date t is $t + 7$. In the trade-level data we keep EURUSD trades that were executed on date t and mature on $t + 7$ in the 1-week maturity bucket. We exclude those that mature on $t + 8$ from the 1-week maturity bucket, for example, but retain them for the all $\leq$ 1y maturity bucket. Maturity bucketing for notional outstanding positions, is done similarly, but uses residual maturity, the maturity of the outstanding position, instead of the days to maturity of the initial trade.

observations have spread information. We aggregate the trade-level panel by taking notional weighted averages of spreads, and the sum of (i) notional traded, (ii) notional outstanding, (iii) new trade count, and (iv) outstanding trade count, respectively. When we aggregate across trade directions to the (d, i, c, m, t) level, we have 521,499 (d, i, c, m, t) observations for our maturity panel.[11] This is significantly smaller than our (d, i, c, t) panel for the all $\leq$ 1y maturity because we exact match on maturity date with the Bloomberg panel, of which the forward price will be used to calculate spreads, as described in Section 3.2.

For more information on the data cleaning process, see Appendix A.

3.2 Spread Measurement

Similar to Hau et al. (2021) and others in the literature, we measure spreads as the difference between the log trade price from a benchmark price, multiplied by a sign indicator to capture the cost paid from the perspective of the client.

Let τ denote a trade between dealer d and client i, in currency pair c and maturity m on date t, where the client is buying or selling USD according to direction dir. Maturity m is measured as the number of days from the trade execution date to the maturity date. The trade price, denoted by $F_{d,i,c,m,t,dir,\tau}$, and the benchmark price for trade τ, F^*_τ, have units $\frac{\text{USD}}{\text{Foreign Currency}}$. We use lower case letters to denote logs of forward rates.

We compute the spread in basis point units for trade τ as

$$spread_{d,i,c,m,t,dir,\tau} = 10,000 \times (f_{d,i,c,m,t,dir,\tau} - f^*_\tau) \times dir \tag{1}$$

where

$$dir = \begin{cases} +1 & \text{if client } i \text{ is selling USD forward} \\ -1 & \text{if client } i \text{ is buying USD forward} \end{cases}$$

So, dir is a directional indicator that normalizes the spread to be positive if the client pays a worse price relative to the benchmark, irrespective of the trading direction. When aggregating to any coarser unit of observation (i.e., (d, i, c, m, t, dir) and (d, i, c, m, t) levels), we take notional weighted averages. The interpretation of the spread is therefore *the spread paid by the client per average dollar of notional traded* at the level of aggregation.

We use Bloomberg forward prices at the currency–maturity–date level as benchmark prices, f^*_τ. The benchmark for trade τ is the Bloomberg price with the same trade execution

11. This excludes the all $\leq$ 1y maturity. Using the all $\leq$ 1y maturity, the dealer–client–date panel has 1,890,718 observations, after conditioning on the observation having a positive trade count for any of the seven currencies.

date, currency pair, and days to maturity as τ.[12] For example, suppose we have EURUSD trades executed on date t, and the Bloomberg forward price $f^*_{EURUSD,1\text{-}month,t}$ for the 1-month EURUSD forward for date t with a settlement date of $t+30$. Then, our 1-month maturity for the EURUSD on date t only includes trades with a maturity date of $t+30$, and we compute spreads relative to $f^*_{EURUSD,1\text{-}month,t}$ for these trades. This keeps prices as comparable as possible when computing spreads.[13]

Table 17 in Appendix D.9 provides descriptive statistics for our spread sample, by currency pair. Most of our observations correspond to EURUSD and GBPUSD. For each of our currency pairs, the median spread at the (d, i, c, m, t) level is slightly positive, ranging from 0.03 basis points for the NZDUSD to 0.86 for the GBPUSD. The median maturity across the currency pairs is 3 weeks or 1 month. The median client for each currency pair has 3 or 4 total observations in the currency-specific spread panel at the (d, i, c, m, t) level.[14]

Relative to Hau et al. (2021), our cross-client distribution of EURUSD spreads, in Appendix D.10, is more narrow and symmetric around zero. This could be because we focus on standard maturity trades that are less bespoke and include many client sectors, while Hau et al. (2021) focus on non-financial firms with low financial sophistication. Since banks and hedge funds account for a large share of notional traded and asset managers account for a large share of trade count in our data, our spread distributions reflect the spreads of these institutions more than non-financial firms.

3.3 Descriptive Statistics

Before examining the characteristics of dealer-client trading relationships, we provide descriptive statistics about our sample. There is cross-client heterogeneity in clients' reliance on dealers for FX derivative trading over our sample period, even within client sector or after controlling for client size or trading frequency.

The daily average notional outstanding positions in our sample from July 1, 2023 through December 31, 2023 for the all $\leq$ 1y maturity cover approximately 20.9% of those reported by the BIS for outright forwards and FX swaps in 2023S2.[15] According to the BIS OTC Derivatives Statistics, total notional outstanding for outright forwards and FX swaps in

12. See Appendix A.1 for more information.

13. We acknowledge that this restricts our spread sample. As an alternative benchmark, we constructed spreads using the mid-executed price for inter-dealer trades in the same currency pair, maturity, and date. However, this spread panel is more sparse. So, we have not included results using this metric.

14. Appendix D.10 provides a table of client-level notional weighted average spreads by currency pair, and Appendix D.6 includes additional information about client-level activity in the maturity panel.

15. The daily average total outstanding positions for the all $\leq$ 1y maturity over the second half of 2023, by currency, are reported in Table 10 in Appendix D.1.

2023S2 was \$67,797 billion and for the USD was \$59,938 billion.[16] Comparing these values to the USD row of Table 10 in Appendix D.1, we cover 18.5% of the total and 20.9% of the USD total reported by BIS. For the EUR, JPY, GBP, CHF, and CAD, we cover about 31.0% on average across these currencies.

Asset managers have the largest count of clients, but hedge funds and banks account for a larger share of notional traded in part due to their higher trading frequency. Over our two-year sample period, there are 26,839 unique clients and 48 dealers that had a positive trade count in the all $\leq$ 1y maturity. The largest sector by client count is Asset Managers with 7,635 clients, followed by Non-financial Corporates with 1,400 clients. However, Hedge Funds and Banks contributed the most to notional trading volume, together accounting for 45% of total notional traded during this period. This is consistent with Bank and Hedge Fund clients making larger transactions or trading more frequently. In fact, the average Hedge Fund and Bank client trade more frequently than other sectors with their average percent of days traded across clients given by 35.0% and 29.6% respectively.[17]

Half of the clients in our sample trade in only one currency pair and with only one dealer during the two-year period.[18] Even within-sector, many clients trade with only one or two dealers, as shown in Figure 1, which plots the cross-client distribution of the unique count of dealers with which a client traded, by client sector. This indicates that dealer-client trading relationships may be persistent and clients may not (i) have other relationships and may need to pay fixed costs to create them or (ii) search efficiently across their set of existing dealer relationships.[19] However, even within-sector, there is heterogeneity in the count of dealers that clients trade with, with most sectors containing clients who traded with more than ten dealers. So, some clients may be more constrained by fixed costs of relationship creation and search frictions than others.

The heterogeneity in dealer count and the low count for many clients could be partially explained by differences in trading activity. Clients who trade more frequently or larger quantities may have more dealers, allowing them to better substitute and pay lower spreads. In our sample, client-level notional trading volume varies significantly with a mean of \$6,462 million and a tenth percentile of less than \$500,000. Additionally, 50% of clients trade on fewer than 2.7% of the 505 trading days in our sample.[20] When we individually control for

16. See Table D6 for OTC foreign exchange derivatives available at https://data.bis.org/topics/OTC_DER/tables-and-dashboards/BIS,DER_D6,1.0?time_period=2023-S2, accessed June 7, 2025.

17. See Table 11 in Appendix D.2 for statistics by client sector over the two-year sample.

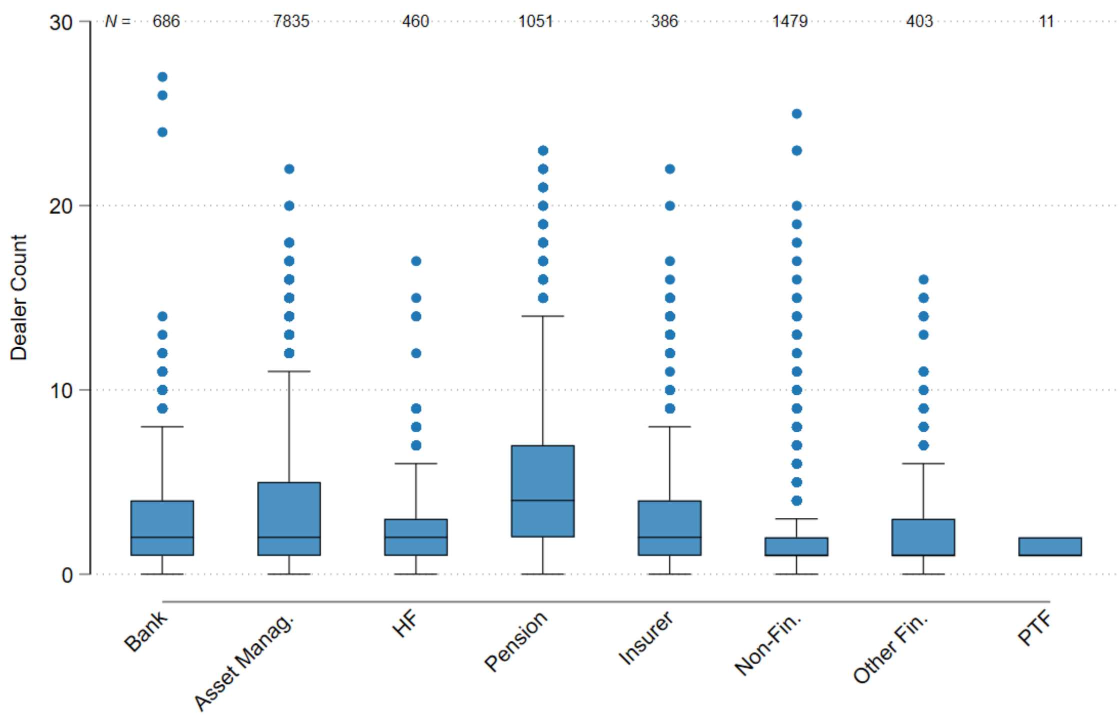
18. See Table 12 in Appendix D.6 for descriptive statistics at the client level for the all $\leq$ 1y maturity over our two-year sample period. We also provide a summary table for the maturity panel in Appendix D.6.

19. Consistent with this intuition, Hau et al. (2021) show that among non-financial clients trading EURUSD FX derivatives, the average spread paid by clients is decreasing in the number of dealers a client has.

20. Table 12 in Appendix D.6 provides descriptive statistics at the client level for the all $\leq$ 1y maturity

notional volume and trading frequency, there is still significant heterogeneity in the count of dealers that clients trade with.[21] This suggests that clients with similar activity have different bilateral trading relationships with their dealers. We examine whether these relationships affect the costs they pay and their ability to substitute in times of dealer stress in Section 5.

Figure 1: Cross-Client Distribution of Dealer Count By Client Sector



Notes: *DealerCount* is the number of dealers the client traded with between January 1, 2022 and December 31, 2023, measured using daily trade count in any of the seven currencies for the all ≤ 1y maturity. The total count of unique clients in each sector distribution are listed across the top of the figure. The sample is the set of dealer–client–date observations with an outstanding notional position in the all ≤ 1y maturity.

The concentration of clients' trading activity across dealers is also heterogeneous, even among clients that traded with the same count of dealers. 90% of the clients in our sample had a dealer that accounted for more than 44% of the client's trading activity over the two-year period.[22] Additionally, in Figure 5 of Appendix D.5 we plot the distributions of the concentration of each client's notional trading activity across dealers over our two-year

over our two-year sample period.

21. See Figures 4a and 4b of Appendix D.4, which plot the cross-client distribution, by sector, of the residuals from a client-level regression of dealer count on the number of days the client traded and the log total notional trading volume, respectively.

22. See Table 12 in Appendix D.6, which provides cross-client distributions of (i) HHI for each client's trading activity across dealers and (ii) the share of the client's activity with the dealer with which they traded with the most over the sample.

sample, by dealer relationship count. Figure 5a plots HHI and Figure 5b normalizes HHI by the corresponding equally distributed benchmark.[23] They show that, even when we account for mechanically higher concentration for low dealer counts, there is heterogeneity in the concentration of client trading activity across dealers for the same dealer relationship count. This heterogeneity can reflect large differences in reliance on an individual dealer.[24]

Thus, bilateral relationships are heterogeneous and many seem persistent. In fact, more than 50% of dealer–client–date observations involve a dealer that composed more than 50% of the clients' activity in the previous 22 trading days.[25] We test for persistence more formally in Section 4. Additional information about our sample may be found in Appendix D.[26]

4 Characteristics of Trading Relationships

Although there is heterogeneity in clients' reliance on dealers, as shown in Section 3.3, we investigate whether bilateral relationships are persistent and shaped by search and bargaining frictions. We show that (i) dealer-client trading relationships in the OTC FX derivatives market are persistent and (ii) dealers tend to charge markups to clients that rely on them more heavily. To do this, we examine the bilateral relationship characteristics that increase the likelihood of trading with a dealer, and whether these characteristics correspond to average premiums paid or discounts received by clients.

As stated in Hypothesis 1, we anticipate that clients persistently trade with dealers with which they ever had a relationship, since there are fixed costs to relationship creation. For example, establishing an ISDA Master Agreement, the standard contract used by OTC market participants to initiate a trading relationship and establish legal terms governing their activity, can take time and effort (Armitage 2022).[27] Indeed, according to FSB (2018), clients expect relationship negotiations and contract completion to take on average 2–6 months.[28]

23. We compute the Herfindahl-Hirschman Index (HHI) as $HHI_i = \sum_{d\in\mathcal{D}} \left(100 \times \frac{N_{d,i}}{N_i}\right)^2$, where $N_{d,i}$ is the total notional traded between dealer d and client i, N_i is the total notional traded by client i across all dealers, and $\mathcal{D}$ represents the set of all dealers. The equal distributed benchmark for a dealer count $DealerCount$, $EqualDistribHHI_{DealerCount}$, is the HHI if $DealerCount$ number of dealers composed an equal share of the client's activity, $EqualDistribHHI_{DealerCount} = \sum_{d\in DealerCount} \left(\frac{100}{DealerCount}\right)^2$.

24. Consider the 5 dealer count bucket. A client with equally distributed activity has a ratio of 1 in Figure 5b and each dealer accounts for 20% of the client's activity. If the client instead had a ratio of 2 and four of the dealers had the same shares, so one dealer is relied on more heavily than the others, then these four dealers would each account for 10% of the client's activity and the fifth accounts for 60%.

25. We provide dealer–client–date-level activity summary statistic distributions in Appendix D.7 Table 14.

26. Appendix D provides statistics tables at different levels of aggregation (e.g. client level, dealer level, dealer–client–date level) and separately for the all $\leq$ 1y maturity and the maturity panel.

27. See, for example, Armitage (2022), which provides some background on the ISDA Master Agreement and considers the implications of the introduction of a smart contract form of the agreement.

28. See Figure E.5, which uses survey responses to the DAT qualitative survey, described in FSB (2018).

We also expect clients to persistently trade with particular dealers, even conditional on having an existing relationship. Persistently trading with a dealer can be valuable to the dealer from an intertemporal competition perspective (Bernhardt et al. 2005). In addition, clients may search inefficiently across their dealer relationships, exhibiting a sticky search process that results in a higher matching propensity with particular dealers.

Hypothesis 1 (Persistence) *Clients have a higher probability of trading with a dealer if they used that dealer more recently or relied more heavily on the dealer in the past.*

Beyond persistence, dealer-client trading relationships can be currency-specific or directional. For instance, as noted by Moskowitz et al. (2024), dealer banks may specialize in specific currency markets, leading to dealer segmentation. This may result in currency-specific trading relationships. In addition, some dealers may be more willing to hold a net USD lending position depending on their balance sheet constraints and cost of trading in particular currencies, which may be influenced by their funding or asset composition.[29] To shed light on the characteristics of trading relationships, we also test Hypothesis 2.

Hypothesis 2 (Characteristics) *Clients have a higher probability of trading with dealers in a currency pair (net direction relative to USD) if they had an outstanding relationship with that dealer in that currency pair (net position relative to USD).*

To test these first two hypotheses, we focus on dealer-client trades and aggregate our panel to the weekly frequency to increase the number of client observations with multiple dealer observations per week. Our trading panel contains dealer–client–week observations where a notional trading position exists. So, we fill the set of dealers for each active client–week to capture all potential dealers in the market even if the client did not use them.[30] Since there is a higher probability of trading with a larger dealer, we include a dealer–client sector–week fixed effect, $\alpha_{d,sec(i),t}$ to control for dealer size with the client sector and dealer-specific supply shocks. Our regression sample is July 1, 2023 through December 31, 2023.

To test Hypothesis 1, we first run regression Equation 2. This tests whether, in weeks when a client trades, there is a higher probability the client trades with dealers with which they ever had a relationship, $\mathbb{I}[HasISDA_{d,i,t-1}]$, and if this probability is higher if the client

29. A net USD lending position is consistent with a position where the dealer is net buying USD forward. If a client wants to borrow USD synthetically, they borrow in foreign currency, spot to USD, and enter a forward contract to sell USD forward and buy foreign currency. From the dealer's perspective, the dealer would net buy USD in the forward leg of the contract.

30. An active client–week is one where the client had a positive notional traded amount for the all $\leq$ 1y maturity. We fill the dealer panel using all dealers that were active on a date prior to that week in our sample. To ensure that any dealers excluded from the filled panel are those that are inactive for more than a year, we restrict the regression sample to July 1, 2023 through December 31, 2023.

only had one relationship, $\mathbb{I}[\mathit{Only1ISDA}_{i,t-1}]$, which was with that dealer.[31] The dependent variable, $\mathbb{I}[\mathit{Trade}_{d,i,t}]$, equals 1 if client i traded with dealer d in week t.[32] The results are presented in column (1) of Table 1.

To test whether clients are even more likely to trade with dealers with which they had a recent relationship, we add three additional terms into Equation 2. We include an indicator for whether the dealer-client pair had an outstanding position in the last 4 weeks, $\mathbb{I}[\mathit{HasOut}_{d,i,t-1}]$, another for whether the client only had one recent dealer relationship, $\mathbb{I}[\mathit{Only1Dealer}_{i,t-1}]$, and their interaction to capture whether that dealer was the client's only recent relationship. The results are presented in column (2) of Table 1.

As the final test of Hypothesis 1, we use regression Equation 3 to document whether clients are more likely to trade with a dealer that they relied on more heavily in the recent past. $\mathit{RelStrength}_{d,i,t-1}$ denotes the client's reliance on the dealer in the last 4 weeks and is defined as either the share of a client's total notional (i) traded or (ii) outstanding positions with dealer d, denoted as $\%\mathit{Traded}$ and $\%\mathit{Outstanding}$ in Table 1 respectively.[33] We include $\mathbb{I}[\mathit{HasISDA}_{d,i,t-1}]$ and $\mathbb{I}[\mathit{HasOut}_{d,i,t-1}]$ to control for the probability of trading with a dealer because the fixed cost of relationship creation has already been paid and there is an existing recent relationship, respectively. We are interested in β_3, which captures the additional probability that a client trades with a dealer that composed an additional 1% of the client's activity in the last 4 weeks.

$$
\begin{aligned}
\mathbb{I}[\mathit{Traded}_{d,i,t}] = {} & \beta_1 \mathbb{I}[\mathit{HasISDA}_{d,i,t-1}] + \beta_2 \mathbb{I}[\mathit{Only1ISDA}_{i,t-1}] \\
& + \beta_3 (\mathbb{I}[\mathit{HasISDA}_{d,i,t-1}] \times \mathbb{I}[\mathit{Only1ISDA}_{i,t-1}]) + \alpha_{d,sec(i),t} + \epsilon_{d,i,t} \qquad (2) \\
\mathbb{I}[\mathit{Traded}_{d,i,t}] = {} & \beta_1 \mathbb{I}[\mathit{HasISDA}_{d,i,t-1}] + \beta_2 \mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \\
& + \beta_3 (\mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \times \mathit{RelStrength}_{d,i,t-1}) + \alpha_{d,sec(i),t} + \epsilon_{d,i,t} \qquad (3)
\end{aligned}
$$

The results of regression Equations 2–3 are displayed in columns (1)–(4) of Table 1 and support that relationships are persistent. Reading column (1), clients are 29.2% more likely to trade with a dealer if they had ever had a relationship with that dealer, which increases by 57.2% if that dealer was their only relationship. The results in column (2) show that clients are even more likely to trade with a dealer that they had ever had a relationship with if they had an outstanding position in the last 4 weeks. In addition, the coefficient on

31. $\mathbb{I}[\mathit{HasISDA}_{d,i,t-1}]$ denotes whether dealer d and client i ever had an outstanding relationship, and $\mathbb{I}[\mathit{Only1ISDA}_{i,t-1}]$ denotes whether a client only ever had one dealer relationship. See Appendix C.1 for measurement details.

32. We compute these indicator variables using the all $\leq$ 1y maturity to capture as much trading activity as possible for identifying relationships. Relationship variables are calculated using data from December 1, 2021 through December 31, 2023.

33. All measures in this section are described in detail in Appendix C.1.

$\mathbb{I}[\mathit{HasOut}] \times \mathbb{I}[\mathit{Only1Dealer}]$ suggests that clients are 31.1% more likely to trade with a dealer with which they had a recent outstanding position if it was their only recent relationship.

Columns (3)–(4) document that clients trade more persistently with dealers that they relied on more heavily. Specifically, when a dealer accounts for a 1% larger share of a client's trading activity in the last 4 weeks, the client is 0.4% more likely to trade with that dealer in an active trading week. In Appendix E.1, we split the measure of clients' reliance on a dealer into a saturated set of indicators for 5% share intervals from 0 to 100%. We find that the probability of trading with a dealer increases across the share intervals. Moreover, there is a discrete jump in this incremental probability when we move from the $(90, 95]$ to the $(95, 100]$ percent share interval, consistent with fixed costs to new relationship creation.

To test Hypothesis 2, whether relationships are directional or currency-specific, we run regression Equations 4 and 5, with results presented in columns (5) and (6) of Table 1 respectively.[34] $\mathbb{I}[\mathit{SellUSD}_{d,i,t}]$ is an indicator for whether client i has a notional traded position over week t with dealer d that is a net sell USD position. The indicator $\mathbb{I}[\mathit{TradedCCY}_{d,i,c,t}]$ equals 1 if client i trades with dealer d in currency pair c at week t, for client trading weeks in currency pair c. $\mathit{NetUSDPosition}_{d,i,t-1}$ and $\mathbb{I}[\mathit{HasOut}_{d,i,c,t}]$ are as defined in Appendix C.1, where $\mathit{NetUSDPosition}_{d,i,t-1}$ is a categorical variable for the direction of the net USD outstanding position for the dealer-client pair in week t and $\mathbb{I}[\mathit{HasOut}_{d,i,c,t}]$ indicates whether they have a relationship in currency pair c.

$$\begin{aligned}
\mathbb{I}[\mathit{SellUSD}_{d,i,t}] &= \beta_1 \mathbb{I}[\mathit{HasISDA}_{d,i,t-1}] + \beta_2 \mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \\
&\quad + \beta_3 (\mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \times \mathit{NetUSDPosition}_{d,i,t-1}) + \alpha_{d,sec(i),t} + \epsilon_{d,i,t} \qquad (4) \\
\mathbb{I}[\mathit{TradedCCY}_{d,i,c,t}] &= \beta_1 \mathbb{I}[\mathit{HasISDA}_{d,i,t-1}] + \beta_2 \mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \\
&\quad + \beta_3 (\mathbb{I}[\mathit{HasOut}_{d,i,t-1}] \times \mathbb{I}[\mathit{HasOut}_{d,i,c,t-1}]) + \alpha_{d,sec(i),c,t} + \epsilon_{d,i,t} \qquad (5)
\end{aligned}$$

Consistent with Hypothesis 2, we find that relationships seem to have a directional component and a currency-specific component. For example, conditional on trading in the currency pair in week t, clients are 33% more likely to trade with a dealer with which they had a recent relationship if they had a recent outstanding position in that same currency pair.

Overall, dealer-client relationships in this market are persistent and have a significant currency-specific component, supporting Hypotheses 1 and 2. Our results are robust to the inclusion of client or client–week fixed effects, which control for the effect of client characteristics on the probability they trade with a dealer (e.g., trading frequency and size).[35]

34. Regression Equation 5 uses a dealer–client–currency pair–week panel. In this case, we fill the set of dealers for each active client–currency pair–week.

35. For these results, see Tables 19 and 20 of Appendix E.2, respectively.

Table 1: Dealer-Client Trading Relationships

	(1) I[Traded]	(2) I[Traded]	(3) I[Traded]	(4) I[Traded]	(5) I[SellUSD]	(6) I[TradedCCY]
I[HasISDA]	0.292***	0.080***	0.074***	0.068***	-0.052***	0.052***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.010)	(0.002)
I[Only1ISDA]	-0.004***	-0.002***				
	(0.000)	(0.000)				
I[HasISDA] × I[Only1ISDA]	0.572***	0.226***				
	(0.006)	(0.009)				
I[HasOut]		0.319***	0.247***	0.266***	0.127***	0.044***
		(0.005)	(0.006)	(0.006)	(0.003)	(0.003)
I[Only1Dealer]		-0.001**				
		(0.000)				
I[HasOut] × I[Only1Dealer]		0.311***				
		(0.011)				
I[HasOut] × %Outstanding			0.005***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.053***	
					(0.005)	
None					-0.089***	
					(0.010)	
I[HasOutCCY]						0.327***
						(0.006)
Observations	4857504	4857504	4749196	4453233	4857504	1.14e+07
Client Clusters	8991	8991	8088	7301	8991	8991
R^2	0.4332	0.4946	0.5104	0.5101	0.2058	0.4262
Adjusted R^2	0.4318	0.4933	0.5091	0.5088	0.2038	0.4219
Within R^2	0.2281	0.3118	0.3333	0.3299	0.1019	0.2690
Dealer-Sector-Date FE	YES	YES	YES	YES	YES	NO
Dealer-Sector-CCY-Date FE	NO	NO	NO	NO	NO	YES
Frequency	weekly	weekly	weekly	weekly	weekly	weekly

Notes: This table reports results from dealer–client–week and dealer–client–currency–week fixed effects panel regressions that we use to test Hypotheses 1 and 2 for the period of July 1, 2023 to December 31, 2023. Dependent variables are indicators that equal 1 if the client traded ($I[\textit{Traded}]$), net sold USD ($I[\textit{SellUSD}]$), and traded in currency c ($I[\textit{TradedCCY}]$) with the dealer that week. Independent variables are: $I[\textit{HasISDA}]$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $I[\textit{Only1ISDA}]$, an indicator equal to 1 if the client has $I[\textit{HasISDA}] = 1$ with only one dealer; $I[\textit{HasOut}]$, an indicator equal to 1 if the client had an outstanding position with the dealer in the last month; $I[\textit{Only1Dealer}]$, an indicator equal to 1 if the client has $I[\textit{HasOut}] = 1$ with only one dealer; *%Outstanding* (*%Traded*), the percent of the client's notional outstanding (trading) positions in the last month with the dealer; *SellUSD* and *None*, levels of a categorical variable that denotes the client's net USD outstanding position with the dealer during the last month (*BuyUSD* is the reference group); $I[\textit{HasOutCCY}]$, an indicator equal to 1 if the client had an outstanding position in the last month with the dealer in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and date level in columns (1)–(5) and the client and currency–date level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we turn our attention to the implications of relationship persistence, documented in Table 1, for client trading outcomes. To inform whether search and bargaining frictions are prevalent in this market, we show whether these relationships correspond to premia paid or discounts received by clients. Spreads and relationships are endogenous throughout the remainder of this section, so we exploit the March 2023 shock to Credit Suisse in Section 5.

Regardless of which currency pair is considered, dealers may take advantage of trading relationship persistence by charging larger spreads to clients who rely on them more heavily. This would be the case if heavy previous reliance on a dealer signals the existence of frictions in the client's search process, resulting in lower client bargaining power. However, if dealers value the existence of trading relationships, relationship clients may receive relative discounts because dealers compete intertemporally (Bernhardt et al. 2005). Thus, we test Hypothesis 3 and find evidence consistent with dealers exerting market power over more heavily reliant clients. As expected, clients pay spreads that are 0.012 basis points larger at a dealer when that dealer accounted for a 1% larger share of the client's trading activity in the last month.

Hypothesis 3 (Spreads) *Clients receive a discount relative to other clients at the same dealer if the dealer and client had a relationship recently or in the same currency pair. However, if the client relied more heavily on the dealer they pay higher average spreads.*

To examine the difference in average spreads paid by clients at a dealer based on bilateral relationship characteristics, we use our spread maturity panel and run regressions at the dealer–client–currency pair–maturity–date level. We run daily regressions of the form presented in Equation 6, which maps the weekly regressions presented in Table 1 into our more granular spread panel.[36]

$$spread_{d,i,c,m,t} = \mathbf{X}'_{d,i,c,t}\boldsymbol{\beta} + \alpha_{c,m,t} + \alpha_{d,t} + \epsilon_{d,i,c,t} \tag{6}$$

The term $\mathbf{X}_{d,i,c,t}$ includes analogous relationship measures to each regression specification in Table 1, which are described in Appendix C.1, but are measured at the daily frequency. So, relationship measures that correspond to 1 month of lagged activity use a 22 trading day, instead of a 4 week, lagged period.[37] We include dealer–date fixed effects, $\alpha_{d,t}$, to

36. Unlike the regression in column (5) of Table 1, in our directional trading specification for spreads, we keep the spread panel disaggregated by trading direction and ask whether clients pay larger spreads at a dealer if the client has a net outstanding position with the dealer over the last 22 trading days that is in the same direction as the spread observation, $\mathbb{I}[NetUSDOut_{d,i,t-1} = dir]$. For all other specifications in Table 2, columns (1)-(4) and (6), we aggregate our panel to the dealer–client–currency pair–maturity–date level across trading directions. For the spread dependent variable, we do this by taking the notional weighted average across trading directions (Buy and Sell USD).

37. As an example, take the $\mathbb{I}[HasOut_{d,i,t-1}]$ indicator. In our spread regressions, this dependent variable

remove spread variation across clients due to pricing differences across dealers and shocks that affect dealers' pricing behavior over time. We include currency pair–maturity–date fixed effects, $\alpha_{c,m,t}$, to control for time-varying currency market-specific trading conditions that may affect spreads in a way that is correlated with lagged bilateral trading relationships. Our spread sample is more sparse than the trading activity sample. So we extend the spread regression sample to cover 1 year, January 1, 2023 through December 31, 2023. The results are presented in Table 2.

We find in columns (2) through (4) that the coefficients on $\mathbb{I}[HasOut_{d,i,t-1}]$ are negative and significant, which suggest that clients tend to receive a 2.4 basis point discount at dealers that they had a relationship with more recently relative to other clients. This is consistent with intertemporal dealer competition, where dealers offer better terms to clients to encourage clients to continue using them for future trading activity.

However, in columns (3) and (4), the coefficients for the client's reliance on the dealer in the previous month are positive and significant. The coefficients on $\%Outstanding$ and $\%Traded$ suggest that relying more heavily on a dealer in the last month corresponds to the client paying a larger relative premium, or receiving a smaller discount, on their FX derivative trades than other clients at that dealer. This is consistent with dealers exerting market power over these clients because their larger reliance on the dealer reflects lower search efficiency or worse alternative options for the client. Alternatively, if the client was more heavily reliant on a dealer, other dealers may charge smaller spreads during bilateral negotiations to compete over this client's business. These findings could result from spreads increasing in trade size or count, which likely correlate with client's reliance on a dealer.[38] In Appendix E.3, we show that our results are similar when we control for log notional traded and trade count.

Although these spread regressions are endogenous, the results in Tables 1 and 2, suggest that clients receive a relative discount at dealers with which they have recent relationships, which are also those they are more likely to trade with. However, more heavily reliant clients on a dealer tend to pay a premium relative to those that relied less on the dealer, and clients are more likely to trade with dealers they relied on more. We take this as evidence that dealers exert market power over clients that relied more heavily on them, consistent with the intuition of Duffie, Gârleanu, and Pedersen (2005) that these clients have worse search efficiency and bargaining power. We address the endogeneity between spreads and trading relationships in Section 5 by exploiting the shock to Credit Suisse in March 2023.

is equal to 1 if dealer d and client i had an outstanding position in at least one of our seven currency pairs in our all $\leq$ 1y maturity, from trading date $t-22$ through trading date $t-1$.

38. It could be that spreads are correlated with the notional amounts traded or the count of trades for a given notional traded (Bernhardt et al. 2005).

Table 2: Spreads and Dealer-Client Trading Relationships

	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread
I[HasISDA]	-4.346	-2.527	-1.958	-1.938		-1.903
	(3.007)	(3.112)	(2.797)	(2.797)		(3.099)
I[Only1ISDA]	-2.447	-2.468				
	(4.686)	(4.696)				
I[HasISDA] × I[Only1ISDA]	4.318	4.169				
	(4.659)	(4.671)				
I[HasOut]		-2.395**	-2.801**	-2.481**	-1.641	-0.960
		(1.100)	(1.093)	(1.082)	(1.231)	(1.035)
I[Only1Dealer]		-2.309				
		(2.012)				
I[HasOut] × I[Only1Dealer]		2.784				
		(2.025)				
%Outstanding			0.020***			
			(0.005)			
%Traded				0.015***		
				(0.005)		
I[NetUSDOut = dir]					-1.533	
					(1.562)	
I[HasOutCCY]						-0.803
						(0.658)
Observations	249,940	249,940	249,940	249,940	278,018	249,940
Client Clusters	12,401	12,401	12,401	12,401	12,401	12,401
R^2	0.1679	0.1679	0.1679	0.1678	0.1407	0.1677
Adjusted R^2	0.0987	0.0987	0.0987	0.0986	0.0748	0.0985
Within R^2	0.0003	0.0004	0.0003	0.0002	0.0003	0.0001
CCY-Maturity-Date FE	YES	YES	YES	YES	YES	YES
Dealer-Date FE	YES	YES	YES	YES	YES	YES

Notes: This table reports results from dealer–client–currency–maturity–date and dealer–client–currency–maturity–date–direction fixed effects panel regressions that we use to test Hypothesis 3 for the period of January 1, 2023 to December 31, 2023, corresponding to Equation 6. The dependent variable is the notional weighted average spread across trades with the same dealer, client, currency, maturity, and execution date, except column (5) which also groups by USD trading direction. Spreads are measured as described in Section 3.2. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $I[Only1ISDA]$, an indicator equal to 1 if the client has $I[HasISDA] = 1$ with only one dealer; $I[HasOut]$, an indicator equal to 1 if the client had an outstanding position with the dealer in the last month; $I[Only1Dealer]$, an indicator equal to 1 if the client has $I[HasOut] = 1$ with only one dealer; $\%Outstanding$ ($\%Traded$), the percent of the client's notional outstanding (trading) positions in the last month with the dealer; $I[NetUSDOut = dir]$, an indicator equal to 1 if the spread observation has the same USD trade direction as the client's net outstanding position with the dealer over the last month; $I[HasOutCCY]$, an indicator equal to 1 if the client had an outstanding position in the last month with the dealer in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and date level in columns (1)–(5) and the client and currency–date level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 March 2023 Credit Suisse Shock

In this section, we use the shock to Credit Suisse in March 2023 to more causally study the role of trading relationships for client access to OTC FX derivatives. Although spreads and the persistence of dealer-client trading activity are endogenous in the analyses in Section 4, using this shock, we can take pre-existing relationships as given and study client outcomes when one of these dealer relationships is adversely affected. Since we documented the persistence of trading relationships in Section 4, we take this shock as one that differentially affects the set of outside options for clients more heavily reliant on the shocked dealer during bilateral trade negotiations at both the shocked dealer and other dealers. We expect more exposed clients to pay greater spreads due to substitution frictions and the exertion of dealer market power, consistent with Duffie, Gârleanu, and Pedersen (2005). To our knowledge, we are the first to examine trading patterns in the OTC FX derivatives market surrounding the shock to Credit Suisse in March 2023.

In the context of this shock, we show that clients that relied more heavily on Credit Suisse pay a larger increase in spreads at other dealers. Our results suggest that the these clients pay a larger increase in spreads at their main non-Credit Suisse dealer in the post-period relative to unexposed clients. In addition, clients that were less reliant on Credit Suisse have a larger reduction in activity with Credit Suisse than more reliant clients, but no significant spread changes at the client level, which suggests that less reliant clients were able to substitute.

5.1 Background and Sample

We begin with context for the shock to Credit Suisse in March 2023, which led to large outflows of deposits from the institution and an increased risk of insolvency, and discuss the sample we use to analyze the trading activity of OTC FX derivatives around the shock.

5.1.1 Background

In March 2023, Credit Suisse faced a series of events that led to its collapse and subsequent acquisition by UBS. Although there were previous events that weakened Credit Suisse's reputation over the years, perhaps making it more vulnerable to additional shocks, a plausibly exogenous news shock beginning on March 8, 2023 led to UBS's agreement to take over Credit Suisse on March 19, 2023.[39]

39. See Englundh (2023) for a timeline of events leading up to UBS agreeing to take over Credit Suisse on March 19, 2023.

As discussed in Englundh (2023) and FINMA (2023), on March 8, 2023, the SEC called Credit Suisse, questioning the bank's financial statements. This delayed the release of Credit Suisse's annual report, which was released on March 14, 2023 after the default of Silicon Valley Bank, when trust in the banking system was low. The report mentioned the existence of "material weaknesses in our internal control over financial reporting as of December 31, 2022 and 2021."[40] Credit Suisse then experienced a sell-off of its shares after an announcement that the Saudi National Bank would not continue providing financial support to the institution (Uppal 2023). On March 16, 2023, the Swiss National Bank provided a 48 Billion CHF ($54 billion USD) liquidity backstop to Credit Suisse to increase confidence in the bank.[41] According to a report by Swiss Financial Market Supervisory Authority, Credit Suisse experienced 17.1 billion CHF of outflows on March 16, 2023 with an additional 10.1 billion CHF of outflows on March 17, 2023 (FINMA 2023). Credit Suisse was approaching insolvency, so the Swiss National Bank and Swiss Financial Market Supervisory Authority brokered a deal with UBS. Finally, on March 19, 2023, UBS agreed to take over Credit Suisse.

The large outflows faced by Credit Suisse and uncertainty around the institution's stability at the time likely affected the institution's trading activity in FX swaps and outright forwards. Credit Suisse likely reduced activity since this shock tightened their balance sheet constraints and reduced liquidity. Additionally, Credit Suisse may have reduced total trading volume and increased spreads due to their higher costs of trading. For example, on March 17, 2023, many professional counterparties and clearing houses restricted or ended entirely their business activity with Credit Suisse (FINMA 2023). Also, when dealers are affected by the leverage ratio, which becomes more binding around insolvency, they reduce derivatives clearing for clients.[42] Relatedly, Credit Suisse's clients may have substituted away from Credit Suisse to other dealers to avoid paying larger spreads.

Since this shock was triggered by the SEC questioning on March 8, 2023 and filing of Credit Suisse's annual report on March 14, 2023, with outflows beginning the week of March 14th, we believe this was a news shock to counterparties of Credit Suisse. Also, as mentioned in International Monetary Fund (2023), although Credit Suisse faced large outflows in March 2023, this was not also occurring for other Swiss banks. Thus, these outflows were idiosyncratic to Credit Suisse, not a reflection of a broader market event.

40. See page 50 ff. Credit Suisse AG Annual Report 2022, https://www.ubs.com/global/en/investor-relations/complementary-financial-information/disclosure-legal-entities/archive-credit-suisse.html.

41. See page 25 of SNB (2023), the SNB's Financial Stability Report 2023, https://www.snb.ch/en/publications/financial-stability-report/2023/stabrep_2023.

42. See Acosta-Smith, Ferrara, and Rodriguez-Tous (2025), which shows that when dealers reduce derivatives clearing activity for clients when they are affected by the leverage ratio requirement.

5.1.2 Sample

For all regression analyses in this section, Section 5, we restrict our sample to focus on EURUSD activity over an 80 trading day period, from January 10, 2023 to May 4, 2023, that is centered around the event date, which we define to be March 8, 2023. The pre-period is defined to be January 10, 2023 through March 8, 2023. The post-period is March 9, 2023 through May 4, 2023. We refer to January 1, 2022 through January 9, 2023 as the out-of-sample pre-period. Our analysis focuses on the EURUSD market since it is the largest currency market, and composes the largest share of Credit Suisse's portfolio, in our data. Including inter-dealer activity, the daily average total notional traded (trade count) in the EURUSD in our all $\leq$ 1y maturity from July 1, 2023 through December 31, 2023 was 303.64 billion USD (10.04 thousand). Summing these averages across currencies, the EURUSD notional trading activity (trade count) accounts for 33.7% (31.0%) of average daily total activity in the second half of 2023. This is 10.8 (9.04) percentage points larger than that accounted for by the GBPUSD, which has the second largest value.

Although our sample will not capture all of Credit Suisse's FX derivatives trading activity, in the cross-section of dealers they lie above the 50th percentile for a range of daily average activity variables in the pre-period. Over the pre-period, the average daily notional traded in EURUSD for all $\leq$ 1y maturity by Credit Suisse lies between the 50th and 75th percentile of our dealer distribution. This is also the case for the average daily (i) unique count of clients they traded with, (ii) trade count, and (iii) notional outstanding, in the EURUSD. We note that the distribution of average daily notional traded in EURUSD across dealers is heavily skewed, with the largest dealer having a value that is more than 11 times larger than the 75th percentile dealer.

We focus on dealer-client activity and use the all $\leq$ 1y maturity to measure trading activity and relationship measures. For spreads, we use our dealer–client–currency pair–maturity–date panel and include a maturity fixed effect in all spread regressions. When we examine how the shock affected dealer-level EURUSD activity, we include all observations and aggregate the panel to the dealer-date level. However, to examine how the shock affects bilateral trading activity, we restrict the sample for all client–date level and dealer–client–date level analyses to the dealer-client pairs that had an instance of positive EURUSD notional trading activity in the 40 day pre-period. This sample restriction uses the all $\leq$ 1y maturity for our quantity regression samples, but the maturity panel for our spread regression samples.[43] One implication of this sample restriction is that we do not include dealer-client pairs that have activity in the post-period, but not the pre-period, which could

43. So, each regression will restrict to the subset of the panel being used where the dealer-client pair had a positive notional traded in the pre-period in that data panel.

provide additional insight into how clients that were exposed to the Credit Suisse shock were able to substitute in the post-period.

We note that since we currently match directly on days to maturity to the Bloomberg panel of forward rates to compute spreads, our spread panel keeps particular trade maturities and is therefore restricted. The sample is particularly limited for observations where the dealer is Credit Suisse. So, we do not examine the effect of the shock on spreads where the dealer in the dealer-client pair is Credit Suisse. However, increasing the range of trade maturities included in the spread sample will allow us to address this and recover results for spreads that are representative of a larger set of trades.

5.2 Nature of Shock in FX Derivatives Market

In this section, we use difference-in-differences and triple-differences regressions, taking Credit Suisse as the treated dealer, to provide insight into the nature of the shock. We document that this event was indeed a shock that differentially reduced Credit Suisse's OTC FX derivative trading activity relative to other dealers. Then, we examine the nature of the shock by documenting whether clients that relied more heavily on Credit Suisse ("more exposed") experienced a smaller reduction in trading quantities at Credit Suisse relative to less exposed clients. This prediction is consistent with heavily reliant clients being less elastic and unable to substitute to other dealers easily.

5.2.1 Dealer-Level Trading Activity

Given that this was a major funding shock to Credit Suisse and the institution's balance sheet became more constrained, as in Cenedese, Della Corte, and Wang (2021), we expect that Credit Suisse reduced its CIP arbitrage activity in the FX derivatives market and increased spreads to clients, consistent with wider CIP deviations. Further, Credit Suisse likely reduced total derivatives trading due to higher trading costs (e.g., higher cost of carry for margining or collateral) or to reduce trading in instruments that may expose them to additional risks, focusing on maintaining solvency and meeting regulatory requirements.

Conceptually framing this shock, suppose a client's counterparty choice across dealers is modeled as a multinomial choice problem and dealers compete on spreads over a client's trading activity in a currency market, taking the spreads charged by other dealers as given. As illustrated in Appendix B, the average spread a dealer charges a client in a currency market increases in the dealer's marginal cost of trading. Since this shock increased the marginal cost of trading FX derivatives for Credit Suisse, we expect that Credit Suisse increased spreads. Thus, we expect trading quantities to fall at Credit Suisse relative to other dealers, given by Hypothesis 4.

Hypothesis 4 (Nature of Shock) *Credit Suisse's total trading volume declined post-shock.*

We test Hypothesis 4 using a difference-in-differences panel regression at the dealer–date level where the treated dealer is Credit Suisse. Consistent with our hypothesis, we identify that Credit Suisse had a differential reduction in trading activity in the EURUSD relative to other dealers due to the shock. Specifically, Credit Suisse's daily average notional traded (trade count) with maturity less than or equal to 1 year declined by 81.2% (74.7%) more than other dealers in our sample from the pre- to the post-period.[44]

Our difference-in-difference regression specification is given by Equation 7, where $Y_{d,t}$ denotes a measure of dealer trading activity on date t, $\mathbb{I}[Treated_d]$ equals 1 if the dealer is Credit Suisse and zero otherwise, and $\mathbb{I}[Post_t]$ equals 1 if the date is after March 8, 2023 and zero otherwise. The results are presented in Table 3. For dependent variables, $Y_{d,t}$, we use the natural logarithm of daily notional traded and trade count in the EURUSD, and an indicator for whether or not the dealer had a positive trade count in the EURUSD on date t for the all $\leq$ 1y maturity. We include the indicator for a positive trade count as a dependent variable to capture the effect of the shock on the external margin of dealer activity. Our coefficient of interest is β, whether Credit Suisse's activity differentially changed post-shock relative to other "untreated" dealers.

$$Y_{d,t} = \beta(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_d]) + \alpha_t + \alpha_d + \epsilon_{d,t} \tag{7}$$

In columns (1) through (3) of Table 3, we can see that the average daily trading activity of Credit Suisse declined by more than the mean untreated dealer from the pre- to the post-period, consistent with Hypothesis 4. Specifically, Credit Suisse's daily average notional traded in EURUSD on days when they traded declined by 81.2 percent more than other dealers. Daily trade count, which measures the external margin of trading activity on active trading days, declined by 74.7% more than untreated dealers.

44. These percentages are computed as $(e^{\beta} - 1) \times 100$ since $Y_{d,t}$ is in logs and independent variables are indicator functions. Suppose $\ln(Y) = \alpha + \beta \times X + \epsilon$ where X is an indicator. Then the percentage change in $\mathbb{E}[Y]$ is $100 \times \big(\frac{\mathbb{E}[Y|X=1]}{\mathbb{E}[Y|X=0]} - 1\big)$. With some assumptions on the distribution of ϵ, such as $\mathbb{E}[e^{\epsilon}|X=0] = \mathbb{E}[e^{\epsilon}|X=1]$ which is the case under strict exogeneity, this becomes $\frac{e^{\alpha+\beta} - e^{\alpha}}{e^{\alpha}} \times 100 = (e^{\beta} - 1) \times 100$.

Table 3: Effect of the Shock on Dealer-Level Activity

	(1) Ln(Not. Traded)	(2) Ln(Trade Count)	(3) $\mathbb{I}[Traded]$
I[Post] × I[Treated]	-1.671***	-1.376***	-0.098***
	(0.095)	(0.038)	(0.019)
Observations	2,594	2,594	3,440
Dealer Clusters	42	42	43
R^2	0.7806	0.9296	0.5799
Adjusted R^2	0.7699	0.9261	0.5644
Within R^2	0.0074	0.0348	0.0007

Notes: This table reports results from dealer–date difference-in-differences regressions, given by Equation 7, that we use to test Hypothesis 4. Dependent variables are: *Ln(Not. Traded)* (*Ln(Trade Count)*), the natural log of the dealer's total EURUSD notional traded (trade count) at date t in the all $\leq$ 1y maturity; $\mathbb{I}[Traded]$, an indicator equal to 1 if the dealer traded in the EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: *I[Post]*, an indicator equal to 1 if the date is after March 8, 2023; *I[Treated]*, an indicator equal to 1 if the dealer is Credit Suisse. All specifications include dealer and date fixed effects. Standard errors are clustered by dealer. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This event is therefore a negative shock to Credit Suisse's trading quantities in the EURUSD, and is also well identified. For identification in our difference-in-differences specification, we need the parallel trends assumption to hold. That is, that Credit Suisse would have evolved similarly to the average untreated dealer from the pre- to the post-period absent this shock.

We test for parallel trends explicitly by running the event study regression presented in Equation 8, where we include a series of indicators for the event week, interacted with an indicator for whether or not a dealer was treated. We use event week indicators to estimate the β_l coefficients so that we include more data in the estimation and capture a broader set of activity for each dealer, aggregating trades to reduce noise coming from daily trading dynamics (e.g., dealers experiencing differences in rollover activity or client trade timing within the week). We set the reference week to the week of March 8, 2023 and plot the β_l coefficients for $Ln(Not.\ Traded_{d,t})$ and $Ln(Trade\ Count_{d,t})$ in Appendix F Figures 7 and 8, respectively.

$$Y_{d,t} = \sum_{l=-L}^{L} \beta_l(\mathbb{I}[EventWeek(t) = l] \times \mathbb{I}[Treated_d]) + \alpha_d + \alpha_t + \epsilon_{d,t} \tag{8}$$

If parallel trends holds, the β_l coefficients for event weeks leading up to the week of March 8, 2023 will be insignificant from zero, supporting that Credit Suisse's trading activity did not evolve differently over the pre-period relative to the average untreated dealer. In the pre-period, parallel trends holds fairly well in Appendix F Figures 7 and 8. Then, from the pre- to the post-period, there is a visible decline in the event study coefficients.

Thus, Credit Suisse's total quantity of EURUSD FX derivatives trading activity differentially declined relative to other dealers due to this shock. We note that this reduction in trading activity could be due to a supply reduction by Credit Suisse or a Credit Suisse-specific decline in client demand. If the demand story were true, we may expect Credit Suisse's clients to increase activity with Credit Suisse immediately after the shock in order to cancel out their existing positions with the shocked dealer. This would correspond to an increase in notional trading activity after the shock, which we do not find in our event study plots.

It is likely the case that a combination of Credit Suisse-specific supply and demand changes occur in response to the shock. However, if trading relationships are persistent and the strength of bilateral trading persistence is higher for clients that rely more heavily on a dealer, with search and bargaining frictions, clients at Credit Suisse may be differentially affected by this shock based on their pre-existing reliance in Credit Suisse. Some clients may find it easier to move to other dealers while others search less and face higher costs. In the next section, we turn to examining which clients of a shocked dealer experience a differential change in their trading activity at the shocked dealer.

5.2.2 Pre-Existing Relationship Strength and Credit Suisse Trading Activity

Next, we determine whether this shock particularly affected clients that were more heavily reliant on Credit Suisse. This shock could also influence the trading decisions of Credit Suisse's clients, driving them to reallocate their demand to alternative dealers. For example, clients may substitute to other dealers to avoid the higher spreads Credit Suisse may charge due to an increase in their marginal cost of trading post-shock. However, the ability of clients to do so may be heterogeneous due to differences in the availability of outside options stemming from the persistence and differences in pre-existing relationships. The results in this section provide insight into the nature of the shock and motivate our measure of client exposure to Credit Suisse, which we use in Section 5.3 to examine the effect of the shock on client-level activity and clients' activity at other dealers.

We hypothesize that the effect of the shock on client trading activity at Credit Suisse is heterogeneous. Specifically, clients that relied more heavily on Credit Suisse have a smaller reduction in trading activity with Credit Suisse relative to less exposed clients, as stated in Hypothesis 5. In the context of Duffie, Gârleanu, and Pedersen (2005), the set of alternative trading options for more reliant clients is limited relative to the set for less reliant clients when trading with Credit Suisse. This is because more heavily reliant clients have a more persistent search process or a smaller set of alternative dealers with which to trade. This would result in heavily reliant clients continuing to trade with Credit Suisse and accepting higher spreads to do so, while less reliant clients can more easily substitute. In this section, we examine whether the differential change in clients' trading quantities with Credit Suisse is consistent with this prediction.

Hypothesis 5 (Nature of Shock: Heterogeneity By Reliance on Dealer) *Clients that relied more heavily on Credit Suisse in EURUSD have a smaller reduction in trading activity at Credit Suisse in the post-period relative to clients that relied less heavily on Credit Suisse.*

We are particularly interested in Hypothesis 5, whether clients that rely more heavily on the shocked dealer fare worse at the shocked dealer since they have persistent trading relationships, face greater difficulty substituting to alternative dealers, and therefore may pay higher markups.[45] However, to confirm whether our results are consistent with results in the literature that measure bilateral dealer-client relationships from the perspective of the dealer instead of the client, we also test Hypothesis 6. Jurkatis et al. (2023) find in the corporate bond market that clients receive discounts when they provide dealers with liquidity when dealers' balance sheets are constrained. In our case, this would correspond to clients that are more important for Credit Suisse's portfolio reducing their activity at Credit Suisse by more when Credit Suisse is constrained and we would expect them to pay a smaller increase in spreads at Credit Suisse. As with Hypothesis 5, we focus on documenting the differential change in trading quantities with the shocked dealer.

Hypothesis 6 (Nature of Shock: Heterogeneity By Importance to Dealer) *Clients that were more important for Credit Suisse's EURUSD portfolio have a reduction in trading activity at Credit Suisse in the post-period relative to clients that were less important to Credit Suisse's EURUSD portfolio.*

Our measures of bilateral dealer-client relationship strength are described in detail in Appendix C.2 and capture two different concepts of relationships: (i) the client's reliance on the dealer for FX derivatives trading and (ii) the importance of the client for the dealer's trading activity. One of our measures is an indicator for whether the client only had a single dealer relationship in the EURUSD, denoted by $\mathbb{I}[OneDealer_i]$.[46] This indicator captures clients with total reliance on a dealer for EURUSD activity, with the intention to separate frictions due to fixed costs of generating new relationships from search and bargaining frictions across existing dealer relationships.

45. See Appendix B for an illustrative model where the average spread a dealer charges a client is increasing in (i) the market share they have for the client and (ii) the inelasticity of the client's demand.

46. $\mathbb{I}[OneDealer_i]$ equals 1 if the client had an outstanding position or any trading activity in the out-of-sample pre-period with a single dealer in the EURUSD.

We also measure the importance of a dealer-client relationship for the client, used to test Hypothesis 5, as the share of client i's total EURUSD notional (i) trading activity and (ii) outstanding positions in the out-of-sample pre-period that is accounted for by dealer d. These measures map into those used earlier, in Section 4, to document that clients trade more persistently with dealers that they rely on more heavily. We use notional outstanding positions for one measure to (i) give more weight to long maturity relationships, (ii) capture that the dealer and client cumulatively had a strong relationship in the past, and (iii) allow for a dealer-client pair to have a strong relationship even though their out-of-sample new trading activity may have been small.[47] Analogous measures, but computed as the share of the dealer's activity accounted for by the client, are used to test Hypothesis 6.[48] We compute relationships using EURUSD activity, since relationships have a currency-specific component, as we previously documented in Section 4.[49]

Using these relationship measures, we examine whether treated dealer-client pairs, those where the dealer is Credit Suisse, (i) had a differential reduction in trading activity relative to untreated dealer-client pairs, and (ii) whether those with stronger bilateral relationships were even more strongly affected than those with weaker relationships post-shock. To test this, we run the triple differences specification given by Equation 9 on the sample of dealer-client pairs that traded notional amounts in EURUSD in the pre-period. The indicator $\mathbb{I}[StrongRel_{d,i}]$ equals 1 if the relationship measure used for the regression is above the cross-client median within the dealer, d, for the dealer-client pair (d, i).[50] So, the bilateral relationship is considered strong when the client (i) relied more heavily on the dealer or (ii) composed a larger share of the dealer's activity than the median client that traded with the dealer in the pre-period, depending on the relationship measure.

$$\begin{aligned} Y_{d,i,t} =& \beta_1(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_d]) + \beta_2(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_d] \times \mathbb{I}[StrongRel_{d,i}]) \\ &+\beta_3(\mathbb{I}[Post_t] \times \mathbb{I}[StrongRel_{d,i}]) + \beta_4(\mathbb{I}[Treated_d] \times \mathbb{I}[StrongRel_{d,i}]) \\ &+\beta_5\mathbb{I}[Post_t] + \beta_6\mathbb{I}[StrongRel_{d,i}] + \alpha_d + \alpha_i + \alpha_w + \epsilon_{d,i,t} \end{aligned} \tag{9}$$

47. The sum of notional outstanding positions gives more weight to long maturity relationships because, for example, if a dealer and client have an outstanding 1 year trade and a 1 week trade, since we sum outstanding positions across days, the 1 year outstanding position will count every day for a year in the sum where the 1 week trade will count only for the 1 week when the trade is still outstanding.

48. Details on the constructions of these measures can be found in Appendix C.2. Equations 29 and 30 show how these measures are computed.

49. For our main specification, presented in Table 4, we also computed the relationship measure using activity across all currencies and obtained similar results. These results are in Appendix H.

50. This cross-client median is taken over the set of clients with which dealer d had a positive EURUSD notional trading position in the pre-period. The definition of this indicator is given explicitly for a relationship measure in Equation 31 of Appendix C.2.

We are interested in β_1 and β_2, where β_2 is the triple differences coefficient and the identification assumption is that the difference between the strong and weak relationship treated (d, i) pairs would have evolved similarly to the difference for the untreated pairs, absent the shock to Credit Suisse.[51] We include a dealer fixed effect, α_d, a client fixed effect α_i, and a calendar week fixed effect α_w. The less granular time fixed effect allows us to keep more variation when estimating the triple differences, comparing activity across observations within the same week instead of the same day of trading.

We use the same dependent variables as were used with Equation 8, except we use alternative measures of notional traded and trade count since many dealer-client pairs have many days on which they do not trade. For these dependent variables, we retain dealer–client–date observations with no trading activity as zeros by using the value on date t for dealer d and client i in the EURUSD as a percent of their out-of-sample pre-period daily average value in the EURUSD on days where the value is positive. This measure allows us to ask whether strong versus weak relationship treated bilateral trading pairs saw a larger increase in their notional trading activity or trade count as a percent of their average active relationship size. These variables are specifically computed as in Equation 10.[52]

We condition the denominator to be an average on active trading days to avoid inflating the dependent variable for observations that trade less frequently. We also winsorize these dependent variables at the first and 99th percentiles to reduce the influence of outliers, as some values can be very large in percentage terms if activity was small in the out-of-sample pre-period.

$$\%\,Value_{d,i,t} = 100 \times \frac{Value_{d,i,t}}{\overline{Value}_{d,i,\{l \in \text{Out of Sample: } Value_{d,i,l} > 0\}}} \tag{10}$$

51. See Olden and Møen (2022) for details regarding the triple differences estimator and identification assumptions.

52. Log transformations of these variables will drop bilateral dealer–client–date observations with zero activity, and many bilateral pairs may not trade on many days in our 80 trading day period. However, we want to capture the external margin of trading activity so that we can speak to the total daily average change in trading activity due to the shock, not just conditional on active trading days.

Table 4: Role of Client Reliance for Activity at the Shocked Dealer

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]
I[Post]	-1.784*	-0.665	-0.008
	(1.023)	(1.212)	(0.008)
I[Post] x I[Treated_d]	-7.965***	-10.548***	-0.103***
	(0.560)	(0.545)	(0.005)
I[StrongRel_di]	-0.322	4.865***	0.059***
	(0.607)	(0.937)	(0.011)
I[Post] x I[StrongRel_di]	0.477	-0.294	-0.004
	(0.421)	(0.457)	(0.003)
I[Post] x I[Treated_d] x I[StrongRel_di]	6.445***	8.998***	0.095***
	(0.943)	(0.842)	(0.006)
I[Treated_d] x I[StrongRel_di]			-0.043***
			(0.011)
Observations	806,988	806,988	847,936
Dealer Clusters	41	41	42
R^2	0.1257	0.2108	0.2575
Adjusted R^2	0.1179	0.2038	0.2507
Within R^2	0.0000	0.0017	0.0034

Notes: This table reports results from dealer–client–date triple differences regressions, given by Equation 9, that we use to test Hypothesis 5. Dependent variables are: % *Not. Traded* (% *Trade Count*), EURUSD notional (trade count) traded by the client with the dealer at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles; $\mathbb{I}[Traded]$, an indicator equal to 1 if the dealer and client trade in EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: $I[StrongRel\_di]$, an indicator equal to 1 if client was more reliant on the dealer in EURUSD than the median client at dealer, across clients that traded EURUSD with the dealer in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_d]$, an indicator equal to 1 if the dealer in the dealer-client pair is Credit Suisse. Measurement details for $I[StrongRel\_di]$ are in Appendix C.2 using *RelStrNDay_i* as defined in that appendix. All specifications include dealer, client, and calendar week fixed effects. Standard errors are double clustered at the dealer and date level. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our main regression equation to test Hypothesis 5 uses the share of a client's notional traded in the EURUSD accounted for by dealer d as the measure of bilateral relationship strength, and the results are presented in Table 4. All of the β_1 coefficients are significant and negative in columns (1)–(3). The -7.965 coefficient in column (1) implies that from the pre- to the post-period, treated dealer-client pairs with weak relationships saw an average reduction in notional trading activity, as a percent of their historical relationship size, that was 8 percent larger than untreated dealer-client pairs with weak relationships. Here, a weak relationship means that the client relied less heavily on the dealer for their historical EURUSD trading activity and therefore, as documented in Section 4, has a less persistent or sticky trading relationship with the dealer.

All of the triple difference coefficients, β_2, are significantly positive with the coefficients in columns (1)–(3) offsetting the negative β_1 coefficients. So, clients that were more heavily reliant on Credit Suisse had a smaller reduction in trading activity with Credit Suisse relative to those that were less reliant on Credit Suisse, compared to the relative change in activity at other dealers between their more versus less reliant clients. These results indicate that clients that were more heavily reliant on the shocked dealer, faced a smaller decline in trading activity at the treated dealer than less reliant clients, supporting Hypothesis 5. We present the same table, but where the client reliance measure is computed across all seven currency pairs in Appendix H and the results are consistent.

The β_1 coefficients and the sum of β_1 and β_2, for all of the regressions used to test Hypotheses 5 and 6, are plotted in Figure 2 for notional traded as the dependent variable. Figures 9 and 10 of Appendix G plot the coefficients for trade count and an indicator equal to 1 if the dealer and client trade as dependent variables, respectively.[53] Within a sub-figure, the x-axis denotes which relationship strength measure was used for $\mathbb{I}[StrongRel_{d,i}]$ in the regression equation. Column (2) corresponds to Table 4. Columns (2), (4), and (5) test Hypothesis 5, where a strong relationship indicates that the client relied more heavily on the dealer for EURUSD activity than other clients and column (5) captures the more extreme case of complete reliance on a dealer. These are of primary interest to us.

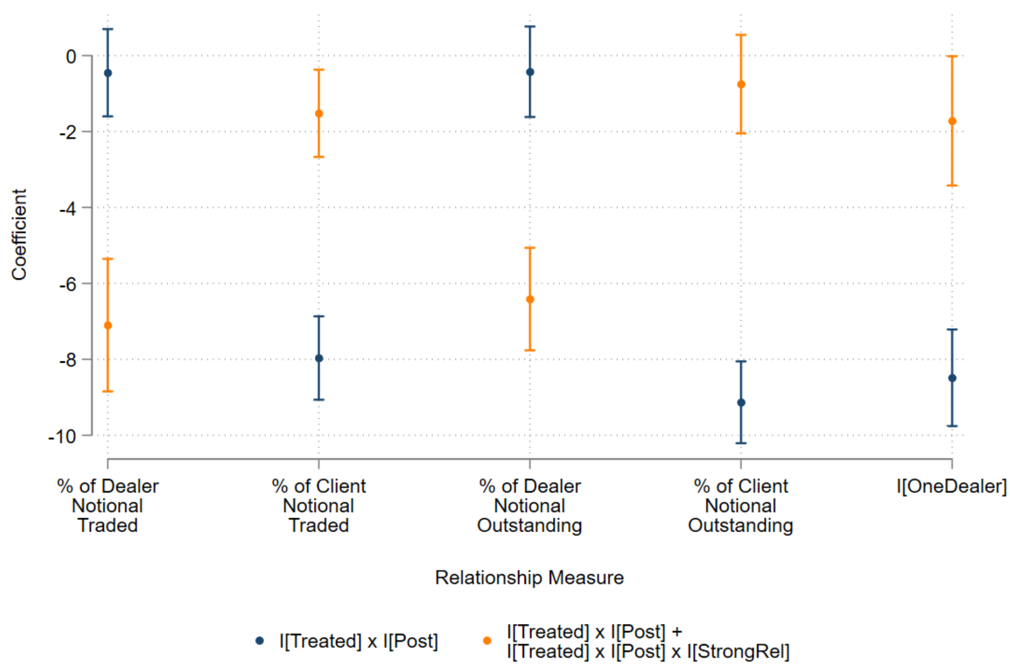
Consistent with Hypothesis 5, we see in columns (2), (4), and (5) of Figure 2 that treated and less reliant dealer-client pairs had a larger decline in trading activity than those that were untreated, captured by β_1, the blue plotted coefficients. However, $\beta_1 + \beta_2$ given by the orange coefficients, which adds in the differential effect for treated pairs with more reliant relative to less reliant clients, is less negative for quantities. That is, the clients that were more heavily reliant on Credit Suisse saw a smaller reduction in activity at Credit Suisse, if any, than the clients that were less reliant on Credit Suisse.

Columns (1) and (3) of Figure 2, and Figures 9 and 10 in Appendix G, instead test Hypothesis 6 and a strong relationship in these cases implies that the client was more important for the dealer's EURUSD activity relative to other clients. Consistent with this hypothesis, we find that the treated and weak relationship pairs had an insignificant differential change in trading activity relative to weak relationship untreated pairs, captured by the blue coefficients, β_1. However, the orange coefficients, $\beta_1 + \beta_2$, are significantly negative. Thus, clients that were more important for Credit Suisse saw a larger reduction in activity at Credit Suisse than clients that were less important for Credit Suisse. It could be that this measure is correlated with client reliance on the dealer and our results are capturing this effect, as we have not included both types of relationship strength measures in the specification. However,

53. We plot the sum of β_1 and β_2 along with the β_1 coefficient to visually show how the triple difference coefficient affects the difference-in-differences term. So, we can see the difference-in-differences effect and the total treatment effect for the more exposed group.

we interpret the patterns of these coefficients as evidence that important clients for Credit Suisse may have been accommodating when Credit Suisse was under stress. Thus, consistent with Hypothesis 6.

Figure 2: Effect of Relationship Strength on % $Not.\ Traded_{d,i,t}$ at Shocked Dealer



Notes: This figure plots the difference-in-differences coefficient, β_1 in blue, and its sum with the triple differences coefficient, $\beta_1 + \beta_2$ in orange, from dealer–client–date-level triple differences regressions that we use to test Hypotheses 5 and 6. All columns correspond to Equation 9, but use different notions of relationship strength, listed along the x-axis and constructed using EURUSD activity in the out-of-sample pre-period. Columns (2), (4), and (5) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is % $Not.\ Traded_{d,i,t}$, EURUSD notional traded by the client with the dealer at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles. Independent variables are: $I[StrongRel]$, an indicator equal to 1 if client was had a stronger EURUSD relationship with the dealer than the median client at dealer, across clients that traded EURUSD with the dealer in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated]$, an indicator equal to 1 if the dealer in the dealer-client pair is Credit Suisse. X-axis labels denote the relationship strength measure used for $I[StrongRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[StrongRel]$. All regressions include dealer, client, and calendar week fixed effects. Standard errors are clustered at the dealer and date level. Error bars plot $\pm 1.96 \times SE$.

Overall, the results of this section's main specification, presented in Table 4, show that clients that relied more on Credit Suisse continue maintaining their trading activity with Credit Suisse into the post-period, while less reliant clients reduce their trading activity. If Credit Suisse passed through higher marginal trading costs to clients, these costs may be born more heavily by clients that are more reliant on Credit Suisse for EURUSD activity, and thus are less elastic because of their greater bilateral trading persistence. Clients that are more reliant on Credit Suisse may have (i) fewer dealer relationships or (ii) lower search efficiency for the same dealer relationship count. In the first case, these clients have fewer outside trading options and generating a new dealer relationship takes time (FSB 2018). In the second case, the market share that Credit Suisse has in the client's EURUSD activity is sticky since the client's outside options are less accessible compared to clients that relied less on Credit Suisse. In both cases, these "strong relationship" clients would have a lower Credit Suisse-specific elasticity of demand and worse bargaining power due to search frictions. Therefore, they reduce their activity at Credit Suisse by less and and may accept higher spreads after the shock. Our evidence supports this mechanism in a reduced form way for quantities.

5.3 Implications for Exposed Clients' Trading Activity

We next document whether the reliance of a client on an adversely shocked dealer affects client trading outcomes overall and with other dealers, not just their activity with the shocked dealer which was examined in the previously. That is, were clients that had a relationship with the shocked dealer able to substitute and did clients that were more reliant on the shocked dealer ("more exposed") face larger spread increases at other dealers due to a worsening of outside options and bargaining power? As shown in Section 5.2.2, clients that were more reliant on Credit Suisse continued trading with Credit Suisse. If they also paid greater spread increases, then these clients would have experienced a greater worsening of their trading conditions at Credit Suisse in the post-period. In the context of search and bargaining frictions with persistent trading relationships, if a main outside trading option for these more exposed clients was adversely affected, we expect these clients to have a reduction in bargaining power at other dealers. This leads to a greater worsening of trading conditions, higher spreads, for more exposed clients at other dealers.

As we documented in Section 5.2.2, the effect of the shock on clients' trading activity at Credit Suisse (CS) depended on the client's previous reliance on Credit Suisse. We define a client's exposure to the Credit Suisse shock as the percent of the client's total notional traded in the EURUSD in the out-of-sample pre-period. This is presented explicitly in Equation 11.[54]

$$E_i = 100 * \frac{\sum_{t \in OutOfSample} Not.\ Traded_{CS,i,t,EURUSD}}{\sum_{t \in OutOfSample} Not.\ Traded_{i,t,EURUSD}} \tag{11}$$

We use this version of relationship strength to measure a client's exposure to Credit Suisse

54. E_i corresponds to $RelStrNDay^{(i)}_{d,i}$ where d is Credit Suisse, as described in Appendix C.2.

since our focus is to document the implications of persistent trading relationships for client trading outcomes in this market. This measure is useful for studying client search and bargaining frictions and whether dealers exert market power over their clients. In particular, as shown in Section 4, relationships that a client more heavily relies on are more persistently used, relationships are currency specific, and heavy reliance by a client on a dealer corresponds to higher premia on average. So, we expect that clients who relied more heavily on Credit Suisse in EURUSD to have greater difficulty substituting to alternative dealers for trading in EURUSD post-shock. We present the distribution of E_i across treated clients in our all $\leq$ 1y maturity in Appendix I Table 23.

5.3.1 Client-Level Trading Activity

We hypothesize, as stated in Hypothesis 7, that clients who relied more heavily on Credit Suisse, "more exposed", faced a larger increase in *client-level* spreads on average in the post-period relative to unexposed clients. As shown in Section 4, trading relationships are persistent based on previous reliance of the client on the dealer. So, we expect more exposed clients to have a more persistent relationship with Credit Suisse, "matching" with Credit Suisse more frequently in their search process or not searching efficiently across other dealers. According to Duffie, Gârleanu, and Pedersen (2005), because of this friction these clients may have paid higher spreads at Credit Suisse, which would result in a main outside trading option in bilateral trade negotiations with non-Credit Suisse dealers becoming less attractive post-shock. So, other dealers can charge larger spread increases to these clients than unexposed clients. Thus, client-level spreads may increase more for more exposed clients.

It is not clear whether trading volumes for more exposed clients should decline by more or not in the post-period. It could be that less exposed clients substitute to other dealers, maintaining their trading volumes while also allowing the more exposed clients to continue maintaining their trading volumes at Credit Suisse. Thus, resulting in no effect on quantities at the client level.

Hypothesis 7 (Exposed Client Bargaining Power) *Clients that relied more on Credit Suisse for EURUSD trading pay higher spreads in the post-period relative to unexposed clients.*

To test Hypothesis 7, we study whether this shock affected client-level activity differentially for exposed clients relative to unexposed clients. As shown in Section 5.2.2, the effect of the shock on a client's trading activity with Credit Suisse from the pre- to the post-period depended on the client's previous reliance on Credit Suisse, but did this shock matter for client-level activity?

Using difference-in-differences panel regressions at the client–date level (client–maturity–date level when spread is the dependent variable), we document that clients that relied more heavily on Credit Suisse in the past do not see differential changes in trading volume in the post-period, but do pay larger increases in spreads relative to unexposed clients. Equations 12 and 13 present our difference-in-differences regression equations. Equation 12 treats all exposed clients as the treated group where $\mathbb{I}[Treated_i]$ equals 1 if E_i is positive. In Equation 13, we use a categorical treatment variable where we further split the treatment group by whether the client was more or less exposed to Credit Suisse, denoted by the variable $TreatExpCat_i$. A more exposed client refers to a treated client whose exposure to Credit Suisse is above the median level among all treated clients. Conversely, a less exposed client is a treated client whose exposure is at or below that median.

$$Y_{i,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_i]) + \alpha_i + \alpha_w + \epsilon_{i,t} \tag{12}$$

$$Y_{i,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2(\mathbb{I}[Post_t] \times TreatExpCat_i) + \alpha_i + \alpha_w + \epsilon_{i,t} \tag{13}$$

The coefficient β_2 estimates the differential change in the outcome variable for clients that were treated (more or less exposed) relative to clients that were unexposed from the pre- to the post-period. We include client, α_i, and week, α_w fixed effects. We use week instead of date fixed effects to allow for comparisons across clients within the same week, instead of the same trading date and avoid removing a lot of variation.

Table 5 displays the results for Equations 12 and 13, for outcome variables % Notional Traded by the client in EURUSD and the notional weighted average spread at the client–maturity–date level. The corresponding table with outcome variables % Trade Count and $\mathbb{I}[Traded_{i,t}]$ can be found in Appendix J Table 24. % $Not.\ Traded_{i,t}$ and % $Trade\ Count_{i,t}$, as before, are winsorized at the first and 99th percentiles, but at the client–date level.

Columns (1) and (2) in Table 5 do not recover any significant differences in daily notional traded or spreads paid by treated clients relative to untreated clients. However, when we split treatment by categorical exposure in columns (3) and (4), we find in column (4) that the "More Exposed" group pay a 16.0 basis point larger increase in average spread per dollar of notional traded in the EURUSD relative to unexposed clients from the pre- to the post-period across maturities.

One reason why the "More Exposed" group pays larger spread increases may be that these clients traded with other dealers and faced higher spreads there since this shock may have affected these clients' outside options and bargaining power. This would also be consistent with the lack of a differential decline in trading quantities for more exposed clients. We address treated clients' activity with other dealers in the following sections.[55]

Table 5: Effect of the Shock on Client-Level Activity

	(1) % Not. Traded	(2) Spread	(3) % Not. Traded	(4) Spread
I[Post]	-27.416***	4.337*	-27.398***	4.463*
	(8.227)	(2.294)	(8.228)	(2.276)
I[Post] × I[Treated_i]	9.646	0.944		
	(8.554)	(3.360)		
I[Post] x Less Exposed			21.039**	-0.975
			(8.875)	(3.059)
I[Post] x More Exposed			-4.455	16.012*
			(12.883)	(9.042)
Observations	485,986	20,881	485,986	20,881
Client Clusters	7300	2138	7300	2138
R^2	0.0464	0.0876	0.0464	0.0879
Adjusted R^2	0.0318	-0.0181	0.0318	-0.0179
Within R^2	0.0001	0.0001	0.0001	0.0004

Notes: This table reports results from client–date and client–maturity–date level difference-in-difference regressions that we use to test Hypothesis 7. Columns (1) and (2) correspond to Equation 12 and columns (3) and (4) correspond to Equation 13, where columns (2) and (4) are at the client–maturity–date level. Dependent variables are: *% Not. Traded*, EURUSD notional traded by the client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles; *Spread*, the notional weighted average spread paid by the client for EURUSD trades in the maturity on the date. Trade-level spreads are measured as described in Section 3.2. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_i]$, an indicator equal to 1 if the client is exposed to Credit Suisse, measured as a positive exposure computed according to Equation 11; *Less Exposed* and *More Exposed*, levels of a categorical variable that indicates whether a client (i) was not exposed to Credit Suisse, (ii) was above the cross-treated client median exposure to Credit Suisse (*More Exposed*) or (iii) was below or equal to the cross-treated client median exposure to Credit Suisse (*Less Exposed*), where exposure to Credit Suisse is measured as in Equation 11 and the unexposed clients are the reference group. All specifications include client and week fixed effects, and columns (2) and (4) include additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, in Table 5 and Appendix J Table 24, which presents the same regression equation but for % *Trade Count* and $\mathbb{I}[Traded_{i,t}]$ as dependent variables, we find that the "Less Exposed" treated client group has a differential increase in trading activity in the post-period relative to unexposed clients. We previously saw that this group of clients faced a differential decline in trading activity at Credit Suisse. This suggests that these less exposed clients substituted and even increased trading activity at other dealers. Additionally, they do not pay larger relative spreads at the client level, suggesting they have a stronger bargaining position than more exposed clients.

55. It is worth noting that in our current spread panel, most of the exposed client observations in the post-period are with non-Credit Suisse dealers.

5.3.2 Exposed Clients' Trading Activity With Other Dealers

Next, as an extension to Hypothesis 7, we test whether non-Credit Suisse dealers increase trading activity more and increase spreads more to more exposed clients relative to unexposed clients in the post-period, within-dealer. That is, whether exposed clients have substitution patterns that are accommodated by other dealers. If this shock is an adverse shock to one of the trading options for exposed clients, non-Credit Suisse dealers have a greater increase in bargaining power over more exposed clients than unexposed clients that they trade with in the post-period. Thus, we expect spreads charged by a non-Credit Suisse dealer to increase by more to more exposed clients than to unexposed clients. In addition, it could be the case that non-Credit Suisse dealers increase their activity by more to exposed clients relative to their unexposed clients to accommodate substitution away from Credit Suisse.

Hypothesis 8 (Exposed Clients With Other Dealers) *Non-Credit Suisse dealers increase activity and spreads more to more heavily exposed clients in the post-period.*

Using variation across clients within the same dealer–week, we document that clients that were more exposed to the Credit Suisse shock pay a larger increase in spreads per notional dollar traded on average across maturities than unexposed clients. This is consistent with other dealers charging larger increased markups to clients that have a worsened set of outside options in the post-period because they relied heavily on Credit Suisse. Our analysis sheds light on the value of the relationship with the shocked dealer for the client with respect to their bilateral trading activity with other dealers.

We run the following specifications, given by Equations 14 and 15, at the dealer–client–date level where we include dealer–week fixed effects and client fixed effects. We exclude any (d, i, t) observations where the dealer, d, is Credit Suisse. The dealer–week fixed effect allows us to control for dealer–time-specific variation in trading activity or dealer-specific changes in marginal trading costs. So, our specification exploits cross-client variation in exposure to the Credit Suisse shock within a dealer-week. The client fixed effect controls for fixed client characteristics, such as sector, trading frequency, number of dealer relationships, etc., which could affect the average markup a client is paid. Independent variables $\mathbb{I}[Treated_i]$ and $TreatExpCat_i$ are as specified in Section 5.3.1.

$$Y_{i,d,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_i]) + \alpha_{d,w} + \alpha_i + \epsilon_{d,i,t} \tag{14}$$

$$Y_{i,d,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2(\mathbb{I}[Post_t] \times TreatExpCat_i) + \alpha_{d,w} + \alpha_i + \epsilon_{d,i,t} \tag{15}$$

The results for Equation 14 (15) with dependent variables % Notional Traded, and notional weighted spread at the dealer–client–maturity–date level, are presented in Table 6 (7).

The corresponding tables with dependent variables % $Trade\ Count_{d,i,t}$, and $\mathbb{I}[Traded_{d,i,t}]$ are presented in Appendix K.[56]

In Table 6, we find no significant differential change in activity within dealer, across treated and untreated clients, for both trading activity or spreads. This is also true when % $Trade\ Count_{d,i,t}$ or $\mathbb{I}[Traded_{d,i,t}]$ are dependent variables. We also find no significant effect on trading quantities for treated clients relative to untreated clients at non-Credit Suisse dealers when we split the sample by categorical exposure to Credit Suisse in Table 7 and in Appendix K Table 26.

However, in Table 7 we split client treatment into a categorical variable and find that more exposed clients paid a larger increase in spreads at other dealers, by 16.8 basis points per average dollar of notional traded with the dealer, relative to unexposed clients that traded with the same dealer in the same week. Columns (2) and (4) of Tables 6 and 7 are the same, but column (4) includes additional interaction terms for a client having one relationship. This is to control for this group of untreated clients because our treated group will mostly, if not only, include clients of Credit Suisse that had multiple relationships and thus may have different characteristics, at least with respect to bargaining power and substitution ability.[57]

Thus, clients that relied more heavily on Credit Suisse do not face a differential increase in activity at non-Credit Suisse dealers in the post-period relative to untreated clients. This is not consistent with non-Credit Suisse dealers accommodating additional trading demand from more exposed clients which is stated in Hypothesis 8. However, they do face a greater increase in spreads which is consistent with Hypothesis 8. In addition, we showed in Section 5.3.1 that more exposed clients did not face a differential change in client-level notional trading activity and we showed in Section 5.2.2 that more exposed clients did not experience much of a reduction in trading activity at Credit Suisse. However, they did face an increase in spreads at the client-level. Thus, clients that were more exposed to the shock did not face a reduction in total quantity traded because they were able to maintain their trading activity at Credit Suisse and other dealers, relative to unexposed clients. However, post-shock, these more exposed clients paid a larger increase in spreads at other dealers.

56. For % *Not. Traded* and % *Trade Count*, we winsorize these variables at the first and 99th percentiles to reduce the influence of outliers. We winsorize before excluding the dealer–client–date observations where the dealer is Credit Suisse.

57. It could be that there are clients in the treated group that only had one relationship in the out-of-sample pre-period with Credit Suisse and trade with another dealer in the pre-period, thus existing in this sample. However, they would only compose a small set of observations and this triple interaction will control for these as well.

Table 6: Effect of the Shock on Clients' Activity With Other Dealers

	(1) % Not. Traded	(2) Spread	(3) % Not. Traded	(4) Spread
I[Post]	-1.540	2.936	-1.792*	1.955
	(1.058)	(2.690)	(1.067)	(2.456)
I[Post] × I[Treated_i]	0.128	1.900	0.373	2.788
	(1.154)	(3.794)	(1.163)	(3.634)
I[Post] x I[OneRel_i]			1.249	3.376
			(0.898)	(2.428)
Observations	802,861	22,376	802,861	22,376
Client Clusters	7,046	2,161	7,046	2,161
R^2	0.1283	0.1038	0.1283	0.1041
Adjusted R^2	0.1198	-0.0095	0.1199	-0.0093
Within R^2	0.0000	0.0001	0.0000	0.0004
Dealer-Week FE	YES	YES	YES	YES
Client FE	YES	YES	YES	YES
Maturity FE		YES		YES

Notes: This table reports results from dealer–client–date and dealer–client–maturity–date level difference-in-difference regressions that we use to test Hypothesis 8. Columns (1) and (2) correspond to Equation 14, where column (2) is at the dealer–client–maturity–date level. Columns (3) and (4) add controls for whether the client had only one relationship. Dependent variables are: *% Not. Traded*, EURUSD notional traded between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; *Spread*, the notional weighted average spread across EURUSD trades for the dealer, client, maturity, and date. Trade-level spreads are measured as described in Section 3.2. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_i]$, an indicator equal to 1 if the client is exposed to Credit Suisse, measured as a positive exposure computed according to Equation 11; $I[OneRel\_i]$, an indicator equal to 1 if the client had an outstanding position with only one dealer, across all seven currencies, in the out-of-sample pre-period. All specifications include dealer–week and client fixed effects, and columns (2) and (4) include additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our results are consistent with the shock adversely affecting the set of outside trading options for exposed clients, specifically for clients that relied more heavily on Credit Suisse. If we take a "market" to be a client–currency pair, our results are consistent with Credit Suisse potentially charging greater spreads, increasing the market share that other dealers get from the client. This increases the markups these dealers can charge. When clients that heavily relied on Credit Suisse match with other dealers in their search process, these other dealers know that these clients may have lower bargaining power post-Credit Suisse shock, because they may be paying higher spreads at Credit Suisse, and charge higher spreads.

Table 7: Effect of the Shock on Clients' Activity With Other Dealers, Categorical Exposure

	(1) % Not. Traded	(2) Spread	(3) % Not. Traded	(4) Spread
I[Post]	-1.541	3.037	-1.792*	2.055
	(1.058)	(2.669)	(1.067)	(2.439)
I[Post] x Less Exposed	-0.240	0.528	-0.000	1.416
	(1.314)	(3.589)	(1.324)	(3.464)
I[Post] x More Exposed	1.578	16.785*	1.842	17.679*
	(1.688)	(9.458)	(1.686)	(9.265)
I[Post] x I[OneRel_i]			1.251	3.377
			(0.898)	(2.430)
Observations	802,861	22,376	802,861	22,376
Client Clusters	7,046	2,161	7,046	2,161
R^2	0.1283	0.1040	0.1283	0.1043
Adjusted R^2	0.1198	-0.0094	0.1199	-0.0091
Within R^2	0.0000	0.0003	0.0000	0.0006
Dealer-Week FE	YES	YES	YES	YES
Client FE	YES	YES	YES	YES
Maturity FE		YES		YES

Notes: This table reports results from dealer–client–date and dealer–client–maturity–date level difference-in-difference regressions that we use to test Hypothesis 8. Columns (1) and (2) correspond to Equation 15, where column (2) is at the dealer–client–maturity–date level. Columns (3) and (4) add controls for whether the client had only one relationship. Dependent variables are: *% Not. Traded*, EURUSD notional traded between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; *Spread*, the notional weighted average spread across EURUSD trades for the dealer, client, maturity, and date. Trade-level spreads are measured as described in Section 3.2. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; *LessExposed* and *MoreExposed*, levels of a categorical variable that indicates whether a client (i) was not exposed to Credit Suisse, (ii) was above the cross-treated client median exposure to Credit Suisse (*MoreExposed*) or (iii) was below or equal to the cross-treated client median exposure to Credit Suisse (*LessExposed*), where exposure to Credit Suisse is measured as in Equation 11 and the unexposed clients are the reference group; $I[OneRel\_i]$, an indicator equal to 1 if the client had an outstanding position with only one dealer, across all seven currencies, in the out-of-sample pre-period. All specifications include dealer–week and client fixed effects, and columns (2) and (4) include additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the next section, Section 5.3.3, we examine how pre-existing relationship strength at non-Credit Suisse dealers affects trading outcomes for clients at these dealers post-shock.

5.3.3 Pre-Existing Relationship Strength and Clients' Trading Activity With Other Dealers

Finally, we include client–week fixed effects to control for changes in client demand over time and ask whether a client's reliance on other dealers in the past affects their substitution patterns and the spreads. Specifically, we study if more exposed clients increased their trading activity and paid higher spreads at the non-Credit Suisse dealer that they relied on the most in the past. The intuition is as follows. When trading relationships are persistent, the most important non-Credit Suisse dealer for an exposed client will have greater market power over the client's trading activity in the post-period and increase markups by more.[58] Hypothesis 9 speaks to the competitive patterns across dealers based on the market share they have in the client's trading activity and whether clients are accommodated by the dealer they have the greatest relationship strength with when one of their relationship dealers is adversely shocked.

Hypothesis 9 (Exposed Client Reliance on Other Dealers) *Clients that were more exposed to Credit Suisse had a larger increase in trading activity and spreads in the post-period with the non-Credit Suisse dealer that they relied on more heavily.*

We generate an indicator $\mathbb{I}[\mathit{StrongRelClient}_{d,i}]$ that equals 1 if dealer d composed the largest out-of-sample pre-period share of client i's notional trading activity over all seven currency pairs, excluding Credit Suisse, and zero otherwise.[59] We use all seven currencies for this measure to capture a broader set of dealer relationships since, as shown in Appendix D.6 Table 12, the median client in our two-year data sample only had 1 dealer relationship. We do not use our previous measure of a strong relationship for this analysis because the more exposed client treatment group will have relied more on Credit Suisse and therefore less on other dealers. By construction it will be the case that these clients are more likely to be identified as weak relationship clients for non-Credit Suisse dealers in the cross-section of the dealers' client sets. Instead, we want to identify the dealer that the client is most likely to substitute to.

The triple differences regression specification that we run is given in Equation 16, excluding (d, i, t) observations where the dealer d is our shocked dealer Credit Suisse. We are interested in the triple interaction coefficient, β_2, which identifies the differential change in $Y_{d,i,t}$ for the $\mathbb{I}[\mathit{StrongRelClient}_{d,i}]$ identified dealer relative to the other dealers in the client's dealer set for the treated clients versus the untreated clients. That is, we take the clients that were not exposed to the Credit Suisse shock and use their dealer-client pairs as control groups for those of the treated group.

We use the same dependent variables as in Section 5.3.2.[60] As before, $\mathbb{I}[\mathit{Treated}_i]$ denotes

58. This is illustrated in Equation 26 of the model in Appendix B. If a dealer has a larger probability that the client trades with them post-shock, proxied by the share of the client's activity that is allocated to the dealer, the client will pay a larger increase in spreads at that dealer due to an increase in markups.

59. $\mathbb{I}[\mathit{StrongRelClient}_{d,i}]$ is computed using the $\mathit{RelStrNDay}^{(i)}_{d,i}$ out-of-sample relationship measure, computed over all seven currencies in our sample, where the construction of $\mathit{RelStrNDay}^{(i)}_{d,i}$ is described in Appendix C.2.

60. % *Not. Traded*$_{d,i,t}$ and % *Trade Count*$_{d,i,t}$ are winsorized at the first and 99th percentiles before excluding (d, i, t) pairs where the dealer is Credit Suisse.

whether or not the client in the (d, i, t) observation was exposed to Credit Suisse. With the client–week fixed effect, we exploit cross-dealer variation, controlling for client demand to test whether treated clients reallocated their trading activity more to this strong relationship dealer and paid a larger increase in spreads at this dealer relative to the activity of untreated clients with their main non-Credit Suisse dealer.

$$\begin{aligned} Y_{d,i,t} = {} & \beta_1(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_i]) + \beta_2(\mathbb{I}[Post_t] \times \mathbb{I}[Treated_i] \times \mathbb{I}[StrongRelClient_{d,i}]) \\ & + \beta_3(\mathbb{I}[Treated_i] \times \mathbb{I}[StrongRelClient_{d,i}]) + \beta_4(\mathbb{I}[Post_t] \times \mathbb{I}[StrongRelClient_{d,i}]) \\ & + \beta_5\mathbb{I}[StrongRelClient_{d,i}] + \alpha_{iw} + \alpha_d + \epsilon_{d,i,t} \end{aligned} \tag{16}$$

Table 8 presents results for regression Equation 16. When we group all exposed clients into a single treatment group, we find no significant differential effects on the allocation of trading quantities to a client's main non-Credit Suisse dealer, columns (1)–(2), the likelihood of trading with the dealer, column (3), or the spread paid at the dealer, column (4). However, we showed in Section 5.3.2 that the more exposed clients, specifically, had significant differential treatment at non-Credit Suisse dealers relative to untreated clients. So, we also run Equation 16 using our categorical treatment variable. As before, this categorical variable denotes whether the client was more, less, or not exposed to the Credit Suisse shock. The results are presented in Table 9. The categorical treatment specification allows us to specifically examine the more exposed group's activity relative to unexposed clients.

We are specifically interested in the triple interaction terms in Table 9. Treated clients did not differentially change their EURUSD trading quantities across their dealer set based on relationship strength, as determined by our triple interaction coefficients which are insignificant across columns (1)–(3). However, we do find evidence that the more exposed client group paid a larger increase in spreads for their EURUSD trading activity at their main non-Credit Suisse dealer compared to their other dealer relationships, relative to the differential change experienced by the unexposed group.

We note that the coefficient on $\mathbb{I}[Post_t] \times \textit{More Exposed}$ in Table 9 is not estimated since the variation is absorbed by the client–week fixed effects.[61] In Table 9 column (4), we find that clients that relied more on Credit Suisse for EURUSD paid a larger increase in the average spread per notional dollar traded across maturities at their main non-Credit Suisse dealer relative to their other dealers from the pre- to the post-period compared to that of untreated clients. The magnitude of this effect based on our results is 24.6 basis points. We interpret this coefficient cautiously, as it is based on our current restrictive spread panel.

61. This is expected to be the case as the $I[Post] \times$ *More* (*Less*) *Exposed* interaction terms are at the client–date level. However, there is still slight variation because $I[Post]$ is not constant within-calendar week in the week of the shock, March 8, 2023.

Table 8: Role of Client Reliance on Other Dealers

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]	(4) Spread
I[Post]	-2.284*	-1.217	-0.013	11.188**
	(1.206)	(1.364)	(0.011)	(4.629)
I[Post] × I[Treated_i]	4.293*	2.386**	-0.004	-14.355
	(2.512)	(0.964)	(0.016)	(11.682)
I[StrongRelClient_di]	0.730	4.822***	0.056***	0.181
	(0.705)	(0.520)	(0.005)	(1.265)
I[Post] x I[StrongRelClient_di]	-0.152	-0.503	-0.004	-3.175*
	(0.809)	(0.499)	(0.004)	(1.802)
I[Treated_i] x I[StrongRelClient_di]	1.181	3.997*	0.050**	-0.139
	(1.966)	(2.036)	(0.019)	(3.742)
I[Post] x I[Treated_i] x I[StrongRelClient_di]	2.475	-1.010	-0.022	2.848
	(2.261)	(1.906)	(0.016)	(4.273)
Observations	801,346	801,346	841,905	14,915
Client Clusters	7,041	7,041	7,625	1,048
R^2	0.2522	0.3171	0.3498	0.2068
Adjusted R^2	0.1426	0.2170	0.2543	-0.0487
Within R^2	0.0001	0.0023	0.0043	0.0005
Client-Week FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Maturity FE				YES

Notes: This table reports results from dealer–client–date and dealer–client–maturity–date level triple difference regressions that we use to test Hypothesis 9. All columns correspond to Equation 16, where column (4) is at the dealer–client–maturity–date level. Dependent variables are: *% Not. Traded* (*% Trade Count*), EURUSD notional (trade count) traded between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; $\mathbb{I}[Traded]$, an indicator equal to 1 if the dealer and client trade in EURUSD at t in the all $\leq$ 1y maturity; *Spread*, the notional weighted average spread across EURUSD trades for the dealer, client, maturity, and date. Spreads are measured as described in Section 3.2. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_i]$, an indicator equal to 1 if the client is exposed to Credit Suisse, measured as a positive exposure computed according to Equation 11; $\mathbb{I}[StrongRelClient\_di]$, an indicator equal to 1 if the dealer composed the largest share of client i's trading activity across all seven currencies in the out-of-sample pre-period for all $\leq$ 1y maturity, across non-Credit Suisse dealers. All specifications include client–week and dealer fixed effects, and column (4) includes additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specifically, there are 70 (d, i, m, t)-level spread observations in the post-period with a client that is defined as More Exposed with 40 observations having $\mathbb{I}[StrongRelClient\_di]$ equal to one and the other 30 equal to zero.[62] With client–week fixed effects, some of these observations are excluded from the regression in Table 9 column (4). Thus, the regression sample includes 30 observations in the pre-period and 21 in the post-period for More Exposed clients with $\mathbb{I}[StrongRelClient\_di]$ equal to one, and 18 observations in the pre-period and 19 in the post-period for the More Exposed clients with $\mathbb{I}[StrongRelClient\_di]$ equal to zero.

62. These 70 observations are used for identifying the interaction coefficient in Table 7.

However, there are 191 observations used in Table 8 column (4) with $\mathbb{I}[Post] \times \mathbb{I}[Treated\_i] \times \mathbb{I}[StrongRelClient\_di]$ equal to 1. We are working to expand our dataset to increase the number of spread observations in our sample and address this.

Table 9: Role of Client Reliance on Other Dealers, Categorical Exposure

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]	(4) Spread
I[Post]	-2.284*	-1.217	-0.013	11.190**
	(1.206)	(1.364)	(0.011)	(4.629)
I[Post] x Less Exposed	4.844*	1.912*	-0.019	-13.799
	(2.880)	(0.962)	(0.016)	(11.452)
I[Post] x More Exposed	3.162	4.189	0.043	
	(5.099)	(2.991)	(0.028)	
I[StrongRelClient_di]	0.731	4.825***	0.056***	0.181
	(0.705)	(0.520)	(0.005)	(1.266)
I[Post] x I[StrongRelClient_di]	-0.152	-0.503	-0.004	-3.176*
	(0.809)	(0.499)	(0.004)	(1.802)
Less Exposed x I[StrongRelClient_di]	1.002	4.798**	0.064***	0.383
	(2.286)	(2.384)	(0.023)	(3.824)
More Exposed x I[StrongRelClient_di]	1.795	0.284	-0.014	-10.231
	(3.392)	(3.232)	(0.022)	(6.315)
I[Post] x Less Exposed x I[StrongRelClient_di]	3.208	-1.187	-0.029	1.427
	(2.529)	(2.212)	(0.018)	(4.051)
I[Post] x More Exposed x I[StrongRelClient_di]	-0.623	-0.533	0.004	24.590***
	(4.354)	(3.560)	(0.028)	(5.931)
Observations	801,346	801,346	841,905	14,915
Client Clusters	7,041	7,041	7,625	1,048
R^2	0.2522	0.3171	0.3499	0.2068
Adjusted R^2	0.1426	0.2170	0.2544	-0.0489
Within R^2	0.0001	0.0023	0.0043	0.0006
Client-Week FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Maturity FE				YES

Notes: This table reports results from dealer–client–date and dealer–client–maturity–date level triple difference regressions that we use to test Hypothesis 9. All columns correspond to Equation 16, but use our categorical treatment instead of $I[Treated\_i]$. Column (4) is at the dealer–client–maturity–date level. Dependent variables are: *% Not. Traded* (*% Trade Count*), EURUSD notional (trade count) traded between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; $\mathbb{I}[Traded]$, an indicator equal to 1 if the dealer and client trade in EURUSD at t in the all $\leq$ 1y maturity; *Spread*, the notional weighted average spread across EURUSD trades for the dealer, client, maturity, and date. Spreads are measured as described in Section 3.2. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; *LessExposed* and *MoreExposed*, levels of a categorical variable that indicates whether a client (i) was not exposed to Credit Suisse, (ii) was above the cross-treated client median exposure to Credit Suisse (*MoreExposed*) or (iii) was below or equal to the cross-treated client median exposure to Credit Suisse (*LessExposed*), where exposure to Credit Suisse is measured as in Equation 11 and the unexposed clients are the reference group; $\mathbb{I}[StrongRelClient\_di]$, an indicator equal to 1 if the dealer composed the largest share of client i's trading activity across all seven currencies in the out-of-sample pre-period for all $\leq$ 1y maturity, across non-Credit Suisse dealers. All specifications include client–week and dealer fixed effects, and column (4) includes additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, this analysis shows that more exposed clients experienced greater spread increases in their EURUSD trading activity at other dealers, and particularly at their main non-Credit Suisse dealer. This supports that this alternative main dealer had a larger "market share" of the client's EURUSD notional trading activity, which is associated with a more persistent trading relationship. So, when the set of outside options for the more exposed client is worsened, this alternative dealer takes advantage of their market position and increased bargaining power, increasing markups to these clients by more.

6 Conclusion

Using the comprehensive UK EMIR trade repository data for FX derivatives, this paper provides the first systematic study of bilateral dealer-client trading relationships in the OTC FX derivatives market and how clients' reliance on a dealer shapes client trading outcomes after that dealer is adversely shocked. Our analyses show that trading relationships are persistent, and clients have a 32% higher probability of trading with a dealer if they had a relationship with the dealer in the last 4 weeks and had recent relationships with more than one dealer. Additionally, a client's probability of trading with a dealer is increasing in the client's reliance on the dealer in the last 4 weeks. Our analyses confirm that clients pay higher average spreads at dealers that compose a larger share of the client's trading portfolio, consistent with dealers charging larger markups to clients that search less intensely.

In the context of the March 2023 shock to Credit Suisse, we empirically document that clients that relied more heavily on Credit Suisse did not face a reduction in total trading volume in the EURUSD, but paid a larger increase in markups in the post-period at the client level and at non-Credit Suisse dealers. We find, at the client level, that the increase in spreads for these clients was 16 basis points higher than unexposed clients per average notional dollar traded across maturities. More exposed clients pay even larger increase in spreads at the non-Credit Suisse dealer that they relied on most heavily relative to other dealers they trade with. Additionally, less reliant clients do not pay any significant differential increase in spreads and seem to substitute away from Credit Suisse.

Our research demonstrates that the over-the-counter structure of this major financial market is an environment where the search frictions across dealers and fixed costs to relationship creation generates persistence in trading relationships, especially for clients with one dealer relationship. The findings of our study show that when a relationship dealer is adversely shocked, relationship persistence affects client trading outcomes by making trading more costly for clients that were more heavily reliant on the shocked dealer.

For policy makers, our results underscore the importance of controlling for dealer relationships and search frictions when evaluating the resilience of this opaque market. In addition, our results document a characteristic of clients that are most affected when dealer shocks occur, which is an insight that policy makers can use to evaluate the repercussions of dealer shocks.

References

Abad, Jorge, Iñaki Aldasoro, Christoph Aymanns, Marco D'Errico, Linda Fache Rousová, Peter Hoffmann, Sam Langfield, Martin Neychev, and Tarik Roukny. 2016. "Shedding Light on Dark Markets: First Insights from the New Eu-Wide OTC Derivatives Dataset." *SSRN Electronic Journal,* https://doi.org/10.2139/ssrn.3723342.

Acosta-Smith, Jonathan, Gerardo Ferrara, and Francesc Rodriguez-Tous. 2025. "Bank Capital Regulation and Derivatives Clearing." *International Journal of Finance & Economics,* ijfe.3104. https://doi.org/10.1002/ijfe.3104.

Afonso, Gara, Anna Kovner, and Antoinette Schoar. 2013. "Trading Partners in the Interbank Lending Market." *SSRN Electronic Journal,* https://doi.org/10.2139/ssrn.2266527.

Argentesi, Elena, and Lapo Filistrucchi. 2007. "Estimating market power in a two-sided market: The case of newspapers." *Journal of Applied Econometrics* 22 (7): 1247–1266. https://doi.org/10.1002/jae.997.

Armitage, Matthew. 2022. "Trust, Confidence, and Automation: The ISDA Master Agreement as a Smart Contract." *Business Law Review* 43 (Issue 2): 56–64. https://doi.org/10.54648/BULA2022009.

Augustin, Patrick, Mikhail Chernov, Lukas Schmid, and Dongho Song. 2024. "The Term Structure of Covered Interest Rate Parity Violations." *The Journal of Finance* 79 (3): 2077–2114. https://doi.org/10.1111/jofi.13336.

Bardoscia, Marco, Ginestra Bianconi, and Gerardo Ferrara. 2019. "Multiplex network analysis of the UK over-the-counter derivatives market." *International Journal of Finance & Economics* 24 (4): 1520–1544. https://doi.org/10.1002/ijfe.1745.

Bernhardt, Dan, Vladimir Dvoracek, Eric Hughson, and Ingrid M. Werner. 2005. "Why Do Larger Orders Receive Discounts on the London Stock Exchange?" *Review of Financial Studies* 18 (4): 1343–1368. https://doi.org/10.1093/rfs/hhi002.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242. https://doi.org/10.2307/2555829.

Cenedese, Gino, Pasquale Della Corte, and Tianyu Wang. 2021. "Currency Mispricing and Dealer Balance Sheets." *The Journal of Finance* 76 (6): 2763–2803. https://doi.org/10.1111/jofi.13079.

Cenedese, Gino, Angelo Ranaldo, and Michalis Vasios. 2020. "OTC premia." *Journal of Financial Economics* 136 (1): 86–105. https://doi.org/10.1016/j.jfineco.2019.09.010.

Cocco, João F., Francisco J. Gomes, and Nuno C. Martins. 2009. "Lending relationships in the interbank market." *Journal of Financial Intermediation* 18 (1): 24–48. https://doi.org/10.1016/j.jfi.2008.06.003.

Di Maggio, Marco, Mark Egan, and Francesco Franzoni. 2022. "The value of intermediation in the stock market." *Journal of Financial Economics* 145 (2): 208–233. https://doi.org/10.1016/j.jfineco.2021.08.020.

Di Maggio, Marco, Amir Kermani, and Zhaogang Song. 2017. "The value of trading relations in turbulent times." *Journal of Financial Economics* 124 (2): 266–284. https://doi.org/10.1016/j.jfineco.2017.01.003.

Du, Wenxin, Salil Gadgil, Michael B. Gordy, and Clara Vega. 2024. "Counterparty Risk and Counterparty Choice in the Credit Default Swap Market." *Management Science* 70 (6): 3808–3826. https://doi.org/10.1287/mnsc.2023.4870.

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan. 2018. "Deviations from Covered Interest Rate Parity." *The Journal of Finance* 73 (3): 915–957. https://doi.org/10.1111/jofi.12620.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen. 2005. "Over-the-Counter Markets." *Econometrica* 73 (6): 1815–1847. https://doi.org/10.1111/j.1468-0262.2005.00639.x.

———. 2007. "Valuation in Over-the-Counter Markets." *Review of Financial Studies* 20 (6): 1865–1900. https://doi.org/10.1093/rfs/hhm037.

Eisfeldt, Andrea L, Bernard Herskovic, Sriram Rajan, and Emil Siriwardane. 2023. "OTC Intermediaries." *The Review of Financial Studies* 36 (2): 615–677. https://doi.org/10.1093/rfs/hhac062.

Englundh, Johanna. 2023. "Credit Suisse's Demise: A Timeline of Scandal and Failures." *Morningstar HK,* accessed June 2, 2025. https://www.morningstar.hk/hk/news/233221/credit-suisses-demise-a-timeline-of-scandal-and-failures.aspx.

Ferrara, Gerardo, Jun Sung Kim, Bonsoo Koo, and Zijun Liu. 2021. "Counterparty choice in the UK credit default swap market: An empirical matching approach." *Economic Modelling* 94:58–74. https://doi.org/10.1016/j.econmod.2020.08.020.

FINMA. 2023. "Lessons learned from the Credit Suisse crisis." *Swiss Financial Market Supervisory Authority FINMA Report,* accessed June 5, 2025. https://www.finma.ch/en/documentation/finma-publications/reports/bericht-zur-credit-suisse-krise/.

FSB. 2018. "Incentives to centrally clear over-the-counter (OTC) derivatives." *Financial Stability Board,* accessed June 5, 2025. https://www.fsb.org/2018/11/incentives-to-centrally-clear-over-the-counter-otc-derivatives-2/.

Gupta, Arun. 2021. "The Internal Capital Markets of Global Dealer Banks." *Finance and Economics Discussion Series* 2021.0 (34): 1–30. https://doi.org/10.17016/feds.2021.036.

Hacioğlu-Hoke, Sinem, Daniel Ostry, Hélène Rey, Adrien Rousset Planat, Vania Stavrakeva, and Jenny Tang. 2024. "Topography of the FX Derivatives Market: A View From London." *Bank of England Staff Working Paper,* no. 1103, https://www.bankofengland.co.uk/working-paper/2024/topography-of-the-fx-derivatives-market-a-view-from-london.

Hau, Harald, Peter Hoffmann, Sam Langfield, and Yannick Timmer. 2021. "Discriminatory Pricing of Over-the-Counter Derivatives." *Management Science* 67 (11): 6660–6677. https://doi.org/10.1287/mnsc.2020.3787.

Hendershott, Terrence, Dan Li, Dmitry Livdan, and Norman Schürhoff. 2020. "Relationship Trading in Over-the-Counter Markets." *The Journal of Finance* 75 (2): 683–734. https://doi.org/10.1111/jofi.12864.

International Monetary Fund. 2023. "Switzerland: 2023 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Switzerland." *IMF Staff Country Reports 2023,* no. 2023/196, https://doi.org/10.5089/9798400243127.002.

Jurkatis, Simon, Andreas Schrimpf, Karamfil Todorov, and Nicholas Vause. 2023. "Relationship Discounts In Corporate Bond Trading." *Bank of England Staff Working Paper,* no. 1049, https://www.bankofengland.co.uk/working-paper/2023/relationship-discounts-in-corporate-bond-trading.

Kloks, Peteris, Edouard Mattille, and Angelo Ranaldo. 2023. "Foreign Exchange Swap Liquidity." *SSRN Electronic Journal,* https://doi.org/10.2139/ssrn.4398052.

Moskowitz, Tobias J., Chase P. Ross, Sharon Y. Ross, and Kaushik Vasudevan. 2024. "Quantities and Covered-Interest Parity." *Finance and Economics Discussion Series,* nos. 2024-061, 1–93. https://doi.org/10.17016/feds.2024.061.

Olden, Andreas, and Jarle Møen. 2022. "The triple difference estimator." *The Econometrics Journal* 25 (3): 531–553. https://doi.org/10.1093/ectj/utac010.

Osler, Carol, Geir Bjonnes, and Neophytos Kathitziotis. 2016. "Bid-Ask Spreads in OTC Markets." Working Paper, accessed February 12, 2025. https://ideas.repec.org//p/brd/wpaper/102.html.

Siriwardane, Emil N., Adi Sunderam, and Jonathan Wallen. 2025. "Segmented Arbitrage." *The Journal of Finance,* https://doi.org/10.1111/jofi.13469.

SNB. 2023. "Financial Stability Report 2023." *Swiss National Bank,* accessed June 9, 2025. https://www.snb.ch/en/publications/financial-stability-report/2023/stabrep_2023.

Uppal, Rachna. 2023. "Credit Suisse's biggest backer says can't put up more cash; share down by a fifth." *Reuters,* accessed June 9, 2025. https://www.reuters.com/business/finance/credit-suisses-saudi-backer-happy-with-transformation-plan-doesnt-think-extra-2023-03-15/.

Wallen, Jonathan. 2022. "Markups to Financial Intermediation in Foreign Exchange Markets." Working Paper, https://www.hbs.edu/faculty/Pages/profile.aspx?facId=1284274.

A Data Cleaning

A.1 Price Cleaning and Maturity Panel Generation

The UK EMIR trade repository data contains two types of reports, activity and state reports. State reports contain trade-level information at date t for all trades that are outstanding at the end of date t. Activity reports contain information on all trades reported on date t. We use the state reports, which are useful for identifying outstanding relationships as these reports contain all outstanding positions. In addition, since there is a 24-hour reporting requirement, some trades can be executed on date t, but reported the next day at $t+1$. These trades appear in the activity reports for $t+1$. Using the state reports, we can identify all trades that were executed on a date but are still outstanding the next day.[63] Our choice to use the state reports primarily excludes intraday and very short-term newly executed trading activity. Since we are interested in documenting more persistent dealer-client trading relationships, we end up excluding trades that are not the focus of our analysis. So, our notional outstanding, notional traded, trade count outstanding, and trade count variables at t are calculated from trades executed on t and still outstanding on $t+1$.

We use the state reports associated with UK EMIR, which contain outstanding trades as of the end of each trading date from December 31, 2021 through December 31, 2023 for seven currency pairs: AUDUSD, CADUSD, CHFUSD, EURUSD, GBPUSD, JPYUSD, and NZDUSD. We restrict our sample to begin on January 1, 2022, but pull an additional month of data for December 2021 to construct any lagged variables for January 2022.

Using these trade-level data, we load one reporting day at a time. A reporting day, t, contains trades that were executed at $t-1$ but reported at t, in addition to those executed and reported at $t-1$ but still outstanding at t. We use these trades to measure notional amounts traded on execution date $t-1$. We define the trade date as the trade execution date. We use the state reports because UK legal entities have 24 hours to report their trades. So, if we only used the trades reported at t, we would miss the trades reported at $t+1$ and were executed at t.

To identify the trades to include in each maturity bucket for our maturity panel and obtain benchmark prices to compute trade-level spreads, we merge in a currency pair–maturity–date (c, m, t) panel of forward rates and settlement dates from Bloomberg.[64] To do this, we start with the Bloomberg panel, which contains forward rates and settlement dates for each (c, m, t) for maturities $m \in${1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 7m, 8m, 9m, 10m, 11m,

63. For example, to identify the trades executed at t and are still outstanding at $t+1$, we use the $t+1$ state reports.

64. The spread computation is described in Section 3.2.

12m} and currencies $c \in${AUDUSD, CADUSD, CHFUSD, EURUSD, GBPUSD, JPYUSD, NZDUSD}. In the Bloomberg panel, for each (c, m, t), we compute the days to maturity as the number of days between the settlement date and t. In the trade-level data, we compute days to maturity as the number of days between the maturity date and the execution date of the trade.[65] Then, we match trade execution date, currency pair, and days to maturity in the trade-level data on date, currency pair, and days to maturity in the Bloomberg forward rate panel. Since the Bloomberg panel contains the days to maturity for "on-maturity" trades, those with a standard maturity listed previously, we assign trades to a maturity bucket if they match with the Bloomberg panel for that standard maturity.[66]

Since we can match to the Bloomberg panel of forward rates, we use these as benchmark prices to compute spreads. Specifically, we have forward rates from Bloomberg, in units of USD to foreign currency, computed using the spot exchange rate and forward points for (c, m, t) observations. So, the Bloomberg benchmark prices, used to compute spreads, is at the (c, m, t) level and is the same for all trades with the same (c, m, t) characteristics. We use the maturity panel for any analysis of spreads, which are measured according to the description in Section 3.2.

Since we use trade repository data, there are errors or inconsistencies in the reported price units (e.g., some trades report prices as $\frac{\text{USD}}{\text{JPY}}$ and others as $\frac{\text{JPY}}{\text{USD}}$). To clean the price data, we do the following:

- In accordance with Article 3a of the Commission Implementing Regulation (EU) No 1247/2012 in case of FX swaps and forwards, the counterparty receiving the currency which is first when sorted alphabetically by ISO 4217 standard is identified as the buyer in the "counterparty side" field. In turn, this rule allows us to understand which counterparty buy or sell each currency.

- If both notional values for each leg exist in the trade report (the notional that the reporting counterparty gives and receives for each leg of the trade), we compute the

65. In the Bloomberg panel, we measure days to maturity using the date and not the settlement date of the spot trade. We do this to correctly identify the maturity bucket of a trade because days to maturity in the trade-level data is the difference between the maturity date and trade execution date. This is analogous to using date and not the settlement date of the spot trade in the Bloomberg panel.

66. For example, for the 1w maturity at date t, we keep trades that match days to maturity and currency pair for the 1-week Bloomberg observation, and drop those that do not exactly match the 1-week Bloomberg characteristics. So, for notional trading activity, suppose that the maturity date for a EURUSD 1-week trade in Bloomberg on date t is $t + 7$. In the trade-level data we keep EURUSD trades executed at t that mature at $t + 7$ for the 1w maturity. We exclude those that mature at $t + 8$ in the 1w maturity, for example, and drop these from the maturity panel but retain them for the all $\leq$ 1y maturity. For notional outstanding positions, the 1w maturity keeps positions with residual maturity equal to seven days. So, the positions that mature at $t + 7$. Similarly, we drop those that mature at $t + 8$, for example, but retain them for the all $\leq$ 1y maturity.

ratio of the notionals for the trade. Denote this by F_format_τ where τ denotes a trade and has dealer–client–currency pair–maturity–direction–date characteristics given by (d, i, c, m, dir, t).

- We replace the values of this variable with the reported price rate if one of the two notional values, one for each leg of the trade, is missing.

- Then, we normalize the values of the variable F_format_τ for all on maturities from Bloomberg (our Bloomberg buckets) to be in units of USD to foreign currency. To do this, we take the Bloomberg price for the (c, m, t) observation associated with trade τ, denoted by $F^*_{c(\tau),m(\tau),t(\tau)}$, which is in units $\frac{\text{USD}}{\text{Currency}}$. Then, we do the following.

  1. Compute $\mathit{Spread1} = \left|\frac{F\_format_\tau}{F^*_{c(\tau),m(\tau),t(\tau)}} - 1\right|$ and $\mathit{Spread2} = \left|\frac{F\_format_\tau^{-1}}{F^*_{c(\tau),m(\tau),t(\tau)}} - 1\right|$
  2. If $\mathit{Spread1} \geq 0.1$ and $\mathit{Spread2} < 0.1$, so the F_format_τ is greater than 10 percent (1000 basis points) larger than the Bloomberg price but its inverse is less than 10% larger from the Bloomberg price, take the inverse value of F_format_τ.
  3. If the opposite holds take F_format_τ, not its inverse.
  4. If neither Spread1 nor Spread2 are less than 10% larger than the Bloomberg price, set the price column to NA.[67]
  5. If it is the case that both Spread1 and Spread2 are less than 10% larger than the Bloomberg price, we take F_format_τ or its inverse conditional on which is closer to the Bloomberg price.[68]

  An alternative to this process could be to drop outliers before normalizing. However, there are cases where prices are correct, but the units are inverted. These would get dropped if we drop outliers. In addition, if we do not normalize the price units before aggregating our panel, we will be taking notional weighted averages of very different price values, depending on the currency pair (e.g. the JPYUSD).

In this price cleaning process, we first use the ratio of the notionals since they are more likely to be reported across all trades. In addition, the ratio of the notionals tends to be consistent with the reported price rate, when available.

We use our normalized forward price column, which is in units of $\frac{\text{USD}}{\text{Currency}}$ when computing our spread measures and their notional weighted averages. To compute the notional weighted

67. We checked the values for some of these cases and this restriction drops prices that are very incorrect (e.g., GBPUSD prices that are larger than 100 or 1000).

68. This occurs most often for the CHFUSD, GBPUSD, and EURUSD, which can get close to 1.

averages, we need a notional traded column associated with the observations for which we have cleaned prices and spreads. So, we include a column that is the notional of the observations in our formatted price (spread) panel and missing for all other trades. This variable is used when we take notional weighted averages of spreads in our analysis. We also have the all $\leq$ 1y maturity for which we download the notionals for all trades with maturity $\leq$ 1 year in our cleaned trade-level data, which is not restricted to the spread maturity panel. We note that we do not want to use these notionals to rescale and aggregate spreads. Instead, we use the all $\leq$ 1y maturity to have a larger coverage of trading quantities to measure relationships and gain a sense of data coverage.

When generating the all $\leq$ 1y maturity, we use information for trades (outstanding positions) on date t in currency pair c with maturity days (residual maturity for outstanding positions) less than or equal to the days to maturity of the associated 1-year Bloomberg observation.

A.2 Aggregating Dealer Entities

From the Bank of England, we have a mapping from LEI to client sector ("Sector Mapping"), which is generated from public and regulatory information. The list of client sectors includes but is not limited to dealers, banks, hedge funds, pension funds, insurers, non-financial corporates, asset managers, official, principal trading firms (PTFs), etc. In our data, we drop observations where the client sector is trading services (e.g., clearing house) or official (e.g., government organization). Using the sector mapping, we aggregate banks and dealers of the same parent institution where a dealer exists for our analysis.

First, there are some LEIs in the Sector Mapping that are identified as dealers but have missing names. We manually replace the names by searching the LEIs on the GLEIF website.

Next, we take the set of names for clients that are identified as dealers and generate "broad dealer names" from this set by performing various string cleaning steps, which are guided by visual inspection. So, for our set of LEIs in Sector Mapping with client sector equal to dealer, we clean the name column to capture the broad dealer name. For example, the broad dealer name will include assignments like "barclays", "bank of america", "morgan stanley", etc. We assign a single LEI to each broad dealer name ("Broad Dealer Name Mapping") as there may be multiple dealer LEIs in a broad entity and we wish to assign these to a single dealer, associated with the same broad parent entity.

So, Sector Mapping now contains LEI, name, and sector, and Broad Dealer Name Mapping contains an LEI for each broad dealer name. We clean the names in Sector Mapping and merge the broad dealer name column in Broad Dealer Name Mapping into Sector Mapping on the new formatted name column. To merge Broad Dealer Name Mapping and Sector Mapping, we fuzzy match using the fuzzywuzzy package in Python and, for each pair of broad dealer name and formatted name, we create two match measures: (i) ratio and (ii) partial ratio. Measure (i) uses the Levenshtein distance, testing whether the two strings are exactly the same. Measure (ii) instead compares the shorter of two strings to substrings of the longer string.[69] Specifically, we loop through each broad dealer name and for each, we compute the two fuzzy match measures, using only the beginning of the formatted names in Sector Mapping up to the length of the broad dealer name string.[70] We take the sum of the two measures, where the match measures are (i) ratio and (ii) partial ratio as before. Then, we generate a column that identifies whether the formatted name in Sector Mapping matched the broad dealer name. This column equals 1 if broad dealer name is missing (that is, the LEI is not classified as a dealer), and measure (i) is greater than or equal to 85, and the sum of measures (i) and (ii) is greater than or equal to 190, and this sum is greater than or equal to the score that the LEI received for its most recent best match. Then, we set the broad name column for the LEI to this broad dealer name if these conditions are satisfied. Note that we replace the broad name for the non-dealer LEIs with a new name if the sum of the two measures is greater than or equal to that of the previous dealers (and the other conditions are met).

The result is a full sector mapping with dealers identified and a broad name associated with each LEI (dealer and other sectors). The broad names are equal to the dealer broad names if they matched and if the LEI name did not match to a broad dealer name, the broad name is replaced with the LEI's formatted name. There is also a broad id column that is equal to the broad dealer name's LEI from the Broad Dealer Name Mapping. So, LEIs that matched with a dealer broad name have a broad id equal to the LEI assigned to the dealer broad name in Broad Dealer Name Mapping. If the LEI did not match to a dealer broad name, then the broad id is the original LEI.

We then aggregate all LEIs that are classified as dealer or bank to a single dealer entity by using the broad name and broad id that are assigned to them. This does not aggregate all banks that are affiliated with the same parent, but where the broad id does not have an affiliated dealer that is in our dealer set. The aggregation only aggregates banks and dealers where a dealer exists for the broad name, parent institution.

We drop activity between client LEIs where each side is taken by an LEI that is not

69. For example, if we compare the two strings "My car is blue" and "blue", measure (ii) will return 100% and measure (i) will not return 100% because these are not the same string.

70. We do this because there are many asset managers or funds that invest in or track particular securities or benchmarks associated with other broad entities, which appear later in the string. However, the name of the affiliated parent institution appears earlier in the string.

identified as a dealer. When we aggregate dealers and banks of the same parent institution, we drop trades that are between dealers and banks of the same aggregated dealer entity.[71] In our final cleaned dealer–counterparty–currency pair–maturity–date–direction panel, we have observations where the counterparty is also a dealer, but we drop these interdealer trades for our analysis. Interdealer activity is only included when we summarize daily average notional outstanding in Appendix D.1 Table 10 to give a sense of data coverage.

71. So, we drop any activity that is "intradealer" based on the aggregated dealer entity classification. That is, activity between two counterparties that are associated with the same aggregated dealer entity, where the aggregated dealer entity is composed of dealer and bank classified LEIs.

B Illustrative Multinomial Discrete Choice Model

B.1 Demand Side

A client i has a set of dealers with which they have paid the fixed cost to set up a formal relationship denoted by $\mathcal{D}_i$. Let $\mathcal{D}$ denote the set of all dealers.

We first model a client's choice to trade with a dealer d in their dealer set for trade τ in currency pair c, maturity m, and time t as a multinomial choice problem. We set up our model following Di Maggio, Egan, and Franzoni (2022), but we are interested explicitly in the bilateral relationship characteristics between dealers and clients rather than dealer-specific characteristics. Assume that each trade corresponds to one notional dollar. So, the client decides which dealer to trade with for each dollar that the client trades. The expected indirect utility that i gets for trading with dealer d for trade τ is

$$\mathbb{E}[u_{d,i,c,m,t,\tau}] = -\alpha_i spread_{d,i,c,m,t,\tau} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \xi_{d,i,c,m,t} + \epsilon_{d,i,c,m,t,\tau} \tag{17}$$

where $X_{d,i,c,t}$ is a vector of dealer–client–date and dealer–client–currency–date specific characteristics that capture the pair's bilateral trading relationships (e.g. the historical share of the client's notional traded with the dealer prior to t). The spread measures the difference in the log price of the trade from a benchmark log price, multiplied by a sign indicator to capture the cost the client pays on the trade. Thus, this equation states that the client gets lower utility from executing this trade τ with dealer d if they need to pay a larger spread relative to the benchmark and α_i captures client i's elasticity of demand to prices.

We can write this expected utility in terms of the average utility across trades and maturities as

$$\mathbb{E}[u_{d,i,c,m,t,\tau}] = \underbrace{-\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \zeta_{d,i,c,t}}_{\overline{u_{d,i,c,t}}} + \epsilon_{d,i,c,m,t,\tau} \tag{18}$$

Then the client's choice problem is to choose a dealer in its dealer set $\mathcal{D}_i = \{d_{i,1}, ..., d_{i,n_i}\}$ with which to trade to maximize their expected utility on the trade τ. As is standard in the literature that employs multinomial discrete choice frameworks, assume that $\epsilon_{d,i,c,m,t,\tau}$ is independently and identically distributed Type 1 Extreme Value. This allows us to write the probability that client i trades with dealer d for trade τ as in Equation 19.

$$P(Dealer = d) = \frac{\exp(-\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \zeta_{d,i,c,t})}{\sum_{d' \in \mathcal{D}_i} \exp(-\alpha_i \overline{spread}_{d',i,c,t} + X'_{d',i,c,t}\beta_i + \mu_{d',c,t} + \mu_{i,d'} + \zeta_{d',i,c,t})} \tag{19}$$

Then, we can use the share of notional traded by the client in the currency pair c and date t that is with the dealer to capture the probability that the client traded with this dealer for currency pair c and time period t, $s_{d,i,c,t}$. As in Berry (1994), we can take logs and write this as

$$\ln(s_{d,i,c,t}) = -\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \mu_{i,c,t} + \zeta_{d,i,c,t} \tag{20}$$

where the market fixed effect, $\mu_{i,c,t}$, absorbs the non-linear term from the denominator which is constant within client–currency pair–time period.

In Equation 20, we can see that the log market share is a linear function, where the betas capture the preference that the client puts on their bilateral relationship characteristics in vector $X_{d,i,c,t}$ with dealer d. α_i, can be used to rescale the β coefficients so that they can be interpreted in terms of basis points as in Di Maggio, Egan, and Franzoni (2022). So, $\frac{\beta_{i,k}}{\alpha_i}$ gives the client's willingness to pay for dealer–client–date (or dealer–client–currency–date) characteristic k in vector $X_{d,i,c,t}$ in terms of basis point additional cost in the spread.

B.2 Supply Side

We provide a simple supply side model to illustrate how markups for clients affect the spreads they pay at dealers and how a shock to the marginal cost at a dealer can affect spreads. Define a market at the client–currency pair–time level and assume dealers compete over this market. This model is standard and is similar in nature to Argentesi and Filistrucchi (2007), but where the dealer is only choosing a single price in its optimization problem. Assume that dealers choose prices to maximize their profits (e.g. Bertrand competition). Let $N_{i,c,t}$ denote the total notional dollars traded by client i in currency pair c at time t. Recall from Appendix B.1 that $s_{d,i,c,t}$ denotes the share of client i's notional dollars traded in currency pair c and time t that is with dealer d. This share will depend on the average spreads the client pays at dealer d and other dealers. Given these components, the total notional dollars traded by i with dealer d in market (c,t) is given by

$$N_{d,i,c,t} = N_{i,c,t} \times s_{d,i,c,t}\left(\overline{spread}_{d,i,c,t}, \overline{spread}_{-\mathbf{d},i,c,t}\right), \tag{21}$$

where $\overline{spread}_{d,i,c,t}$ denotes the average spread dealer d charges i in market (c,t) and $\overline{spread}_{-\mathbf{d},i,c,t}$ denotes the vector of average spreads that other dealers charge.

In addition, the dealer d faces a cost when trading each notional dollar. So total dollar costs that dealer d pays when trading notional amount $N_{d,i,c,t}$ is $C_d\big(N_{d,i,c,t}\big)$. Recall that $N_{d,i,c,t}$ is a function of the average spread that d and those of other dealers charge i in (c,t).

We take a "market" to be a client–currency pair–time period. Dealers compete on price over notional trading activity within this market. Dealer d chooses average spread, $\overline{spread}_{d,i,c,t}$, to maximize its profits taking into account that the average spread the dealer charges to the client affects the notional amount $N_{d,i,c,t}$

$$\max_{\overline{spread}_{d,i,c,t}} \left\{ N_{d,i,c,t} \times \overline{spread}_{d,i,c,t} - C_d(N_{d,i,c,t}) \right\} \tag{22}$$

Take the first-order condition, set it equal to 0 and solve for $\overline{spread}_{d,i,c,t}$. We recover

$$\overline{spread}_{d,i,c,t} = -\frac{N_{d,i,c,t}}{\left(\frac{\partial N_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}}\right)} + \frac{\partial C_d}{\partial N_{d,i,c,t}} \tag{23}$$

where the term $\frac{\partial C_d}{\partial N_{d,i,c,t}}$ is the marginal cost for dealer d trading in market (i, c, t). We can express the notionals for the dealer–client–currency pair–time period as in Equation 21. Market size terms will cancel in the numerator and denominator and we are left with

$$\overline{spread}_{d,i,c,t} = -\frac{s_{d,i,c,t}}{\left(\frac{\partial s_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}}\right)} + MarginalCost_{d,i,c,t} \tag{24}$$

From client demand in Equation 19, the elasticity of the dealer's market share at the client with respect to the average spread the dealer charges the client is

$$\frac{\partial s_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}} = -\alpha_i s_{d,i,c,t}(1 - s_{d,i,c,t}) \tag{25}$$

Combining Equations 24 and Equation 25, we recover an expression for the spread the dealer chooses to set for client i in market (i, c, t)

$$\overline{spread}_{d,i,c,t} = MarginalCost_{d,i,c,t} + \frac{1}{\alpha_i(1 - s_{d,i,c,t})} \tag{26}$$

where $s_{d,i,c,t}$ is the share of client i's notional dollars traded in (c, t) that is with dealer d, dealer d's "market share", and α_i is the demand elasticity for client i. The second term in this expression captures the markup that the dealer charges to the client and is increasing in the market share of the dealer and decreasing in the price sensitivity of the client.

C Measurement

C.1 Characteristics of Trading Relationships: Relationship Measures

This Appendix describes the measures of dealer-client relationships that we use in Section 4 and augment to the daily frequency for the spread panel regression analysis in that section. The regressions we run in Section 4 for Table 1 are at a weekly frequency. So, we present our measures in this appendix for the weekly frequency. To measure relationships, all independent variables in Tables 1 and 2, we use the all $\leq$ 1y maturity to capture as much activity between dealer-client pairs as possible and ensure that we do not miss valuable information about the existence and strength of relationships.

To test Hypothesis 1, that dealer-client trading relationships are persistent, we need measures of dealer-client relationship existence, recency, and client reliance on each dealer. We measure the existence of a relationship with a proxy for the existence of an ISDA, a contractual trading relationship between a dealer-client, at week t, denoted by an indicator $\mathbb{I}[HasISDA_{d,i,t-1}]$. $\mathbb{I}[HasISDA_{d,i,t-1}]$ equals 1 if the dealer and client have a positive trade count or positive outstanding position, in any currency pair, at any week from December 1, 2021 through week $t-1$ and zero otherwise. We also construct an indicator $\mathbb{I}[Only1ISDA_{i,t-1}]$, which equals 1 if the client only had one dealer where the indicator $\mathbb{I}[HasISDA_{d,i,t-1}]$ equals 1. This is to capture that clients with a single contractual relationship have no alternative trading option and would need to pay the fixed cost of relationship creation to trade with a different dealer.

To capture whether the relationship has been used or existed in the recent past, we create an indicator $\mathbb{I}[HasOut_{d,i,t-1}]$, which equals 1 if the dealer-client pair had an outstanding position in any currency pair in our sample in the last 4 weeks, from week $t-4$ through week $t-1$, and zero otherwise. We also compute an indicator $\mathbb{I}[Only1Dealer_{i,t-1}]$ that equals 1 if the client, i, had only one existing dealer relationship in the last 4 weeks, measured by client i having $\mathbb{I}[HasOut_{d,i,t-1}]$ equal to 1 for only one dealer at week t. We use the indicator $\mathbb{I}[Only1Dealer_{i,t-1}]$ to distinguish between having a single dealer ISDA relationship versus having more dealer relationships, but only using one in the recent past.

We compute two measures of client reliance on a dealer (relationship strength). Specifically, we measure (i) the dealer-client pair's total notional trading activity in the last 4 weeks as a share of the client's total notional traded over those 4 weeks, $RelStrClientNDay_{d,i,t}$, and (ii) the dealer-client pair's total notional outstanding positions in the last 4 weeks as a share of the client's total notional outstanding positions over those 4 weeks, $RelStrClientNOut_{d,i,t}$.

Let $NDay_{d,i,t}$ ($NOut_{d,i,t}$) denote the sum of notional traded (outstanding) between dealer d and client i across days and currency pairs in week t. The dealer–client–week specific measures are presented in Equations 27 and 28, respectively.

$$RelStrClientNDay_{d,i,t} = \frac{\sum_{l=t-4}^{t-1} NDay_{d,i,l}}{\sum_{l=t-4}^{t-1} \sum_{m\in\mathcal{D}} NDay_{m,i,l}} \times 100 \tag{27}$$

$$RelStrClientNOut_{d,i,t} = \frac{\sum_{l=t-4}^{t-1} NOut_{d,i,l}}{\sum_{l=t-4}^{t-1} \sum_{m\in\mathcal{D}} NOut_{m,i,l}} \times 100 \tag{28}$$

where $\mathcal{D}$ denotes the complete set of dealers so that the denominator of each computation is the sum of the client's corresponding notional variable across all dealers and lagged weeks. Note that the weekly value of a variable is the sum of the variable across days for the week.

To test Hypothesis 2, the characteristics of bilateral dealer-client trading relationships, we need measures of currency-specific and directional relationships. We use an indicator variable $\mathbb{I}[HasOut_{d,i,c,t-1}]$ to denote whether the dealer-client pair had an outstanding position from week $t-4$ through $t-1$, specifically in currency pair c. As discussed in Section 4, we use this to test whether clients are more likely to trade a currency pair with dealers that they had recently used to trade that same currency pair, above and beyond just having a recent relationship in any currency pair.

We also define a variable $NetUSDPosition_{d,i,t-1}$, which is a categorical variable that denotes whether the dealer-client pair had a net outstanding position over all currency pairs from week $t-4$ through $t-1$ such that the client was (i) net selling USD, (ii) net buying USD, or (iii) neither.[72] We note that the "neither Buy nor Sell" category captures two groups: (i) the net position is 0 and thus completely offset and (ii) the dealer-client pair had no outstanding positions in the lagged 4 weeks.

To test Hypothesis 3, we use the same relationship variables as above with two adjustments. First, since the spread regressions are at a daily frequency, we compute our dependent variables at the daily frequency and using a 22 trading day lag period for variables computed over the last month. That is, from $t-22$ through $t-1$, where t denotes a day. The second adjustment is that we use an independent variable $I[NetUSDOut_{d,i,c,m,t,dir} = dir]$, an indicator equal to 1 if the spread dependent variable, which is at the (dealer, client, currency, maturity, date, USD trading direction of the client) level in the regression specification that

72. We first take the daily notional outstanding for dealer d and client i for each currency pair, keeping the buy USD and sell USD positions separate, and sum the outstanding positions for dealer d and client i across currencies and dates in week t for each direction. This gives us for each week t, the total notional outstanding Buy USD position for (d, i) and their total notional outstanding Sell USD position. We compute the net position by taking the difference of these values for each week t. We then take the sum of the net position across weeks $t-4$ through $t-1$ and define the categories of $NetUSDPosition_{d,i,t-1}$ accordingly.

uses $I[NetUSDOut_{d,i,c,m,t,dir} = dir]$, has the same direction as the client's net USD outstanding position between the dealer and client for the all $\leq$ 1y maturity over the last month, $t-22$ to $t-1$. The total net USD outstanding position of the client is computed as the sum of notionals of all outstanding trades with the dealer from $t-22$ to $t-1$ where the client is buying USD forward, less that where the client is selling USD forward. In robustness Table 21 in Appendix E.3 we include two controls for the size of trading activity at the unit of observation for the regression panels, $Ln(Notional\ Traded)$ and $Trade\ Count$. For regressions where the spread dependent variable is at the dealer–client–currency–maturity–date level, $TradeCount$ ($Ln(Notional\ Traded)$) is the total trade count (natural log of total notional traded) between the dealer d and client i, in the currency pair c and maturity m, on the date t. When the spread dependent variable is at the dealer–client–currency–maturity–date level, $TradeCount$ ($Ln(Notional\ Traded)$) are instead aggregated to this level of observation.

Finally, when testing Hypotheses 1 and 2, using our weekly regressions in Table 1, the dependent variable for columns (1)–(5) is $\mathbb{I}[Traded_{d,i,t}]$ which is an indicator that equals 1 if the dealer and client had a positive notional traded amount in the all $\leq$ 1y maturity in week t, in any currency pair. For column (6), since the regression is at the dealer–client–currency–date level, the dependent variable is $\mathbb{I}[TradedCCY_{d,i,c,t}]$, which is an indicator that equals 1 if the dealer and client had a positive notional traded amount in the all $\leq$ 1y maturity in week t, specifically for currency pair c. For these regressions, since we are studying clients' choice of dealer counterparty, the sample takes each client–week observation where the client actively traded and fills the set of dealers that were active (i.e., had a positive notional outstanding position or a positive trade count) at any point between December 1, 2021 and week t. Similarly, for column (6) of Table 1, we fill the set of dealers for each client–currency–week where the client actively traded.

When testing Hypothesis 3, our dependent variable is the notional weighted average spread across all trades at the unit of observation for the panel. In all columns the unit of observation is dealer–client–currency–maturity–date, except column (5), which is at the dealer–client–currency–maturity–date–direction level. So, for example, the dependent variable in our dealer–client–currency–maturity–date regressions, $Spread_{d,i,c,m,t}$, is the notional weighted average spread across trades with the same dealer, client, currency, maturity, and date. The measurement of trade-level spreads is as defined in Section 3.2.

C.2 Pre-Existing Relationship Strength and Credit Suisse Trading Activity: Relationship Measures

One of our measures, denoted $\mathbb{I}[OneDealer_i]$, is an indicator equal to 1 if the client had an outstanding position or trade count in the out-of-sample pre-period with a single dealer. That is, the client had one relationship. Additional relationship strength measures that we compute are presented in Equations 29 and 30 and are used to test Hypotheses 5 and 6, respectively. $\mathcal{D}$ denotes the full set of dealers and $\mathcal{I}$ of clients. *OutOfSample* denotes the set of trading dates in the out-of-sample pre-period. Equation 29 (30) is the percent of client i's (dealer d's) notional traded activity in the out-of-sample pre-period that is with dealer d (client i). Superscripts in Equations 29 and 30 denote whether the measure is from the perspective of the client (i) or dealer (d). We compute these measures over EURUSD activity since Section 4 showed that relationships have a currency-specific component.[73] We compute a set of measures using notional trading activity and another set using notional outstanding positions. The measures that use notional trading activity will include a term $NDay$ and those computed using notional outstanding positions will include the term $NEver$.

$$RelStrNDay^{(i)}_{d,i} = 100 * \frac{\sum_{t \in OutOfSample} NDay_{d,i,t}}{\sum_{t \in OutOfSample} \sum_{d \in \mathcal{D}} NDay_{d,i,t}} \tag{29}$$

$$RelStrNDay^{(d)}_{d,i} = 100 * \frac{\sum_{t \in OutOfSample} NDay_{d,i,t}}{\sum_{t \in OutOfSample} \sum_{i \in \mathcal{I}} NDay_{d,i,t}} \tag{30}$$

From these relationship strength measures, we define indicator variables that identify whether a dealer-client pair (d, i) have a strong relationship. These indicators equal 1 for pair (d, i) when the corresponding measure of relationship strength is above the cross-client median within the dealer, d. This cross-client median is taken over the set of clients with which dealer d had a positive EURUSD notional trading position in the pre-period. The definition of this indicator is given explicitly for the case of $RelStrNDay^{(i)}_{d,i}$ in Equation 31.

$$\mathbb{I}[StrongRel_{d,i}] = \begin{cases} 1 & \text{if } RelStrNDay^{(i)}_{d,i} > Median_{i \in \mathcal{J}_d}(RelStrNDay^{(i)}_{d,i}) \\ 0 & \text{otherwise} \end{cases} \tag{31}$$

for $\mathcal{J}_d = \{i \text{ s.t. } NDay_{d,i,EURUSD,t} > 0 \text{ for a t } \in PrePeriod\}$. If $\mathbb{I}[StrongRel_{d,i}] = 1$, the interpretation is that the client relied more heavily on dealer d than other clients of d.

73. We also compute the relationship measure $RelStrNDay^{(i)}_{d,i}$ across activity in all seven currency pairs in our data for robustness and present the results for regression Equation 9 using this measure in Appendix H.

D Descriptive Statistics: Tables and Figures

D.1 Daily Average Notional Outstanding By Currency

Table 10: Average Daily Notional Outstanding for 2023S2 by Currency, All $\leq$ 1y Maturity

	(1) Daily Average Notional, USD Billions	N
USD	12,526.54	121
AUD	801.33	121
CAD	813.53	121
CHF	929.40	121
EUR	4,330.21	121
GBP	2,689.79	121
JPY	2,734.96	121
NZD	227.31	121

Notes: This table displays the daily average total notional outstanding by currency in our sample for the period of July 01, 2023 through December 31, 2023, 2023S2, referenced in Section 3.3. Each row displays the daily average for the all $\leq 1y$ maturity using outstanding trades that involved that currency. The USD row displays the value using outstanding positions for all currency pairs since they are bilateral to the USD. The sample includes both dealer-client and inter-dealer trades, but excludes client-client activity and activity between the same aggregated dealer entity. N denotes the number of days used in the daily average.

D.2 Statistics by Client Sector

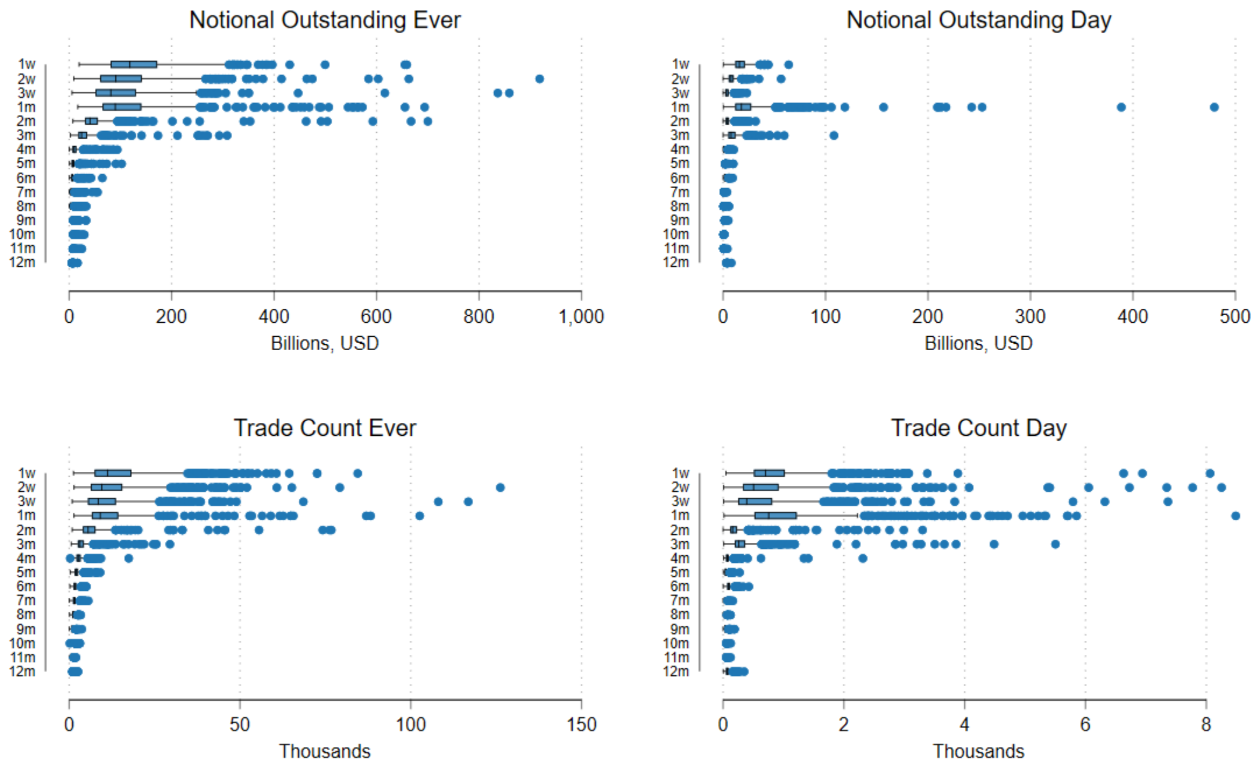
Table 11: Client-Sector Trading Activity Statistics, All $\leq$ 1y Maturity

	Client Count	% Notional Volume	X-Client Average % Days Traded
Asset Manag.	7,635.00	15.84	15.17
Bank	661.00	21.94	29.58
HF	446.00	23.03	35.02
Insurer	373.00	2.87	14.07
Non-Fin.	1,400.00	4.05	11.59
Other Fin.	392.00	15.79	23.27
PTF	11.00	0.52	30.98
Pension	1,035.00	4.51	16.56

Notes: This table provides summary statistics of trading activity by client sector for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.3. *Client Count* is the count of client LEIs in each sector. *% Notional Volume* is the percent of dealer-client total notional volume in USD traded by clients in that sector over the two-year period. These percents do not sum to 100 since there are some clients for which we do not have a sector mapping. *X-Client Average % Days Traded* is the within-sector cross-client mean of the percent of trading days that the client had a positive trade count in any of our seven currency pairs. The sample is the set of dealer–client–date observations with a positive trade count in the all $\leq$ 1y maturity.

D.3 Maturity Panel: Activity Distributions

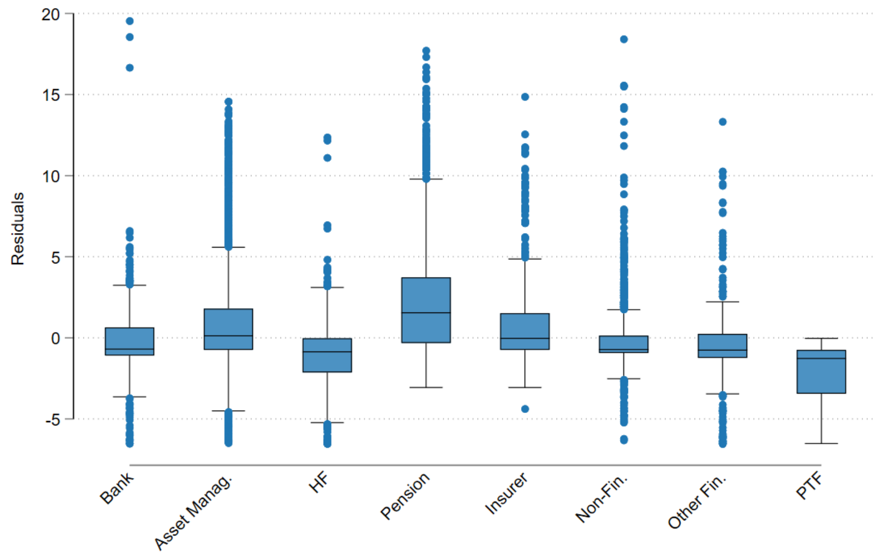
Figure 3: Distribution of Activity Variables Across Dates by Maturity



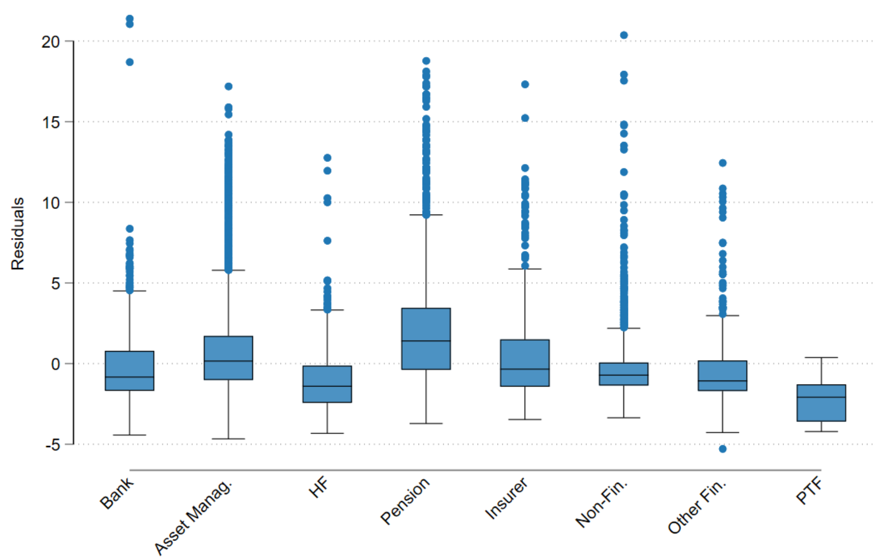
Notes: This figure plots the distributions of total dealer-client activity across dates by maturity, for four trading activity variables, for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.1. *Notional Outstanding Ever* is the total notional outstanding position across trades that are still outstanding at date t. *Notional Outstanding Day* is the total notional traded across trades that were executed at date t and are still outstanding the next trading day. *Trade Count Ever* is the total trade count across trades that are still outstanding at date t. *Trade Count Day* is the total trade count across trades that were executed at date t and still outstanding the next trading day. The sample uses our maturity panel, described in Section 3 and which excludes the all $\leq$ 1y maturity, and uses the total of the corresponding activity variable across all currency pairs with the same maturity.

D.4 Dealer Count Residual Plots

Figure 4: Distribution of Residual from $DealerCount_i = \alpha + \beta X_i + \epsilon_i$ by Client Sector



(a) $X_i = DaysTraded_i$

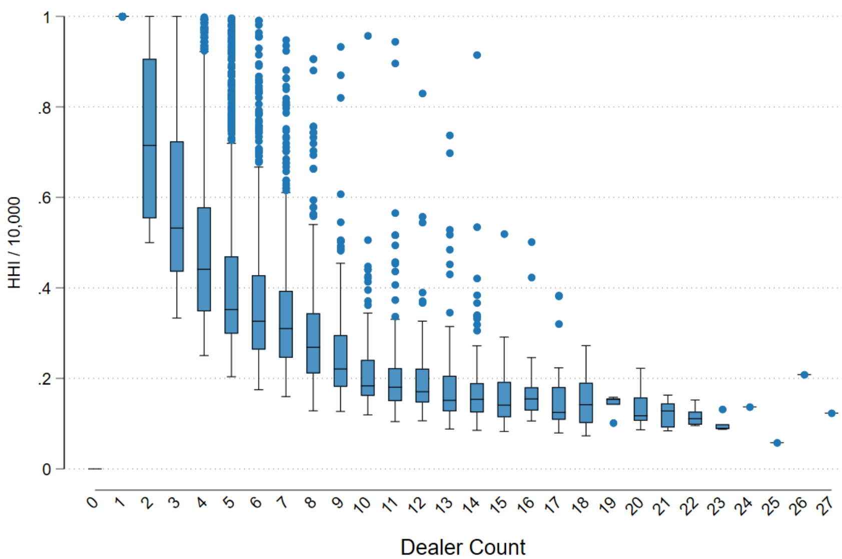


(b) $X_i = \ln(TotalNotionalTraded_i)$

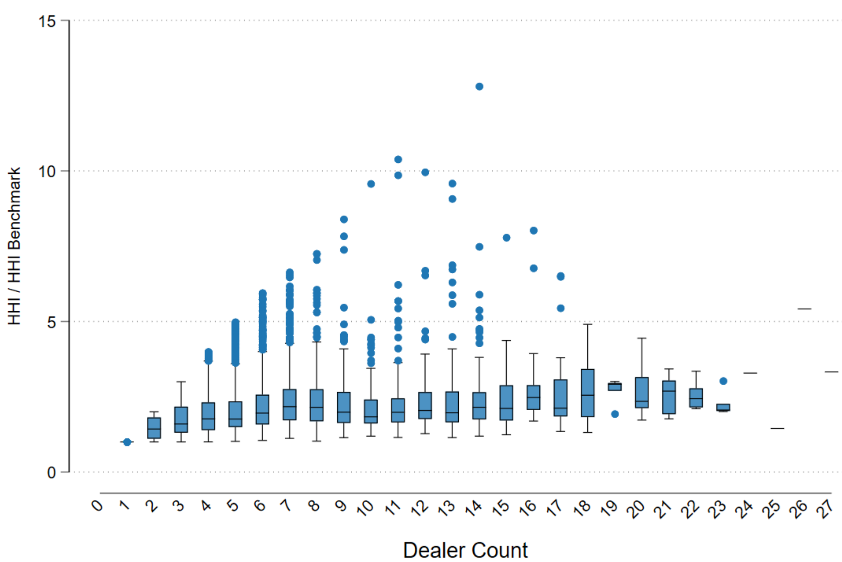
Notes: These figures plot the residual of a cross-client linear regression of dealer count on a control for client-level trading activity for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.3. The cross-client regression is $DealerCount_i = \alpha + \beta X_i + \epsilon_i$. Dependent variable, $DealerCount_i$, is the count of dealers with which the client traded. Figure 4a plots the residual, ϵ_i, where the independent variable, X_i, is the count of days on which client i traded. Figure 4b plots the residual where the independent variable is instead the natural log of total notional traded by the client across all seven currency pairs, $\ln(TotalNotionalTraded_i)$. The residuals are plotted by sector. The sample uses all non-dealer clients.

D.5 Client-Level Concentration of Trading Activity by Dealer Count

Figure 5: Distribution of Notional Traded HHI Measures Across Clients by Dealer Count



(a) HHI_i



(b) $\frac{HHI_i}{EqualDistribHHI}$ by $DealerCount_i$.

Notes: This figure plots the cross-client distribution of trading concentration across dealers by dealer relationship count for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.3. *Dealer Count* is the count of dealers that the client traded with over the period. *HHI* is the Herfindahl–Hirschman Index, computed from the client's total notional traded with each dealer across all currency pairs for the all $\leq$ 1y maturity. Figure 5a plots client-level HHI, which is divided by 10,000 so concentration in a single dealer is denoted by an HHI of 1. Figure 5b, plots the ratio of the client's HHI to the equally distributed HHI benchmark for that dealer count.

D.6 Client-Level Statistics

Table 12: Client-Level Descriptive Statistics, All $\leq$ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	26839	6,461.87	141,906.52	0.49	5.09	63.64	644.02	4,011.93
Total Trade Count	26839	461.34	6,456.33	2.00	5.00	24.00	110.00	419.00
% Days Traded	26839	10.89	19.94	0.21	0.62	2.67	10.08	33.33
Currency Count	26839	2.26	1.92	1.00	1.00	1.00	3.00	6.00
Dealer Count	26839	2.39	2.50	1.00	1.00	1.00	3.00	5.00
% Notional With Main Dealer	26839	84.54	23.33	44.48	68.84	100.00	100.00	100.00
HHI, X-Dealer	26839	0.80	0.28	0.33	0.55	1.00	1.00	1.00
Average Dealer Count, Active Days	26839	1.08	0.29	1.00	1.00	1.00	1.03	1.24

Notes: This table provides client-level statistics of trading activity in the all $\leq$ 1y maturity for the period of January 1, 2022 through December 31, 2023, referenced in Sections 3.3 and 5.3.3. *Total Notional Volume* (*Total Trade Count*) is the sum of notional traded (daily trade count) by the client across all currency pairs. *% Days Traded* is the percent of dates where the client had a positive trade count, where the total number of dates in the sample is 505. *Currency Count* is the unique count of currencies in which the client traded. *Dealer Count* is the unique count of dealers with which the client traded. *% Notional With Main Dealer* is the percent of total notional traded by the client that was accounted for by the largest dealer in the client's trading portfolio. *HHI*, *X-Dealer* measures the HHI, normalized by 10,000, of the client's total notional traded across dealers. *Average Dealer Count*, *Active Days* gives the average count of dealers with which the client traded on days when the client traded. We use dealer–client–currency pair–date observations with a positive trade count to aggregate to the client level.

Table 13: Client-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	15897	2,071.00	22,492.61	0.83	4.98	44.61	327.78	1,749.84
% Days Traded	15897	3.70	8.71	0.21	0.41	1.03	3.09	8.85
Currency Count	15897	2.16	1.79	1.00	1.00	1.00	3.00	5.00
Dealer Count	15897	2.16	2.02	1.00	1.00	1.00	3.00	5.00
Average Dealer Count, Active Days	15897	1.07	0.23	1.00	1.00	1.00	1.00	1.24

Notes: This table provides client-level statistics of trading activity in our maturity panel, described in Section 3, for the period of January 1, 2022 through December 31, 2023. *Total Notional Volume* (*Total Trade Count*) is the sum of notional traded (daily trade count) by the client across all currency pairs. % *Days Traded* is the percent of dates where the client traded in the maturity panel, where the total number of dates in the sample is 505. *Currency Count* is the unique count of currencies in which the client traded. *Dealer Count* is the unique count of dealers with which the client traded. % *Notional With Main Dealer* is the percent of total notional traded by the client that was accounted for by the largest dealer in the client's trading portfolio. *HHI*, *X-Dealer* measures the HHI, normalized by 10,000, of the client's total notional traded across dealers. *Average Dealer Count*, *Active Days* gives the average count of dealers with which the client traded on days when the client traded in the maturity panel. We use dealer–client–currency pair–maturity–date observations with a non-missing spread to aggregate to the client level.

D.7 Dealer–Client–Date-Level Statistics

Table 14: Dealer–Client–Date-Level Descriptive Statistics, All ≤ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	1890718	91.73	1,046.01	0.06	0.34	2.19	17.25	118.97
Total Trade Count	1890718	6.55	40.88	1.00	1.00	2.00	4.00	9.00
Currency Count	1890718	1.53	1.18	1.00	1.00	1.00	2.00	3.00
% Client's Previous Notional	1607334	54.25	40.14	2.42	12.64	51.63	100.00	100.00
% Dealer's Previous Notional	1607334	0.47	3.57	0.00	0.00	0.01	0.07	0.43

Notes: This table provides dealer–client–date-level statistics of trading activity in the all ≤ 1y maturity for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.3. *Total Notional Volume* (*Total Trade Count*) is the sum of notional traded (daily trade count) between the dealer and client across all currency pairs at date t. *Currency Count* is the unique count of currencies in which the dealer and client traded at date t. % *Client's* (*Dealer's*) *Previous Notional* gives the percent of the client's (dealer's) notional traded in the last 22 trading days that was with the dealer (client). We use dealer–client–currency pair–date observations with a positive trade count to aggregate to the dealer–client–date level.

D.8 Dealer-Level Statistics

Table 15: Dealer-Level Descriptive Statistics, All $\leq$ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	48	3,613,130.24	8,792,404.89	471.07	19,783.58	127,544.77	2,863,177.38	7,327,440.99
Total Trade Count	48	257,958.12	718,257.16	35.00	1,855.50	8,412.50	122,803.50	641,876.00
Currency Count	48	6.15	1.95	2.00	7.00	7.00	7.00	7.00
Client Count	48	1,337.19	2,542.95	2.00	25.50	143.50	1,118.00	6,287.00
% Notional With Main Client	48	36.20	29.05	7.97	15.02	22.19	52.79	97.35
% Notional With Median Client	48	11.14	28.94	0.00	0.00	0.04	1.21	50.00
HHI, X-Client	48	0.25	0.30	0.02	0.04	0.11	0.35	0.95
Average Client Count, Active Days	48	81.42	175.43	1.00	2.08	5.93	50.08	330.51

Notes: This table provides dealer-level statistics of dealer-client trading activity in the all $\leq$ 1y maturity for the period of January 1, 2022 through December 31, 2023. *Total Notional Volume* (*Total Trade Count*) is the sum of notional traded (daily trade count) by the dealer across all currency pairs. *Currency Count* is the unique count of currencies in which the dealer traded. *Client Count* is the unique count of clients with which the dealer traded. *% Notional With Main Client* is the percent of total notional traded by the dealer that was accounted for by the largest client in the dealer's trading portfolio. *% Notional With Median Client* gives the cross-client median share of the dealer's notional traded across clients that traded a positive notional with the dealer. *HHI*, *X-Client* measures the HHI, normalized by 10,000, of the dealer's total notional traded across clients. *Average Client Count*, *Active Days* gives the average count of clients with which the dealer traded on days when the dealer traded. We use dealer–client–currency pair–date observations with a positive trade count to aggregate to the dealer level.

Table 16: Dealer-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	44	748,241.38	1,645,684.93	1,497.50	6,587.53	25,617.76	564,234.26	2,317,187.04
Currency Count	44	6.07	1.76	3.00	6.00	7.00	7.00	7.00
Client Count	44	780.09	1,449.19	3.00	19.00	115.50	710.50	3,505.00
Average Client Count, Active Days	44	16.97	34.75	1.00	1.23	2.12	10.27	55.07

Notes: This table provides dealer-level statistics of dealer-client trading activity in our maturity panel, described in Section 3, for the period of January 1, 2022 through December 31, 2023. *Total Notional Volume* is the sum of notional traded by the dealer across all currency pairs. *Currency Count* is the unique count of currencies in which the dealer traded. *Client Count* is the unique count of clients with which the dealer traded. *Average Client Count, Active Days* gives the average count of clients with which the dealer traded on days when the dealer traded in the maturity panel. We use dealer–client–currency pair–maturity–date observations with a non-missing spread to aggregate to the dealer level.

D.9 Dealer–Client–Currency–Maturity–Date-Level Statistics

Table 17: Dealer–Client–Currency–Maturity–Date-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Panel A: AUDUSD								
NW Spread (d,i,c,m,t)	50986	0.50	56.51	-53.36	-22.19	0.26	23.16	54.97
NW Spread, Client Buy USD	27391	2.41	56.73	-53.50	-22.33	1.20	25.75	59.47
NW Spread, Client Sell USD	28061	-1.52	61.56	-61.05	-26.00	-0.02	24.62	55.68
Total Notional, USD Millions	50986	44.30	158.46	0.05	0.38	2.78	21.81	99.52
Maturity Days	50986	43.05	60.54	7.00	14.00	30.00	30.00	90.00
# Observations Per Client	3740	13.63	39.90	1.00	1.00	4.00	10.00	31.00
# Observations Per Dealer	36	1,416.28	2,811.11	7.00	16.00	71.00	1,076.00	6,649.00
Panel B: CADUSD								
NW Spread (d,i,c,m,t)	30376	0.26	33.00	-31.83	-13.48	0.18	13.79	31.91
NW Spread, Client Buy USD	15229	0.32	33.52	-31.97	-13.84	0.54	14.31	35.13

NW Spread, Client Sell USD	17630	-0.07	34.43	-33.95	-15.38	0.17	14.80	31.15
Total Notional, USD Millions	30376	47.88	181.02	0.06	0.49	3.63	22.25	100.14
Maturity Days	30376	42.56	63.52	7.00	7.00	21.00	30.00	90.00
# Observations Per Client	3088	9.84	27.24	1.00	1.00	3.00	7.00	20.00
# Observations Per Dealer	38	799.37	2,081.32	1.00	4.00	42.00	297.00	2,410.00

Panel C: CHFUSD

NW Spread (d,i,c,m,t)	33191	1.31	43.42	-37.35	-15.43	0.48	17.82	41.00
NW Spread, Client Buy USD	18536	1.48	40.06	-38.99	-13.88	2.95	20.33	40.72
NW Spread, Client Sell USD	17532	1.24	53.14	-39.26	-18.92	-1.17	16.70	45.16
Total Notional, USD Millions	33191	62.83	203.56	0.02	0.37	4.89	40.00	161.34
Maturity Days	33191	45.21	62.07	7.00	14.00	30.00	30.00	90.00
# Observations Per Client	2569	12.92	51.92	1.00	1.00	3.00	10.00	27.00
# Observations Per Dealer	36	921.97	1,842.21	3.00	7.50	39.00	693.50	4,001.00

Panel D: EURUSD

NW Spread (d,i,c,m,t)	184290	0.35	45.42	-42.08	-16.28	0.31	16.78	42.81
NW Spread, Client Buy USD	97482	0.57	51.62	-45.17	-16.64	1.29	19.31	45.64
NW Spread, Client Sell USD	109899	-0.27	52.42	-44.10	-18.23	-0.20	17.48	45.92
Total Notional, USD Millions	184290	66.83	340.08	0.04	0.34	2.51	21.77	114.24
Maturity Days	184290	52.82	73.55	7.00	14.00	30.00	60.00	150.00
# Observations Per Client	9439	19.52	102.22	1.00	2.00	4.00	14.00	38.00
# Observations Per Dealer	42	4,387.86	9,946.41	7.00	65.00	283.50	1,968.00	13,999.00

Panel E: GBPUSD

NW Spread (d,i,c,m,t)	145609	1.54	56.56	-44.32	-17.00	0.86	19.80	48.03
NW Spread, Client Buy USD	77033	1.24	73.54	-50.50	-19.11	0.70	20.42	49.08
NW Spread, Client Sell USD	83929	2.35	59.86	-44.37	-17.78	1.49	21.53	52.12
Total Notional, USD Millions	145609	56.80	280.43	0.02	0.20	1.76	16.03	102.07
Maturity Days	145609	51.35	71.31	7.00	14.00	30.00	60.00	120.00
# Observations Per Client	9133	15.94	74.85	1.00	2.00	4.00	12.00	34.00
# Observations Per Dealer	44	3,309.30	7,361.80	2.00	85.50	334.00	2,922.00	9,814.00

Panel F: JPYUSD

NW Spread (d,i,c,m,t)	56410	0.75	49.42	-47.43	-18.05	0.36	19.24	48.03
NW Spread, Client Buy USD	30070	2.93	51.67	-48.98	-14.41	3.70	25.21	51.99

NW Spread, Client Sell USD	31963	-1.49	53.41	-51.88	-25.17	-2.80	16.79	51.56
Total Notional, USD Millions	56410	104.40	397.40	0.15	1.00	6.77	50.45	245.63
Maturity Days	56410	48.29	67.57	7.00	14.00	30.00	60.00	90.00
# Observations Per Client	4570	12.34	47.83	1.00	1.00	3.00	8.00	22.00
# Observations Per Dealer	35	1,611.71	4,015.11	5.00	12.00	50.00	1,096.00	4,170.00

Panel G: NZDUSD

NW Spread (d,i,c,m,t)	20637	-1.44	57.31	-53.55	-21.08	0.03	21.31	51.95
NW Spread, Client Buy USD	11412	-1.11	65.46	-55.24	-21.66	1.84	24.23	57.56
NW Spread, Client Sell USD	11148	-1.19	51.55	-57.30	-23.86	-0.08	22.54	53.68
Total Notional, USD Millions	20637	31.42	102.24	0.11	0.51	2.54	14.16	70.63
Maturity Days	20637	40.63	61.41	7.00	14.00	21.00	30.00	90.00
# Observations Per Client	1867	11.05	25.49	1.00	1.00	3.00	9.00	29.00
# Observations Per Dealer	36	573.25	1,131.38	1.00	2.00	22.00	378.50	2,657.00

Notes: This table provides statistics of dealer–client–currency pair–maturity–date-level (d, i, c, m, t) trading activity in our maturity panel, described in Section 3, for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.2. Each sub-panel presents the distribution of the corresponding variable across observations for that currency pair. Trade-level spreads are calculated as described in Section 3.2. *NW Spread* (d, i, c, m, t) is the notional weighted average spread across trades between dealer d and client i in currency pair c and maturity m on date t. *NW Spread, Client Buy (Sell) USD* is the notional weighted average spread across trades between dealer d and client i in currency pair c and maturity m on date t where the client is buying (selling) USD forward. *Total Notional, USD Millions* is the total notional traded across trades between dealer d and client i in currency pair c and maturity m on date t, for trades with spread information. *Maturity Days* is the days to maturity corresponding to the (d, i, c, m, t) observation, which we set to standard dates for simplicity (e.g., 1-month is 30 days). *# Observations Per Client (Dealer)* is the count of (d, i, c, m, t) observations per client (dealer), and is at the client (dealer) level.

D.10 Client–Currency-Level Statistics

Table 18: Client–Currency-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Panel A: AUDUSD								
NW Spread	3740	3.25	49.62	-33.84	-14.44	1.58	17.48	38.54
NW Maturity Days	3740	45.00	52.25	9.98	18.14	29.67	55.43	90.00
% of Days with Spread	3740	2.39	5.70	0.21	0.21	0.62	1.85	5.76
Maturity Count	3740	2.68	2.06	1.00	1.00	2.00	4.00	5.00
Dealer Count	3740	1.95	1.52	1.00	1.00	1.00	2.00	4.00
(d,i,c,m,t) Observations per (i,c)	3740	13.63	39.90	1.00	1.00	4.00	10.00	31.00
Panel B: CADUSD								
NW Spread	3088	-0.10	22.42	-23.76	-9.41	-0.38	9.48	20.69
NW Maturity Days	3088	37.07	39.32	7.00	14.11	26.93	38.81	89.81
% of Days with Spread	3088	1.81	4.20	0.21	0.21	0.62	1.44	3.91
Maturity Count	3088	2.54	1.97	1.00	1.00	2.00	3.00	5.00
Dealer Count	3088	1.63	1.15	1.00	1.00	1.00	2.00	3.00
(d,i,c,m,t) Observations per (i,c)	3088	9.84	27.24	1.00	1.00	3.00	7.00	20.00
Panel C: CHFUSD								
NW Spread	2569	1.61	31.19	-26.77	-9.91	1.11	13.88	28.65
NW Maturity Days	2569	44.21	44.36	11.80	20.29	29.87	60.00	90.00
% of Days with Spread	2569	2.24	5.27	0.21	0.21	0.62	1.85	5.35
Maturity Count	2569	2.64	2.03	1.00	1.00	2.00	4.00	5.00
Dealer Count	2569	1.75	1.38	1.00	1.00	1.00	2.00	3.00
(d,i,c,m,t) Observations per (i,c)	2569	12.92	51.92	1.00	1.00	3.00	10.00	27.00
Panel D: EURUSD								
NW Spread	9439	0.72	47.98	-25.60	-9.95	-0.09	9.27	25.80
NW Maturity Days	9439	49.74	53.82	10.96	21.00	29.96	66.12	90.00

% of Days with Spread	9439	3.00	6.89	0.21	0.41	0.82	2.67	7.20
Maturity Count	9439	3.03	2.28	1.00	1.00	2.00	4.00	6.00
Dealer Count	9439	2.01	1.69	1.00	1.00	1.00	2.00	4.00
(d,i,c,m,t) Observations per (i,c)	9439	19.52	102.22	1.00	2.00	4.00	14.00	38.00
Panel E: GBPUSD								
NW Spread	9133	3.38	45.25	-27.19	-9.95	1.59	15.28	33.75
NW Maturity Days	9133	53.35	56.88	12.23	21.00	30.00	76.89	90.00
% of Days with Spread	9133	2.56	5.85	0.21	0.41	0.82	2.26	6.17
Maturity Count	9133	2.89	2.22	1.00	1.00	2.00	4.00	5.00
Dealer Count	9133	2.15	2.16	1.00	1.00	1.00	2.00	5.00
(d,i,c,m,t) Observations per (i,c)	9133	15.94	74.85	1.00	2.00	4.00	12.00	34.00
Panel F: JPYUSD								
NW Spread	4570	1.71	36.39	-32.06	-11.25	1.31	14.55	37.31
NW Maturity Days	4570	42.09	42.14	9.56	18.49	29.87	56.60	90.00
% of Days with Spread	4570	2.06	5.56	0.21	0.21	0.62	1.65	4.12
Maturity Count	4570	2.57	2.08	1.00	1.00	2.00	3.00	5.00
Dealer Count	4570	1.56	1.09	1.00	1.00	1.00	2.00	3.00
(d,i,c,m,t) Observations per (i,c)	4570	12.34	47.83	1.00	1.00	3.00	8.00	22.00
Panel G: NZDUSD								
NW Spread	1867	-0.43	39.23	-35.96	-14.34	-0.09	12.60	31.60
NW Maturity Days	1867	44.14	45.67	9.71	17.36	30.00	60.00	90.00
% of Days with Spread	1867	2.00	4.03	0.21	0.21	0.62	1.65	5.35
Maturity Count	1867	2.54	1.89	1.00	1.00	2.00	4.00	5.00
Dealer Count	1867	1.89	1.48	1.00	1.00	1.00	2.00	4.00
(d,i,c,m,t) Observations per (i,c)	1867	11.05	25.49	1.00	1.00	3.00	9.00	29.00

Notes: This table provides statistics of client–currency pair-level trading activity in our maturity panel, described in Section 3, for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.2. Each sub-panel presents the cross-client distribution of the corresponding variable for that currency pair. Trade-level spreads are calculated as described in Section 3.2. *NW Spread* is the notional weighted average spread across trades for client i in currency pair c. *NW Maturity Days* is the notional weighted average maturity days across trades for client i in currency pair c, where we set maturities to standard dates for simplicity (e.g., 1-month is 30 days). *% of Days with Spreads* is the percent of dates for which i had a spread observation. *Maturity* (*Dealer*) *Count* is the number of unique maturities (dealers) for which client i has spread observations in currency c. (d, i, c, m, t) *Observations per* (i, c) is the number of observations in the maturity panel where client i is the client in the observation for currency pair c.

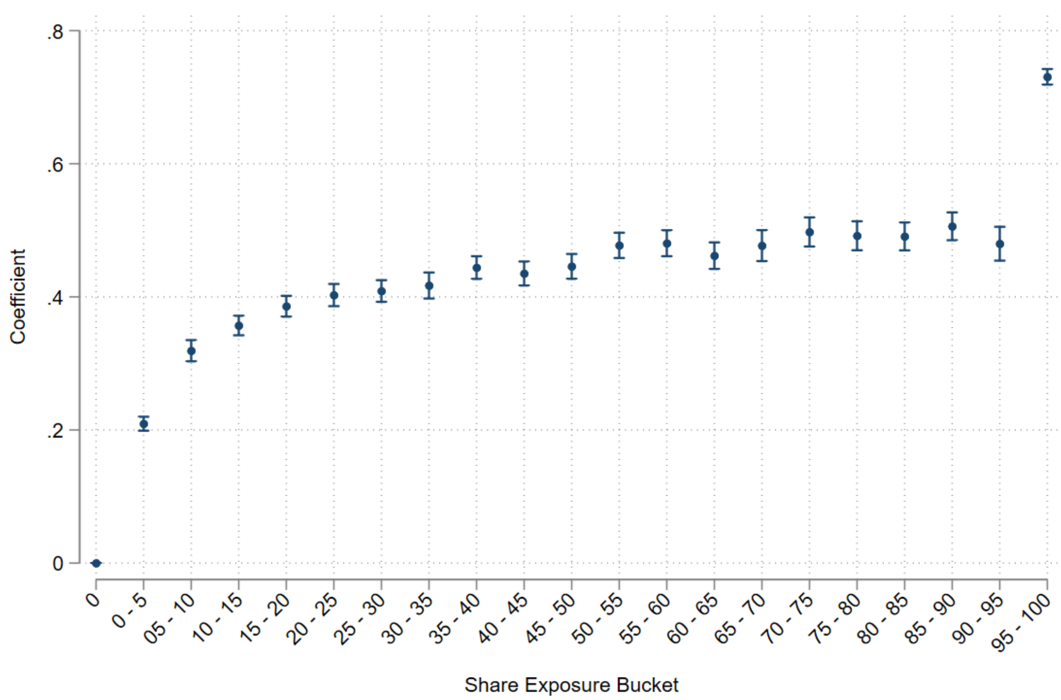
E Characteristics of Trading Relationships: Robustness

E.1 Trading Probability By Share Exposure Bucket

We run regression Equation 32 using the same data as the regressions of Table 1 in Section 4, where $\alpha_{d,sec(i),t}$ is a dealer–client sector–date fixed effect. We split the measure of client reliance on a dealer into a saturated set of indicators for 5% share intervals from 0 to 100%.

$$\mathbb{I}[Traded_{d,i,t}] = \sum_{b \in Buckets} \beta_b \mathbb{I}[RelStrength_{d,i,t-1} \in b] + \gamma \mathbb{I}[HasISDA_{d,i,t-1}] + \alpha_{d,sec(i),t} + \epsilon_{d,i,t} \quad (32)$$

Figure 6: Additional Trading Probability by Share Exposure Bucket



Notes: The coefficients plotted correspond to the β_b coefficients in regression Equation 32, which uses the sample for regression Table 1. Dependent variable $\mathbb{I}[Traded_{d,i,t}]$ is an indicator equal to 1 if the dealer and client at date t. The independent variables are: $\mathbb{I}[HasISDA_{d,i,t-1}$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $\mathbb{I}[RelStrength_{d,i,t-1} \in b]$, an indicator equal to 1 if the client's reliance on the dealer in the last 4 weeks, denoted by $RelStrength_{d,i,t-1}$, fell into share interval bucket b. $RelStrength_{d,i,t-1}$ is calculated using outstanding notional positions for the all $\leq$ 1y maturity across all currencies, measured by $RelStrNOut_{d,i,t-1}$ as defined by Equation 28 in Appendix C.1. The share buckets buckets are {0, (0,5], (5,10], (10,15], ... (95,100]}. Standard errors are clustered by client and date. Error bars plot $\pm 1.96 \times SE$.

E.2 Trading Relationships: Additional Fixed Effects

Table 19: Dealer-Client Trading Relationships With Client Fixed Effects

	(1) I[Traded]	(2) I[Traded]	(3) I[Traded]	(4) I[Traded]	(5) I[SellUSD]	(6) I[TradedCCY]
I[HasISDA]	0.296***	0.087***	0.080***	0.074***	-0.051***	0.060***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.002)
I[Only1ISDA]	-0.009***	-0.004***				
	(0.001)	(0.001)				
I[HasISDA] × I[Only1ISDA]	0.560***	0.222***				
	(0.005)	(0.009)				
I[HasOut]		0.314***	0.240***	0.259***	0.125***	0.049***
		(0.005)	(0.006)	(0.006)	(0.003)	(0.003)
I[Only1Dealer]		-0.001***				
		(0.000)				
I[HasOut] × I[Only1Dealer]		0.306***				
		(0.010)				
I[HasOut] × %Outstanding			0.004***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.051***	
					(0.005)	
None					-0.093***	
					(0.010)	
I[HasOutCCY]						0.323***
						(0.005)
Observations	4857469	4857469	4749173	4453211	4857469	1.14e+07
Client Clusters	8956	8956	8065	7279	8956	8959
R^2	0.4442	0.5021	0.5175	0.5175	0.2149	0.4334
Adjusted R^2	0.4418	0.4999	0.5155	0.5154	0.2115	0.4281
Within R^2	0.2201	0.3012	0.3231	0.3200	0.0976	0.2670
Dealer-Sector-Date FE	YES	YES	YES	YES	YES	NO
Dealer-Sector-CCY-Date FE	NO	NO	NO	NO	NO	YES
Client FE	YES	YES	YES	YES	YES	NO
Client-Product FE	NO	NO	NO	NO	NO	YES
Frequency	weekly	weekly	weekly	weekly	weekly	weekly

Notes: This table reports results from dealer–client–week and dealer–client–currency–week fixed effects panel regressions that we use to test Hypotheses 1 and 2 for the period of July 1, 2023 to December 31, 2023, with client fixed effects. Dependent variables are indicators that equal 1 if the client traded ($I[Traded]$), net sold USD ($I[SellUSD]$), and traded in currency c ($I[TradedCCY]$) with the dealer that week. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $I[Only1ISDA]$, an indicator equal to 1 if the client has $I[HasISDA] = 1$ with only one dealer; $I[HasOut]$, an indicator equal to 1 if the client had an outstanding position with the dealer in the last month; $I[Only1Dealer]$, an indicator equal to 1 if the client has $I[HasOut] = 1$ with only one dealer; *%Outstanding* (*%Traded*), the percent of the client's notional outstanding (trading) positions in the last month with the dealer; *SellUSD* and *None*, levels of a categorical variable that denotes the client's net USD outstanding position with the dealer during the last month (*BuyUSD* is the reference group); $I[HasOutCCY]$, an indicator equal to 1 if the client had an outstanding position in the last month with the dealer in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and date level in columns (1)–(5) and the client and currency–date level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Dealer-Client Trading Relationships With Client–Week Fixed Effects

	(1) I[Traded]	(2) I[Traded]	(3) I[Traded]	(4) I[Traded]	(5) I[SellUSD]	(6) I[TradedCCY]
I[HasISDA]	0.296***	0.086***	0.079***	0.073***	-0.051***	0.059***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.002)
I[HasISDA] × I[Only1ISDA]	0.560***	0.221***				
	(0.005)	(0.009)				
I[HasOut]		0.316***	0.242***	0.261***	0.126***	0.049***
		(0.005)	(0.006)	(0.006)	(0.003)	(0.003)
I[HasOut] × I[Only1Dealer]		0.307***				
		(0.010)				
I[HasOut] × %Outstanding			0.004***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.052***	
					(0.005)	
None					-0.092***	
					(0.010)	
I[HasOutCCY]						0.325***
						(0.005)
Observations	4856556	4856556	4748309	4452423	4856556	1.14e+07
Client Clusters	8866	8866	7994	7218	8866	8921
R^2	0.4474	0.5059	0.5213	0.5216	0.2277	0.4369
Adjusted R^2	0.4339	0.4938	0.5097	0.5099	0.2089	0.4218
Within R^2	0.2219	0.3043	0.3260	0.3230	0.0997	0.2693
Dealer-Sector-Date FE	YES	YES	YES	YES	YES	NO
Dealer-Sector-CCY-Date FE	NO	NO	NO	NO	NO	YES
Client-Date FE	YES	YES	YES	YES	YES	NO
Client-CCY-Date FE	NO	NO	NO	NO	NO	YES
Frequency	weekly	weekly	weekly	weekly	weekly	weekly

Notes: This table reports results from dealer–client–week and dealer–client–currency–week fixed effects panel regressions that we use to test Hypotheses 1 and 2 for the period of July 1, 2023 to December 31, 2023, with client–week fixed effects. Dependent variables are indicators that equal 1 if the client traded ($I[Traded]$), net sold USD ($I[SellUSD]$), and traded in currency c ($I[TradedCCY]$) with the dealer that week. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $I[Only1ISDA]$, an indicator equal to 1 if the client has $I[HasISDA] = 1$ with only one dealer; $I[HasOut]$, an indicator equal to 1 if the client had an outstanding position with the dealer in the last month; $I[Only1Dealer]$, an indicator equal to 1 if the client has $I[HasOut] = 1$ with only one dealer; *%Outstanding* (*%Traded*), the percent of the client's notional outstanding (trading) positions in the last month with the dealer; *SellUSD* and *None*, levels of a categorical variable that denotes the client's net USD outstanding position with the dealer during the last month (*BuyUSD* is the reference group); $I[HasOutCCY]$, an indicator equal to 1 if the client had an outstanding position in the last month with the dealer in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and date level in columns (1)–(5) and the client and currency–date level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.3 Spreads and Relationships: Additional Controls

Table 21: Spreads and Dealer-Client Trading Relationships With Size Controls

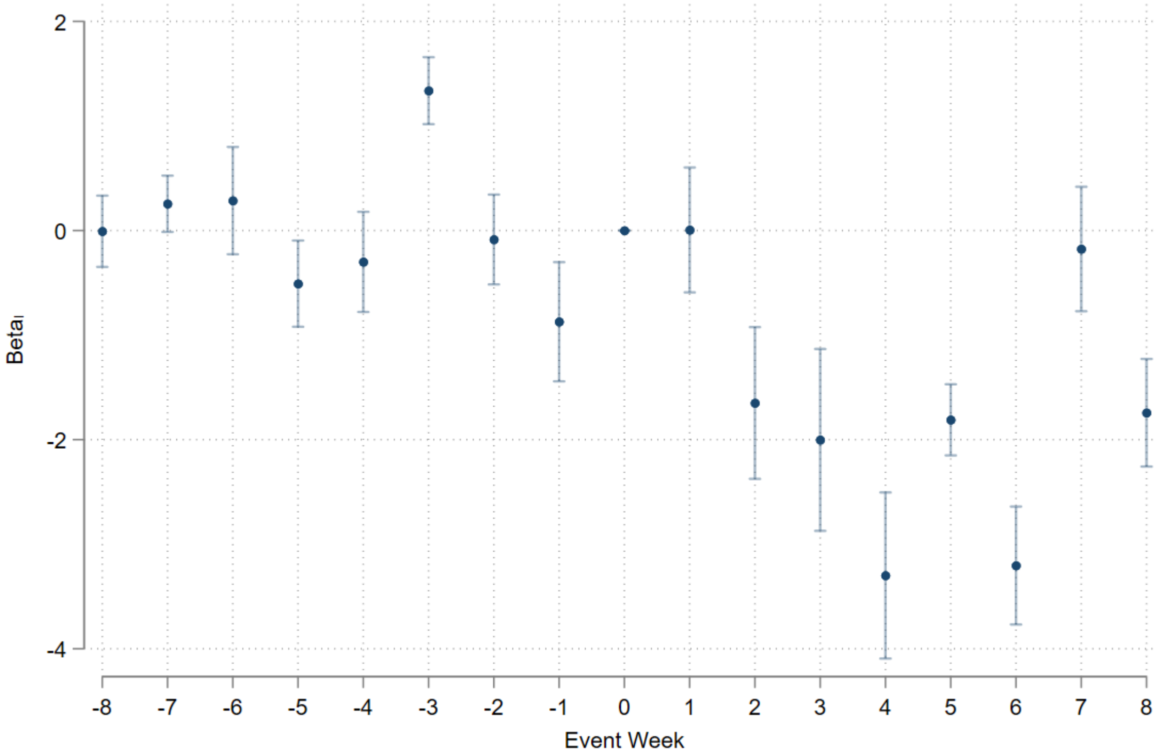
	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread
I[HasISDA]	-4.338	-2.476	-1.916	-1.895		-1.857
	(3.010)	(3.116)	(2.800)	(2.800)		(3.099)
I[Only1ISDA]	-2.467	-2.487				
	(4.685)	(4.695)				
I[HasISDA] × I[Only1ISDA]	4.213	4.072				
	(4.660)	(4.671)				
Ln(Notional Traded)	-0.102	-0.099	-0.117	-0.123*	-0.094	-0.141**
	(0.068)	(0.069)	(0.072)	(0.072)	(0.070)	(0.070)
Trade Count	0.034**	0.034**	0.031*	0.032**	0.034**	0.036**
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
I[HasOut]		-2.433**	-2.766**	-2.451**	-1.689	-0.983
		(1.102)	(1.093)	(1.082)	(1.232)	(1.035)
I[Only1Dealer]		-2.317				
		(2.010)				
I[HasOut] × I[Only1Dealer]		2.776				
		(2.022)				
%Outstanding			0.019***			
			(0.005)			
%Traded				0.013***		
				(0.005)		
I[NetUSDOut = dir]					-1.572	
					(1.569)	
I[HasOutCCY]						-0.842
						(0.657)
Observations	249,940	249,940	249,940	249,940	278,018	249,940
Client Clusters	12,401	12,401	12,401	12,401	12,401	12,401
R^2	0.1680	0.1680	0.1680	0.1679	0.1407	0.1678
Adjusted R^2	0.0988	0.0988	0.0988	0.0987	0.0749	0.0986
Within R^2	0.0004	0.0005	0.0004	0.0003	0.0004	0.0002
CCY-Maturity-Date FE	YES	YES	YES	YES	YES	YES
Dealer-Date FE	YES	YES	YES	YES	YES	YES

Notes: This table reports results from dealer–client–currency–maturity–date and dealer–client–currency–maturity–date–direction fixed effects panel regressions, with controls for the size of trading activity, that we use to test Hypothesis 3 for the period of January 1, 2023 to December 31, 2023, corresponding to Equation 6. The dependent variable is the notional weighted average spread across trades with the same dealer, client, currency, maturity, and execution date, except column (5) which also groups by USD trading direction. Spreads are measured as described in Section 3.2. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client ever traded or had an outstanding position with the dealer between December 1, 2021 and $t-1$; $I[Only1ISDA]$, an indicator equal to 1 if the client has $I[HasISDA] = 1$ with only one dealer; $I[HasOut]$, an indicator equal to 1 if the client had an outstanding position with the dealer in the last month; $I[Only1Dealer]$, an indicator equal to 1 if the client has $I[HasOut] = 1$ with only one dealer; *%Outstanding* (*%Traded*), the percent of the client's notional outstanding (trading) positions in the last month with the dealer; $I[NetUSDOut = dir]$, an indicator equal to 1 if the spread observation has the same USD trade direction as the client's net outstanding position with the dealer over the last month; $I[HasOutCCY]$, an indicator equal to 1 if the client had an outstanding position in the last month with the dealer in currency c; *Trade Count* (*Ln(Notional Traded)*), trade count (natural log of notional traded) for the dealer, client, currency, maturity, date (column (5) also groups by USD trade direction). Variables are defined in Appendix C.1. Standard errors are double clustered at the client and date level in columns (1)–(5) and the client and currency–date level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Dealer-Level Trading Activity: Event Study Plots

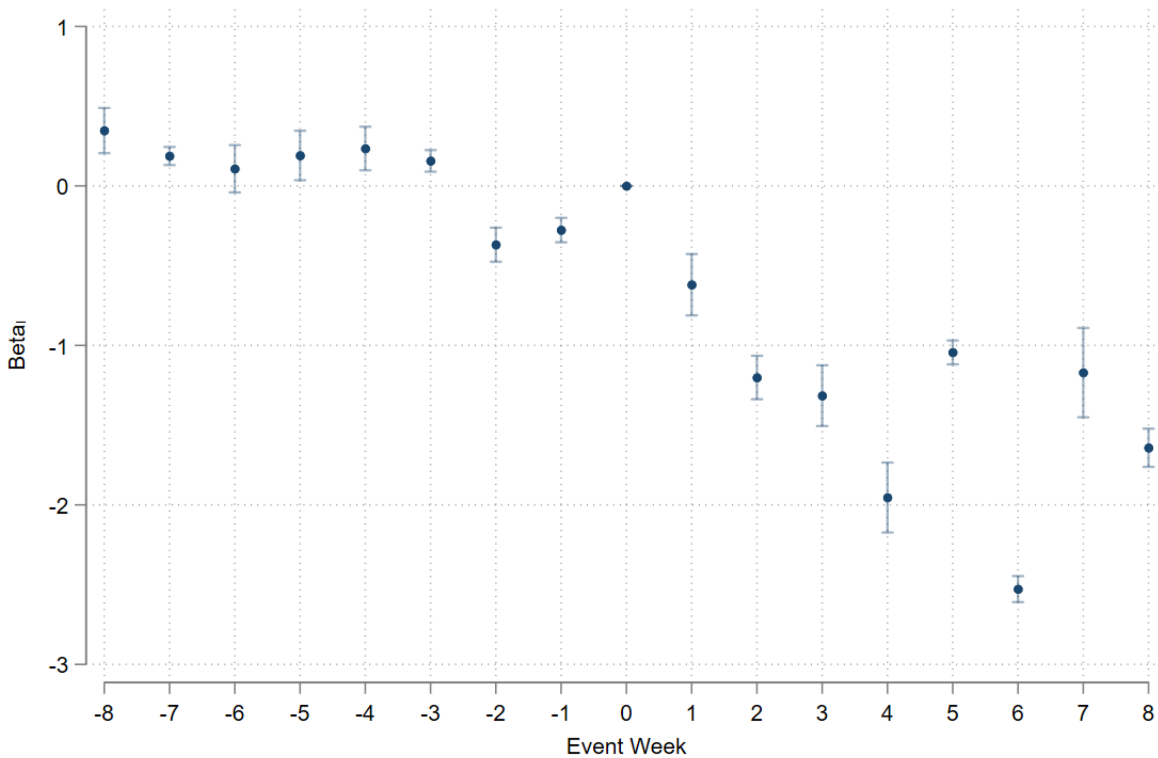
The event study regressions are given by Equation 8.

Figure 7: Effect of the Shock Dealer-Level Event Study, $Y_{d,t} = Ln\big(Not.\ Traded_{d,t}\big)$



Notes: This figure plots the β_l coefficients from the dealer–date level event study regression, Equation 8, that we use to test Hypothesis 4. The regression equation is $Y_{d,t} = \alpha_d + \alpha_t + \sum_{l=-L}^{L} \beta_l \times \mathbb{I}[EventWeek(t) = l] \times \mathbb{I}[Treated_d] + \epsilon_{d,t}$, where α_d and α_t are dealer and date fixed effects. Dependent variable $Ln(Not.\ Traded_{d,t})$ is the natural log of the dealer's total EURUSD notional traded at date t for the all $\leq$ 1y maturity. Dependent variables are: $\mathbb{I}[Treated_d]$, an indicator equal to 1 if the dealer is Credit Suisse; $\mathbb{I}[EventWeek(t) = l]$, an indicator equal to 1 if the calendar week of date t is l. Event week 0 is defined as the week of March 8, 2023. Standard errors are double clustered by dealer and date. Error bars plot $\pm 1.96 \times SE$.

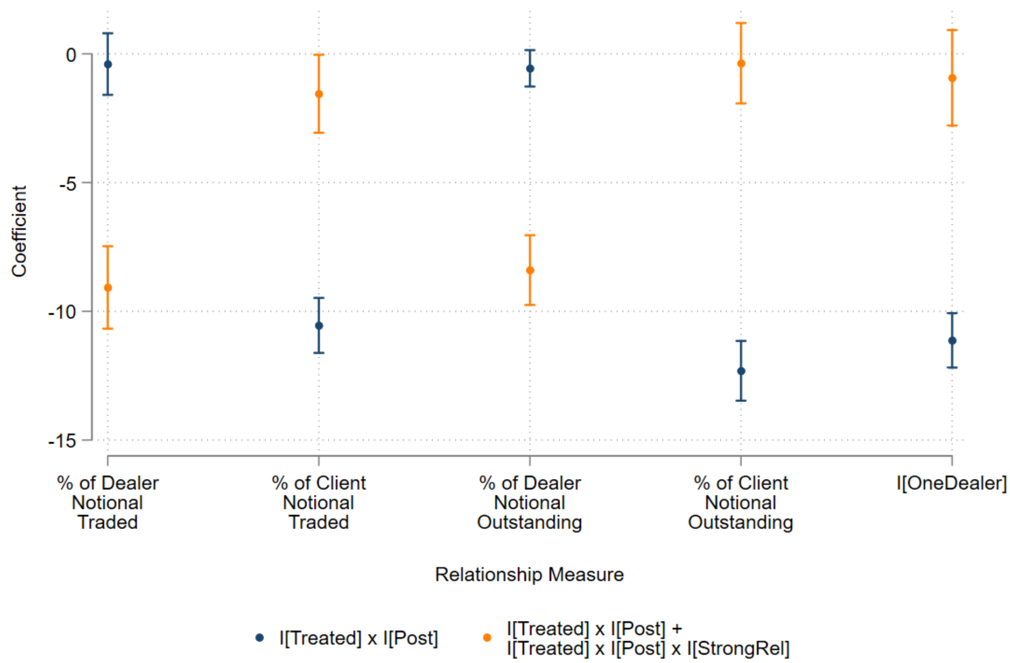
Figure 8: Effect of the Shock Dealer-Level Event Study, $Y_{d,t} = Ln\big(Trade\ \ Count_{d,t}\big)$



Notes: This figure plots the β_l coefficients from the dealer–date level event study regression, Equation 8, that we use to test Hypothesis 4. The regression equation is $Y_{d,t} = \alpha_d + \alpha_t + \sum_{l=-L}^{L} \beta_l \times \mathbb{I}[EventWeek(t) = l] \times \mathbb{I}[Treated_d] + \epsilon_{d,t}$, where α_d and α_t are dealer and date fixed effects. Dependent variable $Ln(Trade\ \ Count_{d,t})$ is the natural log of the dealer's total EURUSD trade count at date t for the all $\leq$ 1y maturity. Dependent variables are: $\mathbb{I}[Treated_d]$, an indicator equal to 1 if the dealer is Credit Suisse; $\mathbb{I}[EventWeek(t) = l]$, an indicator equal to 1 if the calendar week of date t is l. Event week 0 is defined as the week of March 8, 2023. Standard errors are double clustered by dealer and date. Error bars plot $\pm 1.96 \times SE$.

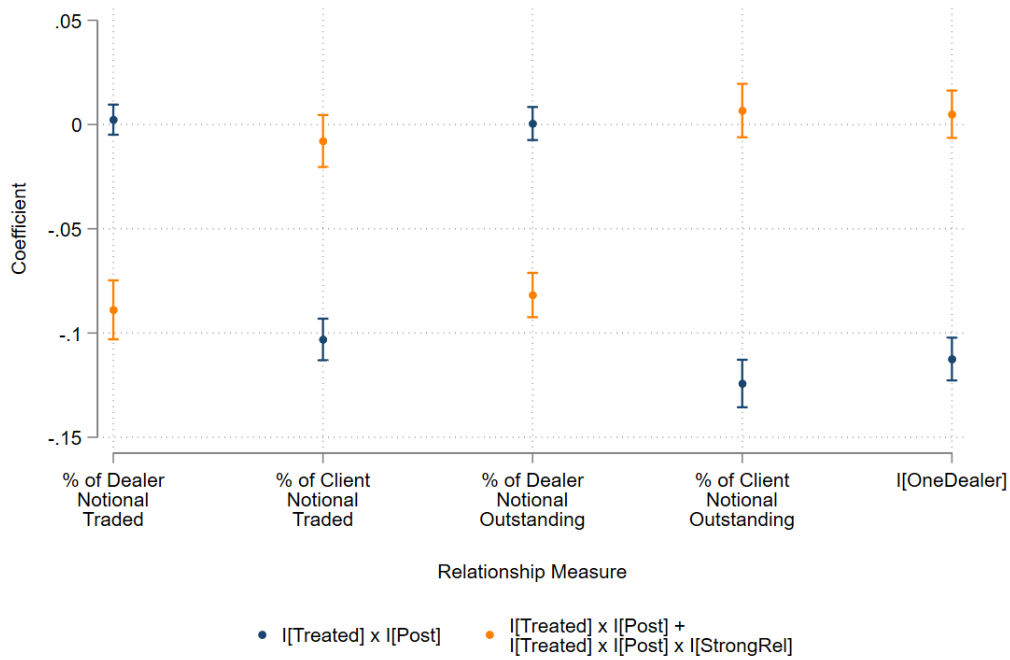
G Pre-Existing Relationship Strength and Credit Suisse Trading Activity: EURUSD

Figure 9: Effect of Relationship Strength on $\%$ $Trade\ Count_{d,i,t}$ at Shocked Dealer



Notes: This figure plots the difference-in-differences coefficient, β_1 in blue, and its sum with the triple differences coefficient, $\beta_1 + \beta_2$ in orange, from dealer–client–date-level triple differences regressions that we use to test Hypotheses 5 and 6. All columns correspond to Equation 9, but use different notions of relationship strength, listed along the x-axis and constructed using EURUSD activity in the out-of-sample pre-period. Columns (2), (4), and (5) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is $\%$ $Trade\ Count_{d,i,t}$, EURUSD trade count by the client with the dealer at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles. Independent variables are: $I[StrongRel]$, an indicator equal to 1 if client was had a stronger EURUSD relationship with the dealer than the median client at dealer, across clients that traded EURUSD with the dealer in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated]$, an indicator equal to 1 if the dealer in the dealer-client pair is Credit Suisse. X-axis labels denote the relationship strength measure used for $I[StrongRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[StrongRel]$. All regressions include dealer, client, and calendar week fixed effects. Standard errors are clustered at the dealer and date level. Error bars plot $\pm 1.96 \times SE$.

Figure 10: Effect of Relationship Strength on $\mathbb{I}[Traded_{d,i,t}]$ at Shocked Dealer



Notes: This figure plots the difference-in-differences coefficient, β_1 in blue, and its sum with the triple differences coefficient, $\beta_1 + \beta_2$ in orange, from dealer–client–date-level triple differences regressions that we use to test Hypotheses 5 and 6. All columns correspond to Equation 9, but use different notions of relationship strength, listed along the x-axis and constructed using EURUSD activity in the out-of-sample pre-period. Columns (2), (4), and (5) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is $\mathbb{I}[Traded_{d,i,t}]$, an indicator equal to 1 if the dealer and client traded in the EURUSD in the all $\leq$ 1y maturity on date t. Independent variables are: $I[StrongRel]$, an indicator equal to 1 if client was had a stronger EURUSD relationship with the dealer than the median client at dealer, across clients that traded EURUSD with the dealer in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated]$, an indicator equal to 1 if the dealer in the dealer-client pair is Credit Suisse. X-axis labels denote the relationship strength measure used for $I[StrongRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[StrongRel]$. All regressions include dealer, client, and calendar week fixed effects. Standard errors are clustered at the dealer and date level. Error bars plot $\pm 1.96 \times SE$.

H Pre-Existing Relationship Strength and Credit Suisse Trading Activity: All Currencies

This section of the Appendix gives the regression table for regression Equation 9 where a strong relationship, $\mathbb{I}[StrongRel_{d,i}]$, is measured using the dealer's share of the client's notional trading activity across all seven currency pairs.

Table 22: Role of Client Reliance Over all Currencies for Activity at the Shocked Dealer

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]
I[Post]	-1.648	-0.551	-0.008
	(1.011)	(1.217)	(0.008)
I[Post] x I[Treated_d]	-8.110***	-10.588***	-0.102***
	(0.600)	(0.565)	(0.005)
I[StrongRel_di]	0.210	4.810***	0.058***
	(0.543)	(0.948)	(0.012)
I[Post] x I[StrongRel_di]	0.227	-0.499	-0.005*
	(0.480)	(0.433)	(0.003)
I[Post] x I[Treated_d] x I[StrongRel_di]	6.704***	9.129***	0.095***
	(1.008)	(0.865)	(0.007)
Observations	806,988	806,988	847,936
Dealer Clusters	41	41	42
R^2	0.1257	0.2107	0.2574
Adjusted R^2	0.1179	0.2037	0.2506
Within R^2	0.0000	0.0016	0.0033

Notes: This table reports results from dealer–client–date triple differences regressions, given by Equation 9, that we use to test Hypothesis 5, but uses a relationship strength measure computed across all currencies. Dependent variables are: % *Not. Traded* (% *Trade Count*), EURUSD notional (trade count) traded by the client with the dealer at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles; $\mathbb{I}[Traded]$, an indicator equal to 1 if the dealer and client trade in EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: $I[StrongRel\_di]$, an indicator equal to 1 if client was more reliant on the dealer across all seven currencies than the median client at dealer, across clients that traded EURUSD with the dealer in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_d]$, an indicator equal to 1 if the dealer in the dealer-client pair is Credit Suisse. Measurement details for $I[StrongRel\_di]$ are in Appendix C.2 using *RelStrNDay_i* as defined in that appendix but using activity in all seven currencies. All specifications include dealer, client, and calendar week fixed effects. Standard errors are double clustered at the dealer and date level. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I Treated Client Exposure To Credit Suisse

Table 23: Distribution of Exposure to Credit Suisse Across Treated Clients

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Exposure_i	279	27.90	37.52	0.04	0.43	5.17	47.76	100.00

Notes: This table provides the distribution of client-level exposure to Credit Suisse. Exposure to Credit Suisse is measured as E_i, the percent of a client's EURUSD notional traded in the out-of-sample pre-period that was with Credit Suisse, and is defined in Equation 11. The distribution is across clients with a positive exposure to Credit Suisse and that traded a positive EURUSD notional amount in the pre-period in the all $\leq$ 1y maturity.

J Client-Level Trading Activity

Table 24: Effect of the Shock on Client-Level Trade Count and Probability of Trading

	(1) % Trade Count	(2) I[Traded]	(3) % Trade Count	(4) I[Traded]
I[Post]	-19.442**	-0.010	-19.438**	-0.010
	(9.212)	(0.014)	(9.213)	(0.014)
I[Post] × I[Treated_i]	0.775	-0.007		
	(6.069)	(0.010)		
I[Post] x Less Exposed			3.780	-0.014
			(5.772)	(0.015)
I[Post] x More Exposed			-2.945	0.002
			(9.523)	(0.011)
Observations	485,986	499,833	485,986	499,833
Client Clusters	7300	7677	7300	7677
R^2	0.0508	0.3848	0.0508	0.3848
Adjusted R^2	0.0363	0.3751	0.0363	0.3751
Within R^2	0.0001	0.0000	0.0001	0.0000

Notes: This table reports results from client–date level difference-in-difference regressions that we use to test Hypothesis 7. Columns (1) and (2) correspond to Equation 12. Columns (3) and (4) correspond to Equation 13. Dependent variables are: *% Trade Count*, EURUSD trade count by the client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles; $I[Traded]$, an indicator equal to 1 if the client traded in the EURUSD in all $\leq$ 1y maturity at date t. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_i]$, an indicator equal to 1 if the client is exposed to Credit Suisse, measured as a positive exposure computed according to Equation 11; *LessExposed* and *MoreExposed*, levels of a categorical variable that indicates whether a client (i) was not exposed to Credit Suisse, (ii) was above the cross-treated client median exposure to Credit Suisse (*MoreExposed*) or (iii) was below or equal to the cross-treated client median exposure to Credit Suisse (*LessExposed*), where exposure to Credit Suisse is measured as in Equation 11 and the unexposed clients are the reference group. All specifications include client and week fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

K Exposed Clients' Trading Activity With Other Dealers

Table 25: Effect of the Shock on Clients' Trade Count and Probability of Trading With Other Dealers

	(1) % Trade Count	(2) I[Traded]	(3) % Trade Count	(4) I[Traded]
I[Post]	-0.820	-0.010	-0.819	-0.010
	(1.343)	(0.010)	(1.347)	(0.010)
I[Post] × I[Treated_i]	-0.478	-0.002	-0.479	-0.003
	(0.816)	(0.007)	(0.825)	(0.007)
I[Post] x I[OneRel_i]			-0.007	-0.004
			(0.529)	(0.004)
Observations	802,861	843,664	802,861	843,664
Client Clusters	7,046	7,632	7,046	7,632
R^2	0.2125	0.2576	0.2125	0.2576
Adjusted R^2	0.2049	0.2502	0.2049	0.2502
Within R^2	0.0000	0.0000	0.0000	0.0000
Dealer-Week FE	YES	YES	YES	YES
Client FE	YES	YES	YES	YES

Notes: This table reports results from dealer–client–date level difference-in-difference regressions that we use to test Hypothesis 8. Columns (1) and (2) correspond to Equation 14. Columns (3) and (4) add controls for whether the client had only one relationship. Dependent variables are: % *Trade Count*, EURUSD trade count between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; $I[Traded]$, an indicator equal to 1 if the dealer and client traded in the EURUSD in all $\leq$ 1y maturity at date t. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; $I[Treated\_i]$, an indicator equal to 1 if the client is exposed to Credit Suisse, measured as a positive exposure computed according to Equation 11; $I[OneRel\_i]$, an indicator equal to 1 if the client had an outstanding position with only one dealer, across all seven currencies, in the out-of-sample pre-period. All specifications include dealer–week and client fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 26: Effect of the Shock on Clients' Trade Count and Probability of Trading With Other Dealers, Categorical Exposure

	(1) % Trade Count	(2) I[Traded]	(3) % Trade Count	(4) I[Traded]
I[Post]	-0.821	-0.010	-0.820	-0.010
	(1.343)	(0.010)	(1.347)	(0.010)
I[Post] x Less Exposed	-1.013	-0.005	-1.014	-0.006
	(0.916)	(0.008)	(0.926)	(0.008)
I[Post] x More Exposed	1.630	0.008	1.629	0.007
	(1.132)	(0.009)	(1.132)	(0.009)
I[Post] x I[OneRel_i]			-0.003	-0.004
			(0.528)	(0.004)
Observations	802,861	843,664	802,861	843,664
Client Clusters	7,046	7,632	7,046	7,632
R^2	0.2125	0.2576	0.2125	0.2576
Adjusted R^2	0.2049	0.2502	0.2049	0.2502
Within R^2	0.0000	0.0000	0.0000	0.0000
Dealer-Week FE	YES	YES	YES	YES
Client FE	YES	YES	YES	YES

Notes: This table reports results from dealer–client–date level difference-in-difference regressions that we use to test Hypothesis 8. Columns (1) and (2) correspond to Equation 15. Columns (3) and (4) add controls for whether the client had only one relationship. Dependent variables are: *% Trade Count*, EURUSD trade count between the dealer and client at date t in the all $\leq$ 1y maturity as a percent of their out-of-sample pre-period average when they trade, computed as in Equation 10, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs; $I[Traded]$, an indicator equal to 1 if the dealer and client traded in the EURUSD in all $\leq$ 1y maturity at date t. Independent variables are: $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023; *LessExposed* and *MoreExposed*, levels of a categorical variable that indicates whether a client (i) was not exposed to Credit Suisse, (ii) was above the cross-treated client median exposure to Credit Suisse (*MoreExposed*) or (iii) was below or equal to the cross-treated client median exposure to Credit Suisse (*LessExposed*), where exposure to Credit Suisse is measured as in Equation 11 and the unexposed clients are the reference group; $I[OneRel\_i]$, an indicator equal to 1 if the client had an outstanding position with only one dealer, across all seven currencies, in the out-of-sample pre-period. All specifications include dealer–week and client fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.