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Trading relationships in FX derivatives: lessons from Credit Suisse's collapse

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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. In this episode, although Credit Suisse's EURUSD notional traded and trade count declined sharply, clients who had previously relied less heavily on Credit Suisse did not differentially reduce their Credit Suisse-specific trading activity relative to more reliant clients. Instead, clients who had previously relied more heavily on the bank were able to substitute to other existing dealer relationships without incurring additional costs. Overall, these findings suggest that search and bargaining frictions were not particularly costly for heavily reliant clients after the shock: relationship persistence did not differentially prevent them from reallocating activity to existing alternative dealers when their relationship dealer came under stress.

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 corporations, 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] So, 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.

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

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 tend to expect relationship negotiations and contract completion for new clearing relationships to take 2–6 months.[2] 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 could affect clients' trading outcomes, especially when one of their dealers is adversely

[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.

[2] According to FSB (2018), the average reported expected time for new clearing relationship creation is 6.7 months, across client survey participants.

shocked. For example, if bilateral trading persistence is indicative of the client's search technology, then the client's trading portfolio allocation reflects their propensity to trade across dealers and, therefore, their set of outside trading options. When a dealer is adversely shocked, it may pass through higher costs to clients via larger spreads, and this pass through may be heterogeneous depending on clients' substitution ability. Since the ability to substitute 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 fixed effects panel regressions, we show that trading relationships are persistent. In weeks when a client trades, they 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 relationship, (ii) relied on more heavily, and (iii) had an outstanding position in the same currency pair. Focusing on a client's recent reliance on a dealer, we find that, in weeks when a client trades, they 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. To our knowledge, these results are the first to characterize bilateral dealer-client trading relationships in this market.

Additionally, we have 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. Using this panel, we provide evidence that clients pay higher average spreads at dealers that compose a larger share of the client's trading portfolio, consistent with dealers charging 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, we exploit an adverse shock to a dealer to more causally identify the role of pre-existing relationship strength on clients' trading activity. In particular, we study the implications of relationship strength 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 regression analyses using this shock to study trading activity in the EURUSD. Specifically, we study how trading conditions changed for clients from the pre- to the post-period depending on their reliance on Credit Suisse, where we exploit that the shock is exogenous to pre-existing bilateral trading relationships but affects exposed clients' trading options as long as relationships are persistent. This allows us to more causally identify how client reliance on a dealer affects spreads relative to our granular panel analysis.

Our results show that Credit Suisse's average weekly dealer-client EURUSD notional traded and trade count declined due to the shock and that clients that were differentially reliant on Credit Suisse did not face relatively different changes in trading conditions post shock. Instead, we find evidence that more reliant Credit Suisse clients were able to substitute without paying a relative increase in costs, which we would not expect if this shock more adversely affected these clients' bargaining power. Specifically, less reliant Credit Suisse clients do not reduce their Credit Suisse-specific trading activity more than more reliant clients. Additionally, client-level trading activity does not decline by more for more reliant clients and, exploiting within-dealer–week variation across clients, more reliant clients have a relative increase in their trading activity with non-Credit Suisse dealers compared to less reliant clients. These results support that more reliant clients were able to substitute post shock.

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 are able to substitute to their other dealer relationships. This suggests that clients with persistent relationships have resilient trading activity in times of dealer distress. Clients without an alternative relationship may face worse trading outcomes after their dealer is shocked, due to the fixed costs of relationship creation. Our results do not shed light on this, but are informative for clients that wish to develop an additional dealer relationship 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.

2 Related Literature

Our paper contributes 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. For example, under sequential search and bargaining, less sophisticated clients pay larger spreads due to lower search efficiency and worse bargaining power (Duffie *et al.*, 2005, 2007). 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. First, we document that clients trade persistently with dealers that they previously relied on, highlighting that they do not necessarily search across all dealers. Then, we exploit an adverse shock to Credit Suisse in March 2023 as a shock to the set of trading options for exposed clients to empirically study the importance of search and bargaining frictions in the OTC FX derivatives market. We show that clients more exposed to the shocked dealer do not face differentially worse trading conditions overall or at non-Credit Suisse dealers post shock. Our results highlight that these clients can substitute to their existing alternative dealers post shock.

In the empirical literature studying OTC markets, there has been evidence of price dispersion that is consistent with price discrimination (Cenedese *et al.*, 2020; Cocco *et al.*, 2009; Hau *et al.*, 2021; Hendershott *et al.*, 2020; Osler *et al.*, 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 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 EURUSD, and 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 relationships, particularly the client's reliance on the dealer, for client trading outcomes. Additionally, measures of client sophistication in their paper are endogenous. We exploit a shock to a dealer as a shock to exposed clients' bargaining power or set of outside options—thus, their ability to prevent price discrimination—to address endogeneity. Our trade-level data set is similar to Hau *et al.* (2021), but is restricted to trades where at least one counterparty is a UK legal entity. However, we include more currency pairs and client sectors, and cover a more recent time period.

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 tends to find that stronger trading relationships are associated with smaller transaction costs (Afonso *et al.*, 2014; Bernhardt *et al.*, 2005; Di Maggio *et al.*, 2017; Hendershott *et al.*, 2020; Jurkatis *et al.*, 2023). 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 literature that studies the effects of dealer shocks in OTC markets (Cenedese *et al.*, 2021; Di Maggio *et al.*, 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 *et al.* (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 OTC FX derivatives and emphasizing heterogeneity in client trading outcomes, particularly in the context of the March 2023 shock to Credit Suisse.

Cenedese *et al.* (2021) 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 provide evidence that highly exposed clients substituted to existing untreated dealer relationships, they focus on documenting 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. We similarly find that more exposed clients have a relative increase in trading activity with existing non-shocked dealer relationships post shock. Additionally, we find that they do not pay significantly greater costs to do so.

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 *et al.*, 2021; Du *et al.*, 2018; Kloks *et al.*, 2024; Moskowitz *et al.*, 2024; Wallen, 2022). This literature has documented that CIP deviations widen when dealer banks become constrained (Du *et al.*, 2018) and the role of segmentation and market power for FX prices (Moskowitz *et al.*, 2024; Siriwardane *et al.*, 2025; Wallen, 2022). However, these papers primarily focus on prices at the (currency, maturity, date) level. Cenedese *et al.* (2021) use trade-level price data to document that the leverage ratio affects CIP deviations at this granular level. We provide additional insight into which clients bear the costs of dealer balance sheet shocks. Specifically, costs do not increase differentially for exposed clients based on their reliance on the shocked dealer.

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 *et al.*, 2019; Cenedese *et al.*, 2021; Hacioğlu-Hoke *et al.*, 2024; Hau *et al.*, 2021) and to literature that studies counterparty choice (Di Maggio *et al.*, 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. We also outline our computation of spreads, which measure the costs that clients pay on their trades, and provide descriptive information about our data.

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 and outstanding positions of OTC FX outright forwards or forward legs of FX swaps where at least one counterparty is a UK legal entity, from January 1, 2022 through December 31, 2023.[3]

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 registered with the Financial Conduct Authority.[4] There are two report types, activity and state reports. State reports provide trade-level information for all trades outstanding at the end of each day, while activity reports cover all trades 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, while also identifying trades executed each day and still outstanding the next day. 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 outstanding at the end of each date in our sample period where at least one counterparty is a UK legal entity.

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, and insurer.[5] We also identify intragroup trades and drop activity between counterparties that have ever marked a trade as intragroup in our sample period.

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.[6] When aggregating, we drop trades between a dealer and bank of the same parent institution. So, a dealer-client relationship captures activity between a client and the set of dealers and banks that we identify as belonging to the same parent.[7]

We restrict our sample to trades and outstanding positions for seven major currencies to

[3] Cenedese *et al.* (2021) also use this FX derivative trade repository data, but our sample is more recent.

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

[5] 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.

[6] Gupta (2021) provides evidence that internal capital markets of holding companies are important and dealers rely on internal capital markets with sibling subsidiaries of the same parent institution. Although non-bank subsidiaries' use of sibling banks' commercial deposits for financing faces limitations, 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.

[7] For example, JP Morgan Chase Bank and Dealer LEIs would be aggregated to a single JP Morgan Chase Dealer Bank and trades between these LEIs would be dropped. See Appendix A.2 for more information on this process.

the USD—AUDUSD, CADUSD, CHFUSD, EURUSD, GBPUSD, JPYUSD, and NZDUSD. Our cleaned dataset aggregates trade-level information into a maturity panel with maturity buckets labeled by standard maturities, and an additional bucket for trades with maturity less than or equal to 1 year. When bucketing outstanding positions on a date, we use the trade's residual maturity. The maturity buckets are: 1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 7m, 8m, 9m, 10m, 11m, 1y, all $\leq$ 1y. Since the all $\leq$ 1y maturity bucket captures a larger set of activity, we use it to measure dealer-client relationship strength and existence.[8] We use the term "maturity panel" going forward to refer to the observations with maturity bucket not equal to the all $\leq$ 1y. Consistent with trading patterns in FX OTC derivatives (BIS, 2025), a larger share of activity in our maturity panel is in shorter maturities.[9]

To compute spreads and create maturity buckets, we merge our trade data with a (currency pair, days to maturity, date) panel of linearly interpolated forward rates. We interpolate forward rates from Bloomberg data on spot rates, forward points, and settlement dates, for the currency pairs and maturities listed previously. These interpolated forward rates are used as benchmark prices in our spread computations. To generate maturity buckets, we use days to maturity for the "on maturity" Bloomberg prices. Specifically, a trade for a currency pair and date is included in a maturity bucket if the days to maturity for the trade is closest to that of the "on maturity" given by the maturity bucket's label.[10] We use the maturity panel for any analysis of spreads, the measurement of which is described in Section 3.2.

The trade-level dataset is very large, so we aggregate our panel across trades with the same dealer d, client i, currency pair c, maturity bucket m, date t, and direction dir, where direction indicates whether the client in the counterparty pair is buying or selling USD. The resulting dataset is a (d, i, c, m, t, dir) level panel containing trading and outstanding positions, and spreads, for each dealer-client pair at a daily frequency. We aggregate the trade-level data by taking notional weighted averages of spreads, and sums for (i) notional traded, (ii) notional outstanding, (iii) new trade count, and (iv) outstanding trade count. After aggregating across trade directions to the (d, i, c, m, t) level, our maturity panel contains 2,671,220 (d, i, c, m, t) observations.[11]

[8] For example, a dealer and client may have trades with maturity less than those included in the 1-week bucket, which are not included in the maturity panel. Or, they may have a trade useful for identifying relationships, but not included in the spread panel after cleaning prices.

[9] See Appendix D.3 Figure 3 for box plots of daily activity totals by maturity over our 2-year sample.

[10] The "on maturity" days to maturity values are determined from the settlement dates for their currency pair, maturity, and date from Bloomberg. For example, assume days to maturity for the 1-week, 1-month, and 2-month EURUSD forwards at t—the difference between the settlement date and t—are 7, 30, and 60 days, respectively. The 1-month maturity bucket for the EURUSD on date t aggregates trades with days to maturity greater than 18.5 and less than or equal to 45. For notional outstanding positions, we use residual maturity, the maturity of the outstanding position from t. See Appendix A.1 for information on our interpolation of Bloomberg forward rates, cleaning of price data, and generation of maturity buckets.

[11] This excludes the all $\leq$ 1y maturity. Using the all $\leq$ 1y maturity, the (dealer, client, date) panel has

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 and a benchmark price, multiplied by a sign indicator to capture the cost paid by the client.

Let τ denote a trade between dealer d and client i on date t, in currency pair c, with days to maturity DTM, where the client is buying or selling USD according to direction dir. DTM is the number of days from the trade's execution date to its maturity date. The trade price, $F_{d,i,c,DTM,t,dir,\tau}$, and the benchmark price for trade τ, F^*_τ, have units $\frac{\text{USD}}{\text{Foreign Currency}}$. We use lower case letters in Equation 1 to denote logs of forward rates.

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

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

where

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

The directional indicator, dir, normalizes the spread to be positive if the client pays a worse price relative to the benchmark, which depends on the direction of the trade. To aggregate from the trade level to a coarser unit of observation, we take notional weighted averages. So, our spread variable measures *the spread paid by the client per average dollar of notional traded* at the level of aggregation.

The benchmark for trade τ is the linearly interpolated Bloomberg price with the same execution date, currency pair, and days to maturity as τ. Benchmark prices are generated by interpolating Bloomberg prices across days to maturity between standard "on maturity" observations within a currency pair and date. To create our panel, we aggregate across trades with differing DTM but with the same maturity bucket.[12]

Table 15 in Appendix D.9 provides descriptive statistics for spreads, by currency pair. Most of the observations correspond to EURUSD and GBPUSD. For each currency pair, the median spread at the (d, i, c, m, t) level is slightly positive, ranging from 0.16 basis points for the JPYUSD to 0.80 for the GBPUSD. The median maturity bucket across (d, i, c, m, t)-level

1,958,335 observations with a positive trade count in at least one of the seven currencies.

[12] See Appendix A.1 for more information on this process.

observations for each currency pair is 1-month. The count of (d, i, c, m, t) observations for the median client in each currency-specific cross-client distribution ranges from 8, for the CADUSD, to 16, for the GBPUSD.[13] There are large tails in our distribution of spreads.[14] To reduce the influence of outliers on our spread analysis, we trim spreads at the 5th and 95th percentiles at the (d, i, c, m, t)-level. When our analysis splits by trade direction, we use spreads trimmed at the 5th and 95th percentiles at the (d, i, c, m, t, dir)-level.

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 in our sample for the all $\leq$ 1y maturity from July 1, 2023 through December 31, 2023 cover approximately 19.4% 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 2023S2 was \$67,797 billion and for the USD was \$59,938 billion.[16] Comparing these values to the USD row of Table 8 in Appendix D.1, we cover 17.2% of the total and 19.4% of the USD total reported by BIS. For the EUR, JPY, GBP, CHF, and CAD, we cover about 25.7% on average across these currencies.

Our two-year sample contains 26,892 unique clients and 46 dealers with a positive trade count in the all $\leq$ 1y maturity, where Asset Managers is the sector with the largest client count of 7,648. Non-financial Corporations have the next largest client count with 1,405. However, Hedge Funds and Banks contributed the most to notional trading volume, together accounting for 51% 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 many other sectors in our sample, with their average percent of days traded across clients given by 34.8% and 28.8%

[13] Appendix D.10 provides a client-level summary table of the maturity panel by currency pair, including notional weighted average spreads, and Appendix D.6 includes additional information on client-level activity in the maturity panel.

[14] For example, the 5th and 95th percentiles of the EURUSD (d, i, m, t) distribution of spreads across our 2-year sample have magnitudes of about 60 basis points across maturities, but spread values can reach about 1000 basis points in magnitude.

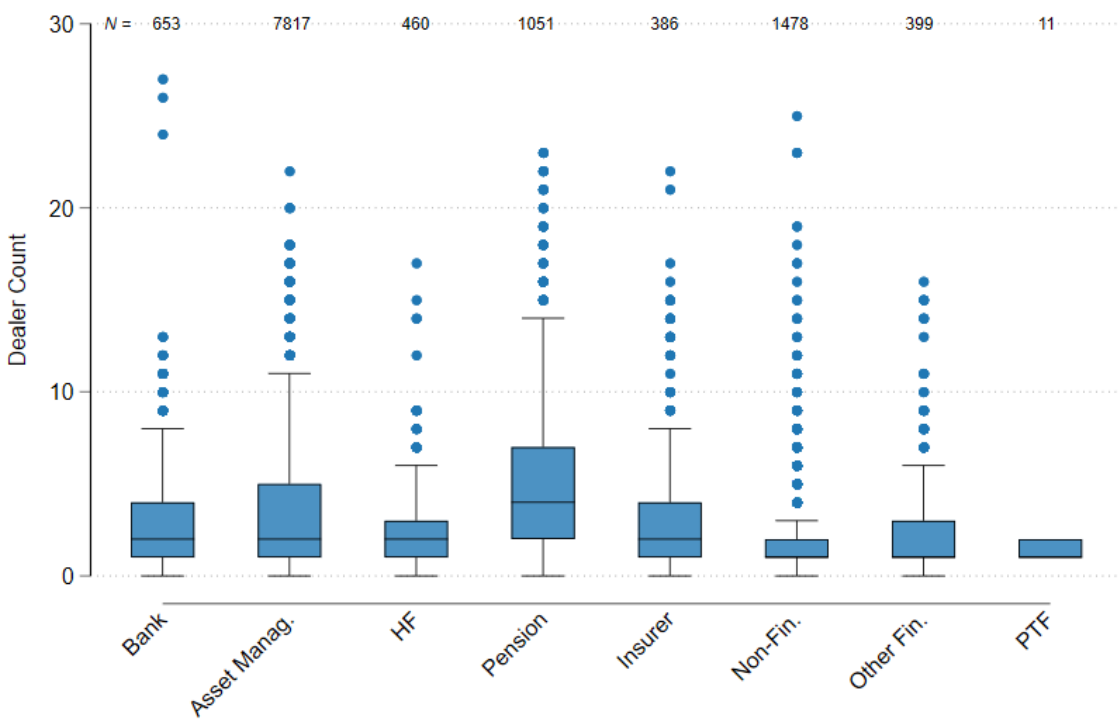
[15] Daily average notional outstanding positions for the all $\leq$ 1y maturity over the second half of 2023, by currency, are reported in Table 8 of Appendix D.1.

[16] See Table D6 for OTC foreign exchange derivatives in 2023S2 available at https://data.bis.org/topics/OTC_DER/tables-and-dashboards, accessed January 23, 2026.

respectively.[17]

At least 50% of clients 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. This is illustrated by 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.

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 $\leq$ 1y maturity. The 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 $\leq$ 1y maturity.

[17] See Table 9 in Appendix D.2 for statistics by client sector over the two-year sample.

[18] See Table 10 in Appendix D.6 for descriptive statistics at the client level for the all $\leq$ 1y maturity over our two-year sample period. A summary table for the maturity panel can be found 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.

The heterogeneity in dealer count and the low count for many clients could be partially explained by differences in trading activity. Clients trading 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 $4,964 million and a tenth percentile of less than $500,000. Additionally, at least 50% of clients trade on fewer than 2.6% of the 510 trading days in our sample.[20] When we individually control for 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 relationships with dealers. In Section 5, we examine whether these relationships affect the costs they pay and their ability to substitute in times of dealer stress.

The concentration of clients' trading activity across dealers is also heterogeneous, even among clients that traded with the same count of dealers. At least 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 distributions of the concentration of each client's notional trading activity across dealers over our two-year sample, by dealer relationship count. Figure 5a plots HHI and Figure 5b normalizes HHI by the corresponding equally distributed benchmark.[23] These figures highlight the heterogeneity in the concentration of client trading activity across dealers, for the same dealer relationship count, which 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. Appendix D contains additional information about our sample.[26]

[20] Table 10 in Appendix D.6 provides client-level descriptive statistics for the all $\leq$ 1y maturity 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 log total notional trading volume, respectively.

[22] See Table 10 in Appendix D.6, for cross-client distributions of (i) HHI for each client's trading activity across dealers and (ii) the share of the client's activity for the dealer they traded with most over the sample.

[23] We compute the Herfindahl-Hirschman Index (HHI) as $HHI_i = \sum_{d \in \mathcal{D}} \left(100 \times (N_{d,i}/N_i)\right)^2$, 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, $EqualDistribHHI_{DealerCount} = \sum_{d \in DealerCount} \left(100/DealerCount\right)^2$.

[24] Consider the 5 dealer count bucket. A client with equally distributed activity, a 20% share for each dealer, has a ratio of 1 in Figure 5b. Supposed they instead have a ratio of 2 and four of the dealers compose equal shares. Then, one dealer accounts for 60% of the client's activity and each of the others for 10%.

[25] See Appendix D.7 Table 12 for summary information at the (dealer, client, date) level.

[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.

4 Characteristics of Trading Relationships

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

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, 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]

We also expect clients to persistently trade with particular dealers, even conditional on having an existing relationship. Trading persistently 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 could result in currency-specific trading relationships. Additionally, 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.

[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 of FSB (2018), which uses survey responses to the DAT qualitative survey as described in FSB (2018).

[29] A net USD lending position is consistent with the dealer having a net buy USD forward position. If a client wants to borrow USD synthetically, they borrow foreign currency, spot to USD, and enter a contract to sell USD forward and buy foreign currency. The dealer would therefore buy USD in the forward leg of the contract.

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 clients with multiple dealer observations per week. Our trading panel consists of (dealer, client, week) observations where a notional trading position exists. So, we fill the set of dealers for each active (client, week) to capture the full set of potential dealers a client could trade with, even if they did not use them.[30] Since there is a higher probability of trading with a larger dealer, we include dealer × client sector × week fixed effects, $\alpha_{d,sec(i),w}$, to control for dealer size with the client sector and dealer-specific supply shocks. Our regression sample is the week of July 1, 2023 through December 31, 2023.

First, we estimate regression Equation 2 to test Hypothesis 1. 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, $\mathbb{I}[HasISDA_{d,i,w-1}]$, and whether this probability is higher when the client only had one relationship, $\mathbb{I}[Only1ISDA_{i,w-1}]$, which was with that dealer.[31] The dependent variable, $\mathbb{I}[Trade_{d,i,w}]$, equals 1 if client i traded with dealer d in week w.[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 to Equation 2. We include an indicator for whether the dealer-client pair had an outstanding position in the last 4 weeks, $\mathbb{I}[HasOut_{d,i,w-1}]$, another for whether the client only had one recent dealer relationship, $\mathbb{I}[Only1Dealer_{i,w-1}]$, 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 estimate Equation 3 to document whether clients are more likely to trade with a dealer that they relied on more heavily in the recent past. $RelStrength_{d,i,w-1}$ 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

[30]An active (client, week) is one where the client traded a positive notional amount in the all $\leq$ 1y maturity. We fill the dealer panel with all dealers that were active on a date prior to that week in our sample, except those with an intragroup relationship to the client. 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 the week of July 1, 2023 through December 31, 2023.

[31]$\mathbb{I}[HasISDA_{d,i,w-1}]$ denotes whether dealer d and client i ever had an outstanding relationship, and $\mathbb{I}[Only1ISDA_{i,w-1}]$ denotes whether a client only ever had one dealer relationship prior to week w. 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 beginning on January 1, 2022.

dealer d, denoted as $\%Traded$ and $\%Outstanding$ in Table 1 respectively.[33] We include $\mathbb{I}[HasISDA_{d,i,w-1}]$ and $\mathbb{I}[HasOut_{d,i,w-1}]$ to control for the greater probability of trading with a dealer because the fixed cost of relationship creation has already been paid and the existence of a recent relationship. 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.

$$\begin{aligned}\mathbb{I}[Traded_{d,i,w}] &= \beta_1 \mathbb{I}[HasISDA_{d,i,w-1}] + \beta_2 \mathbb{I}[Only1ISDA_{i,w-1}] \\ &\quad + \beta_3(\mathbb{I}[HasISDA_{d,i,w-1}] \times \mathbb{I}[Only1ISDA_{i,w-1}]) + \alpha_{d,sec(i),w} + \epsilon_{d,i,w} \qquad (2) \\ \mathbb{I}[Traded_{d,i,w}] &= \beta_1 \mathbb{I}[HasISDA_{d,i,w-1}] + \beta_2 \mathbb{I}[HasOut_{d,i,w-1}] \\ &\quad + \beta_3(\mathbb{I}[HasOut_{d,i,w-1}] \times RelStrength_{d,i,w-1}) + \alpha_{d,sec(i),w} + \epsilon_{d,i,w} \qquad (3)\end{aligned}$$

The results are displayed in columns (1)–(4) of Table 1 and support that relationships are persistent. Reading column (1), clients are 29.6% more likely to trade with a dealer if they had ever had a relationship with that dealer, which increases by 57.1% 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 also had an outstanding position in the last 4 weeks. If the dealer with which the client had a recent outstanding position was their only recent relationship, the client's probability of trading with that dealer increases by another 30.1%, as the coefficient on $\mathbb{I}[HasOut] \times \mathbb{I}[Only1Dealer]$ suggests.

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 dealer reliance 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 and there is a jump in this incremental probability when we move from the $(90, 95]$ to the $(95, 100]$ interval. This jump is consistent with the existence of fixed costs to new relationship creation.

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

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]	0.296***	0.082***	0.076***	0.070***	0.035***	0.053***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)
I[Only1ISDA]	-0.004***	-0.002***				
	(0.000)	(0.000)				
I[HasISDA] × I[Only1ISDA]	0.571***	0.234***				
	(0.005)	(0.009)				
I[HasOut]		0.322***	0.251***	0.269***	0.013	0.044***
		(0.005)	(0.006)	(0.006)	(0.010)	(0.003)
I[Only1Dealer]		-0.001**				
		(0.000)				
I[HasOut] ×I[Only1Dealer]		0.301***				
		(0.011)				
I[HasOut] × %Outstanding			0.004***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.041***	
					(0.005)	
None					-0.115***	
					(0.010)	
I[HasOutCCY]						0.327***
						(0.005)
Observations	4929011	4929011	4818043	4534115	4929011	1.15e+07
Client Clusters	8975	8975	8070	7349	8975	8975
R^2	0.4359	0.4969	0.5121	0.5117	0.1971	0.4276
Adjusted R^2	0.4345	0.4957	0.5108	0.5104	0.1951	0.4234
Within R^2	0.2306	0.3138	0.3345	0.3311	0.0965	0.2691
Dealer-Sector-Date FE	YES	YES	YES	YES	YES	NO
Dealer-Sector-CCY-Date FE	NO	NO	NO	NO	NO	YES

Notes: This table reports results from the (dealer, client, week) and (dealer, client, currency, week) regressions that test Hypotheses 1–2 for the period of June 25, 2023 to December 31, 2023. Dependent variables are indicators equal to 1 if the client traded ($I[Traded]$), net sold USD ($I[SellUSD]$), or traded in currency c ($I[TradedCCY]$) with the dealer that week. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client and dealer traded or had an outstanding position between January 1, 2022 and $w-1$; $I[Only1ISDA]$, 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 and dealer had an outstanding position 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 over the last month (*BuyUSD* is the reference group); $I[HasOutCCY]$, an indicator equal to 1 if the client and dealer had an outstanding position in the last month in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and week level in columns (1)–(5) and the client and (currency, week) level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

$$\begin{aligned}
\mathbb{I}[SellUSD_{d,i,w}] &= \beta_1 \mathbb{I}[HasISDA_{d,i,w-1}] + \beta_2 \mathbb{I}[HasOut_{d,i,w-1}] \\
&\quad + \beta_3(\mathbb{I}[HasOut_{d,i,w-1}] \times NetUSDPosition_{d,i,w-1}) + \alpha_{d,sec(i),w} + \epsilon_{d,i,w} \quad (4) \\
\mathbb{I}[TradedCCY_{d,i,c,w}] &= \beta_1 \mathbb{I}[HasISDA_{d,i,w-1}] + \beta_2 \mathbb{I}[HasOut_{d,i,w-1}] \\
&\quad + \beta_3(\mathbb{I}[HasOut_{d,i,w-1}] \times \mathbb{I}[HasOut_{d,i,c,w-1}]) + \alpha_{d,sec(i),c,w} + \epsilon_{d,i,w} \quad (5)
\end{aligned}$$

Consistent with Hypothesis 2, relationships seem to have a directional component and a currency-specific component. For example, conditional on trading in currency pair c in week w, 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 $\times$ 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]

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

Regardless of the currency pair traded, dealers may take advantage of 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 a 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 that clients pay a 0.01 basis point larger spread when the dealer accounted for a 1% larger share of

[34] To estimate Equation 5, we use a (dealer, client, currency pair, week) panel and fill the set of dealers for each active (client, currency pair, week), excluding dealer-client pairs with an intragroup relationship.

[35] For these results, see Tables 17 and 18 of Appendix E.2, respectively.

the client's trading activity in the last month, consistent with dealers exerting market power over more reliant clients. We do not find evidence of intertemporal dealer competition.

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 at a dealer by clients with different bilateral relationship characteristics, we use our spread maturity panel and estimate regressions at the (dealer, client, currency pair, maturity, date) level of the form presented in Equation 6. The specifications map the weekly regressions in Table 1 into our 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, described in Appendix C.1, but measured at the daily frequency. So, a 22 trading day, instead of 4 week, period is used to compute measures over the last month.[37] We include dealer $\times$ date fixed effects, $\alpha_{d,t}$, to control for dealer-specific characteristics that affect pricing on average and dealer-specific shocks that affect pricing over time. We include currency pair $\times$ maturity $\times$ date fixed effects, $\alpha_{c,m,t}$, to control for currency market-specific trading conditions. To increase our sample size, we extend the sample period to cover 1 year, January 1, 2023 through December 31, 2023. Table 2 presents the results.

In columns (1) and (2), we find that clients pay a 2.1 basis point larger spread at a dealer if it is the only dealer with which they had a relationship previously in our sample, relative to clients that had multiple dealer relationships. This highlights the importance of relationship creation costs for clients' ability to substitute to better alternatives.

[36] Unlike the regression in column (5) of Table 1, in our directional trading specification for spreads, we disaggregate our panel by trading direction and ask whether clients pay larger spreads 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, $\mathbb{I}[NetUSDOut_{d,i,t-1} = dir]$. All other specifications in Table 2, columns (1)–(4) and (6), aggregate across trading directions (Buy and Sell USD) by taking the notional weighted average of spreads.

[37] For example, $\mathbb{I}[HasOut_{d,i,t-1}]$ in our spread regressions is equal to 1 if dealer d and client i had an all $\leq$ 1y maturity outstanding position in at least one currency pair from trading dates $t-22$ through $t-1$.

Table 2: Spreads and Dealer-Client Trading Relationships

	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread
I[HasISDA]	-0.040	-0.006	0.285	0.291	0.267	0.295
	(0.442)	(0.449)	(0.431)	(0.431)	(0.414)	(0.433)
I[Only1ISDA]	-1.077	-1.075				
	(1.135)	(1.136)				
I[HasISDA] × I[Only1ISDA]	2.271*	2.143*				
	(1.155)	(1.159)				
I[HasOut]		-0.159	-0.468*	-0.345	-0.015	0.137
		(0.286)	(0.265)	(0.258)	(0.246)	(0.309)
I[Only1Dealer]		-0.016				
		(0.455)				
I[HasOut] ×I[Only1Dealer]		0.272				
		(0.468)				
%Outstanding			0.011***			
			(0.002)			
%Traded				0.009***		
				(0.002)		
I[NetUSDOut = dir]					0.007	
					(0.212)	
I[HasOutCCY]						-0.042
						(0.227)
Observations	1209305	1209305	1209305	1209305	3981549	1209305
Client Clusters	16,915	16,915	16,915	16,915	16,949	16,915
R^2	0.0877	0.0877	0.0875	0.0874	0.0640	0.0872
Adjusted R^2	0.0646	0.0647	0.0645	0.0644	0.0562	0.0642
Within R^2	0.0005	0.0005	0.0003	0.0002	0.0000	0.0000
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 the (dealer, client, currency, maturity, date) and (dealer, client, currency, maturity, date, direction) regressions that 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 bucket, 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 and dealer traded or had an outstanding position between January 1, 2022 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 and dealer had an outstanding position 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 and dealer had an outstanding position in the last month 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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Additionally, in columns (3) and (4), the coefficients for the client's reliance on the dealer in the previous month, $\%Outstanding$ and $\%Traded$, are positive and significant. Clients pay a 0.01 basis point larger average spread when the dealer composed a 1% larger share of the client's activity over the last month. This is consistent with dealers exerting market power over clients because greater reliance reflects lower search efficiency or worse alternative trading options. Relatedly, if the client was more reliant on a dealer, other dealers may charge smaller spreads to compete over this client's business. Our findings could result from spreads decreasing in trade size, which likely correlate with client's reliance on a dealer. For example, smaller clients may trade a smaller notional amount with the dealer and be more reliant on the dealer, but receive smaller discounts.[38] However, when we control for log notional traded and trade count, our results are similar.[39]

We recover a negative coefficient for $\mathbb{I}[HasOut_{d,i,t-1}]$ that is significant at the 10% level in column (3). However, across columns (2) through (6) the coefficients are not consistently negative or significant. Thus, we do not find strong evidence of intertemporal dealer competition, namely that clients receive a discount at dealers they had a relationship with more recently relative to other clients.

Although these spread regressions are endogenous, the results in Tables 1 and 2, suggest that clients who are more dependent on a dealer tend to pay a relative premium, 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 intuition of Duffie *et al.* (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.

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. Specifically, we take pre-existing relationships as exogenous with respect to the shock and study client outcomes when one of their 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 trading options for clients more heavily reliant on the shocked dealer. If search and bargaining frictions matter for substitution ability, we expect clients with more persistent relationships with Credit Suisse, more exposed to the shock, to pay relatively larger spreads post shock due to the exertion of dealer market power. To our knowledge, we are the first to examine trading patterns in the OTC FX derivatives market surrounding the shock to

[38]Bernhardt *et al.* (2005) emphasizes that intertemporal dealer competition can lead larger price improvements for more valuable clients, for example those that trade a larger notional with the dealer.

[39]See Appendix E.3.

Credit Suisse in March 2023.

In the context of this shock, we provide evidence against the importance of search and bargaining frictions, particularly on the intensive margin for clients that had another dealer relationship. We show that, within dealer–week, clients more reliant on Credit Suisse have a relative increase in trading activity with other dealers compared to less reliant clients, as a percent of their typical active relationship size. We do not find any significant differential change in spreads paid by these clients at other dealers or at the client level post shock. Our results suggest that greater reliance on the shocked dealer did not make trading relatively more costly for more exposed clients. In fact, more reliant clients seem to substitute without facing differentially greater costs. Additionally, clients less reliant on Credit Suisse, which we expect to be able to more frictionlessly substitute, do not have a significantly greater reduction in Credit Suisse-specific trading activity than those that were more reliant.

5.1 Background and Sample

First, we provide some background information and a description of the sample we use to analyze trading activity around the shock to Credit Suisse in March 2023, which led to large outflows of deposits from the institution and an increased risk of insolvency.

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 increasing its vulnerability 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.[40]

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" (Credit Suisse, 2022).[41] Credit Suisse then experienced a sell-off of its shares after an announcement that the Saudi National Bank would not continue providing financial

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

[41]See page 50 of Credit Suisse (2022), the Credit Suisse 2022 Annual Report, available at https://www.ubs.com/global/en/investor-relations/complementary-financial-information/disclosure-legal-entities/archive-credit-suisse.html.

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 (SNB, 2023).[42] 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.[43] 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.

5.1.2 Sample

For all analyses in this section, we restrict our sample to EURUSD activity over an 80 trading day period around the event date, which we define as March 8, 2023. The pre-period is January 12, 2023 through March 8, 2023 and the post-period is March 9, 2023 through May 4, 2023. We refer to January 1, 2022 through January 11, 2023 as the out-of-sample pre-period. We focus on the EURUSD market since it is the largest currency market, and composes the largest share of Credit Suisse's dealer-client notional outstanding positions, in our data. Including interdealer activity, the EURUSD daily average total notional traded (trade count)

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

[43] See Acosta-Smith *et al.* (2026), which shows that dealers reduce derivatives clearing activity for clients when they are affected by the leverage ratio requirement.

in the all $\leq$ 1y maturity from July 1, 2023 through December 31, 2023 was 247.82 billion USD (8.85 thousand).[44] Summing these averages across currencies, the EURUSD notional trading activity (trade count) accounts for 33.5% (30.8%) of average daily total activity in the second half of 2023. This is 10.8 (8.8) 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. Over the pre-period, the EURUSD average daily notional traded in the all $\leq$ 1y maturity by Credit Suisse lies between the 50th and 75th percentile of our dealer distribution. This is also the case for EURUSD average daily (i) count of clients traded with, (ii) trade count, and (iii) notional outstanding. We note that the distribution of EURUSD average daily notional traded across dealers is heavily skewed—the largest dealer has a value that is more than 15 times larger than the 75th percentile dealer.

To measure dealer-client trading activity and relationship measures, we use the all $\leq$ 1y maturity. For spreads, we use our maturity panel and include maturity fixed effects in all spread regressions. When we examine how the shock affected dealer-level EURUSD activity, we include all dealer-client observations for dealers that trade in every week of the sample period and aggregate the panel to the dealer-week level.[45] However, to examine how the shock affects client level and bilateral dealer-client trading activity in our other analyses, we restrict the sample to dealer-client pairs that had 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.[46] One implication of this restriction is that we exclude dealer-client pairs with activity in the post-period, but not the pre-period, which could provide additional insight into how clients that were exposed to the Credit Suisse shock were able to substitute in the post-period.

Moreover, in Section 5.2.2, we examine Credit Suisse-specific activity for clients that traded a positive EURUSD notional with Credit Suisse in the pre-period, where we split clients based on their previous relationship strength with Credit Suisse. Then in Section 5.3, we examine the trading activity of clients that were exposed to Credit Suisse, those with a positive EURUSD notional traded with Credit Suisse from January 1, 2022 through January 11, 2023, and split these clients based on the degree of their exposure.

[44] This excludes intragroup activity.

[45] This is because we use logs of activity variables as dependent variables and a balanced panel is used to perform a synthetic difference-in-differences analysis with placebo-based standard errors. Additionally, at the dealer-level, those not active every week are not an ideal control set for our treated unit.

[46] So, we restrict the panel being used for the regression to the subset where the dealer-client pair had a positive notional traded in the pre-period in that data panel.

5.2 Nature of Shock in FX Derivatives Market

In this section, we use difference-in-differences regression analyses to shed light on the nature of the shock. We provide evidence that this event was a shock that reduced Credit Suisse's OTC FX derivative trading activity. Then, we document whether clients that were less reliant on Credit Suisse experienced a relative reduction in Credit Suisse-specific trading activity compared to more reliant clients. This would be consistent with more reliant clients facing greater frictions to substitute to other dealers.

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 *et al.* (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 that a client's counterparty choice is modeled as a multinomial choice problem where dealers compete on spreads over a client's trading activity in a currency market, taking the spreads charged by other dealers as given. In Appendix B, we illustrate that the average spread a dealer charges a client 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 and therefore had a decline in trading quantities relative to other dealers, stated in Hypothesis 4.

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

We test Hypothesis 4 using a synthetic difference-in-differences (SDID) specification, described by Arkhangelsky *et al.* (2021), akin to the typical difference-in-differences two-way fixed effects (TWFE) regression given by Equation 7. In Equation 7, $Y_{d,w}$ denotes a measure of dealer trading activity in week w, $\mathbb{I}[Treated_d]$ equals 1 if the dealer is Credit Suisse and zero otherwise, $\mathbb{I}[Post_w]$ equals 1 if the week is after the week of March 8, 2023 and zero otherwise, and α_w and α_d are calendar week and dealer fixed effects.

$$Y_{d,w} = \beta(\mathbb{I}[Post_w] \times \mathbb{I}[Treated_d]) + \alpha_w + \alpha_d + \epsilon_{d,w} \tag{7}$$

The SDID is a weighted TWFE regression that can be used to estimate the average effect of the treatment on the treated, which in our case is the effect of the shock on Credit

Suisse's EURUSD FX derivatives trading activity. Specifically, control units are weighted to generate a weighted control group that better matches pre-shock trends of the treated unit, which makes the specification more robust to deviations in the parallel trends assumption for the standard TWFE difference-in-differences regression of Equation 7. There are also time period weights, which weight more heavily the time periods that are more similar to the post-treatment periods for the control units (Arkhangelsky *et al.*, 2021).[47]

We run the SDID on a balanced (dealer, week)-level panel where the treated dealer is Credit Suisse. The post-period is identified by the indicator $\mathbb{I}[Post_w]$. For dependent variables, $Y_{d,w}$, we use the natural logarithm of weekly notional traded and trade count in the EURUSD for the all $\leq$ 1y maturity. Table 3 presents the results of the SDID regressions with placebo-based standard errors, as described in Arkhangelsky *et al.* (2021). To reiterate, the goal of this analysis is to study whether this shock led to a reduction in EURUSD dealer-client trading activity for Credit Suisse relative to if the shock had not occurred, where in this case the control group is a weighted average of control dealers.

Table 3: Synthetic Difference-in-Differences: Effect of the Shock on Dealer-Level Activity

	(1) Ln(Not. Traded)	(2) Ln(Trade Count)
I[Post] × I[Treated]	-1.033*	-1.219***
	(0.560)	(0.250)
95% CI	[-2.131,0.064]	[-1.710,-0.728]
Observations	512	512
Dealer Clusters	32	32
Repetitions	500	500

Notes: This table reports results from the (dealer, week) synthetic difference-in-differences regressions as in Arkhangelsky *et al.* (2021), akin to Equation 7, that 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) in week w in the all $\leq$ 1y maturity. Independent variables are: $I[Post]$, an indicator equal to 1 if the week is after that of March 8, 2023; $I[Treated]$, an indicator equal to 1 if the dealer is Credit Suisse. All specifications incorporate dealer and calendar week fixed effects. We report placebo standard errors and 95% confidence intervals constructed as in Arkhangelsky *et al.* (2021), based on 500 iterations. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In column (1), we find that the shock reduced Credit Suisse's dealer-client EURUSD log notional traded. This effect is significant at the 10% level and implies that, relative to what would have occurred absent the shock, Credit Suisse's average weekly notional traded declined by approximately 64%. Further, we also find a significant reduction in log trade

[47] See Arkhangelsky *et al.* (2021), who write: "Time weights are designed so that the average posttreatment outcome for each of the control units differs by a constant from the weighted average of the pretreatment outcomes for the same control units." For more information on SDID, see Arkhangelsky *et al.* (2021).

count for Credit Suisse in column (2). The coefficient implies a 70% reduction in Credit Suisse's average weekly EURUSD dealer-client trade count due to the shock.[48]

To examine the time trends of our dependent variables for Credit Suisse relative to the control dealer average, we plot the difference in log notional traded and log trade count between Credit Suisse and the weighted control group in each week relative to the base week, that of March 8, 2023. These can be found in Appendix F, Figures 7a and 7b for log dealer-client notional traded and log dealer-client trade count in the EURUSD with maturity less than or equal to 1 year, respectively.

We see that in the pre-period, the difference in log notional traded fluctuates around zero and does not seem to have a clear trend. Additionally, for log trade count the difference moves around zero with less volatility and may have a very slight downward trend. Even so, the SDID specification helps remove bias relative to the typical TWFE difference-in-differences specification. Further, the time weights, plotted along the bottom of the figures, can also help remove bias since they reduce the influence of pre-shock weeks that differ a lot from post-shock weeks (Arkhangelsky *et al.*, 2021). In both figures, there is a visible decline from the pre- to the post-period, indicating that Credit Suisse's trading quantities declined relative to the control group in the post-period.

Thus, we provide evidence that Credit Suisse's total quantity of EURUSD FX derivatives trading activity declined due to the shock, relative to if this shock had not occurred. We note that this reduction could be due to a supply reduction by Credit Suisse or a Credit Suisse-specific decline in client demand. In the case of a demand reduction, we may expect clients to increase activity with Credit Suisse after the shock to cancel out their existing positions. This would correspond to an increase in Credit Suisse-specific trading activity post shock, which we do not see strong evidence of in Figures 7a and 7b.

It is likely 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, clients may be differentially affected by this shock based on their pre-existing reliance on Credit Suisse. In the next section, we examine which clients 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 the Credit Suisse-specific trading activity of clients that were more heavily reliant on Credit Suisse. Then, we examine the

[48]These percentages are computed as $(e^{\beta} - 1) \times 100$.

effect of the shock on client-level activity and clients' activity with other dealers based on their exposure to the shock in Section 5.3.

This shock could influence the trading decisions of Credit Suisse's clients, who may 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 if differences in pre-existing relationships and their persistence affect the availability of clients' outside options.

We hypothesize that the effect of the shock on client trading activity at Credit Suisse is heterogeneous. Specifically, clients that relied less heavily on Credit Suisse have a relative reduction in trading activity with Credit Suisse compared to more reliant clients, as stated in Hypothesis 5. In the context of Duffie *et al.* (2005), with persistent trading relationships, we expect the set of alternative trading options for more reliant clients to be 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. We examine whether the differential change in clients' Credit Suisse-specific trading quantities is consistent with this prediction.

Hypothesis 5 (Credit Suisse-Specific Activity By Client Reliance) *Clients that relied less heavily on Credit Suisse in EURUSD have a relative reduction in Credit Suisse-specific trading activity post shock compared to clients that relied more 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.[49] 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 test Hypothesis 6. For example, in corporate bond markets, Jurkatis *et al.* (2023) find that clients that are important for the dealer, compose a larger share of the dealer's past trading volume, receive better prices. This is in part due to clients providing the dealer with liquidity when the dealer's balance sheet is constrained.

So, we examine whether clients that are more important for Credit Suisse's client portfolio reduce their Credit Suisse-specific activity relative to less important clients after the shock,

[49] See Appendix B for an illustrative model where the average spread a dealer charges a client is increasing in the market share they have for the client and decreasing in the elasticity of the client's demand.

thereby helping the dealer accommodate its balance-sheet tightening.[50] As with Hypothesis 5, we focus on documenting the differential change in trading quantities.

Hypothesis 6 (Credit Suisse-Specific Activity By Client Importance) *Clients that were more important for Credit Suisse's EURUSD portfolio have a relative reduction in Credit Suisse-specific trading activity post shock compared to clients that were less important for Credit Suisse.*

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. We measure the importance of a dealer-client relationship for the client 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 are similar into those from Section 4, used to document that clients trade more persistently with dealers that they rely on more heavily. One of the measures uses notional outstanding positions 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.[51] Analogous measures, but computed as the share of the dealer's activity accounted for by the client, are used to test Hypothesis 6.[52] We compute relationships using EURUSD activity, since relationships have a currency-specific component, as we previously documented in Section 4.[53]

Using these relationship measures, we examine whether among dealer-client pairs where the dealer is Credit Suisse, those with weaker bilateral relationships had a differential change in their Credit Suisse-specific activity post shock than stronger relationship clients. To test this, we estimate Equation 8 on the sample of dealer-client pairs that traded EURUSD in the pre-period and where the dealer is Credit Suisse. The dependent variables, $Y_{CS,i,t}$, measure client i's activity on date t with Credit Suisse. The indicator $\mathbb{I}[WeakRel_{d,i}]$ is equal to 1 if the client's relationship measure with the dealer is less than or equal to the cross-client

[50]We would also expect them to pay a smaller increase in spreads at Credit Suisse. However, we focus on examining quantities here as we do not have many Credit Suisse-specific spread observations.

[51]The sum of notional outstanding positions weights long maturity relationships more heavily because, when we sum outstanding positions across days, outstanding positions count in the sum every day until they mature. This day count is greater for longer-term positions.

[52]Details on the constructions of these measures can be found in Appendix C.2. Equations 28 and 29 show how these measures are computed.

[53]For our main specification, presented in Table 4, we also compute the relationship measure using activity across all currencies and obtain similar results. These results are in Appendix H.

median for the dealer, Credit Suisse.[54] So, depending on the relationship measure used, the relationship is considered weak when the client (i) relied less heavily on Credit Suisse or (ii) composed a smaller share of Credit Suisse's activity than the median client that traded with Credit Suisse in the pre-period.

$$Y_{CS,i,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2 \mathbb{I}[Post_t] \times \mathbb{I}[WeakRel_{CS,i}] + \alpha_i + \epsilon_{CS,i,t} \tag{8}$$

We are interested in coefficients β_1, which informs us of whether strong-relationship Credit Suisse clients reduced their Credit Suisse-specific activity on average from the pre- to the post-period, and β_2, which tests whether weak-relationship clients has a relative reduction in their Credit Suisse-specific activity compared to strong-relationship clients. When testing Hypothesis 5, we expect β_2 to be negative and significant if more reliant clients have greater difficulty substituting to alternative dealers than less reliant clients due to trading relationship persistence. We include client fixed effects, α_i, to control for time-invariant client characteristics. We also estimate Equation 8, including week fixed effects, α_w, which exploits variation across observations within the same week instead of the same day of trading.

Since many dealer-client pairs have days on which they do not trade, for our notional traded and trade count dependent variables, we retain (dealer, client, date) observations with no trading activity as zeros. We specifically measure the value of the activity variable on date t for dealer d and client i in EURUSD as a percent of their out-of-sample pre-period daily average value in EURUSD on days where the value is positive. This measure allows us to incorporate the intensive and extensive margin of trading activity and ask whether strong versus weak relationship clients had a relative increase in their notional traded or trade count as a percent of their average active relationship size. These variables are specifically computed as in Equation 9.[55] We also use this measure for notional traded and trade count dependent variables for our analyses in Section 5.3.

$$\%\,Value_{d,i,t} = 100 \times \frac{Value_{d,i,t}}{\overline{Value}_{d,i,\{l \in \text{Out of Sample: } Value_{d,i,l} > 0\}}} \tag{9}$$

In the denominator of Equation 9, we use an average over active trading days to avoid

[54]This cross-client median is taken over the set of clients with which dealer had a positive EURUSD notional trading position in the pre-period. The definition of this indicator for a given relationship measure is presented explicitly in Equation 30 of Appendix C.2.

[55]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 extensive 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.

inflating the dependent variable for observations that trade less frequently. We also winsorize these variables at the first and 99th percentiles at the (dealer, client, date) level before restricting to Credit Suisse observations to reduce the influence of outliers, as some values can be large in percentage terms if activity was small in the out-of-sample pre-period.

Our main test of Hypothesis 5 uses the share of a client's notional traded in EURUSD accounted for by Credit Suisse as the measure of bilateral relationship strength. The results are presented in Table 4. All β_1 coefficients are significant and negative. However, though the coefficients on $\mathbb{I}[Post_t] \times \mathbb{I}[WeakRel_{d,i}]$ are negative, they are insignificant. These suggest that the more reliant clients at Credit Suisse had a reduction in their trading activity with Credit Suisse post shock, as a percent of their historical relationship size. Additionally, we do not find significant evidence that less reliant clients had a differentially larger reduction in Credit Suisse activity relative to more reliant clients.[56]

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

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]
I[Post]	-2.997**	-4.875**	-0.047**
	(1.455)	(2.111)	(0.021)
I[Post] x I[WeakRel_di]	-3.520	-1.132	-0.019
	(2.601)	(2.851)	(0.032)
Observations	5,360	5,360	6,000
Client Clusters	67	67	75
R^2	0.0974	0.1529	0.2143
Adjusted R^2	0.0858	0.1421	0.2042
Within R^2	0.0061	0.0141	0.0189

Notes: This table reports results from difference-in-differences regressions at the (client, date) level, given by Equation 8, that test Hypothesis 5. Dependent variables are: *% Not. Traded* (*% Trade Count*), EURUSD notional (trade count) traded by the client with Credit Suisse 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 9, and winsorized at the first and 99th percentiles before restricting to Credit Suisse observations; $\mathbb{I}[Traded]$, an indicator equal to 1 if Credit Suisse and the client trade in EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: $I[WeakRel\_di]$, an indicator equal to 1 if client was less reliant on Credit Suisse in EURUSD than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. Measurement details for $I[WeakRel\_di]$ are in Appendix C.2, which uses EURUSD activity. All specifications include client fixed effects. Standard errors are double clustered at the client and date level. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our results are consistent with Credit Suisse's dealer-level activity declining from the pre- to the post-period. Further, they indicate that Credit Suisse activity for clients declined, as a percent of their typical active trading relationship size, in a way that did not depend

[56]We may also not have enough power to identify the effect in our Credit-Suisse specific trading sample.

significantly on their reliance on Credit Suisse, a proxy for trading relationship persistence.

This goes against Hypothesis 5 since a weak relationship here means that the client relied less heavily on Credit Suisse for their historical EURUSD trading activity and therefore, as documented in Section 4, has a less persistent or sticky trading relationship with Credit Suisse. However, we do not find evidence consistent with less reliant clients more readily substituting away from Credit Suisse. The results are consistent when we include calendar week fixed effects to control for common time series shocks—the coefficients on $\mathbb{I}[Post_t] \times \mathbb{I}[WeakRel_{d,i}]$ are negative but insignificant.[57] They are also similar when we compute client reliance using activity in all seven currency pairs, as shown in Appendix H.

The β_2 coefficients 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 8 and 9 of Appendix G plot the coefficients for trade count and an indicator equal to 1 if Credit Suisse and the client trade as dependent variables, respectively. Within a sub-figure, the x-axis denotes which relationship strength measure was used to compute $\mathbb{I}[WeakRel_{d,i}]$ in the regression equation. Columns (2) and (4) test Hypothesis 5, where column (2) corresponds to Table 4 and a weak relationship indicates that the client relied less heavily on Credit Suisse for EURUSD activity than other clients. These are of primary interest to us.

The signs of the coefficients are negative but insignificant from zero in columns (2) and (4) of Figure 2. So, although the sign of these coefficients are consistent with Hypothesis 5, that less reliant clients had a relative decline in trading activity with Credit Suisse than those that were more reliant, we cannot identify a significant difference.

This is similarly the case in columns (1) and (3) of Figure 2, which instead test Hypothesis 6. A weak relationship in these cases implies that the client was less important for the Credit Suisse's EURUSD activity relative to other clients. These coefficients are positive, consistent with our hypothesis that clients more important for Credit Suisse's portfolio may be more accommodating than less important clients after the adverse shock to Credit Suisse's balance sheet. However, these effects are insignificant from zero.[58]

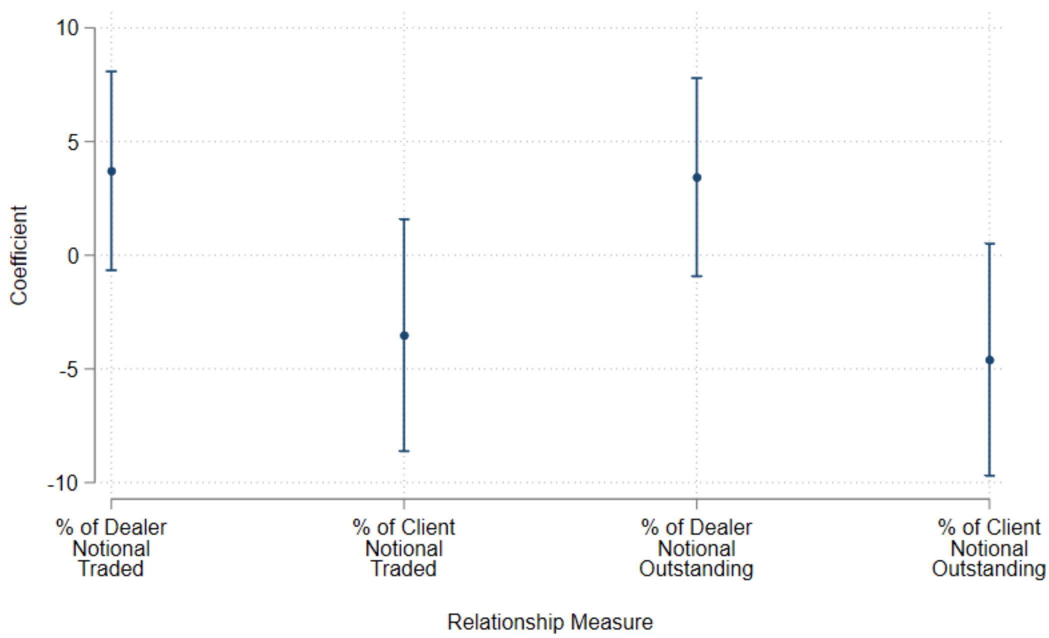
In summary, the results presented in Table 4, suggest that clients of both types may have been able to substitute to alternative dealers. Additionally, though we do not identify a differential decline in Credit Suisse activity for the less reliant clients than the more reliant clients, it could still be more difficult or costly for heavily reliant clients to trade with alternative dealers even if their Credit Suisse-specific activity declined. For example, the clients that are more reliant on Credit Suisse for EURUSD activity may have (i) fewer dealer relationships or (ii) lower search efficiency for the same dealer relationship count. Moreover,

[57] See Table 20 of Appendix G.

[58] This is also the case for columns (1) and (3) in Appendix G, Figures 8 and 9, which test Hypothesis 6.

this shock may more negatively affect the bargaining power of more reliant clients when they trade with other dealers. We test how client-level activity and non-Credit Suisse-specific activity changed post shock, based on clients' reliance on Credit Suisse in the out-of-sample pre-period, in the next section.

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_2, from regressions at the (client, date) level that test Hypotheses 5 and 6. All columns correspond to Equation 8 with additional calendar week fixed effects, 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) and (4) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is $\%\ Not.\ Traded_{CS,i,t}$, EURUSD notional traded by the client with Credit Suisse 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 9, and winsorized at the first and 99th percentiles before restricting to Credit Suisse observations. Independent variables are: $I[WeakRel]$, an indicator equal to 1 if client was had a weaker EURUSD relationship with Credit Suisse than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. X-axis labels denote the relationship strength measure used for $I[WeakRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[WeakRel]$. All regressions include client and calendar week fixed effects. Standard errors are clustered at the client and date level. Error bars plot $\pm 1.96 \times SE$.

5.3 Implications for Exposed Clients' Trading Activity

Next, we document whether the reliance of a client on an adversely shocked dealer affects client trading outcomes overall and with other dealers. That is, were clients that had a more reliant relationship with the shocked dealer ("more exposed") able to substitute and did they face larger spread increases at other dealers due to a worsening of outside options and bargaining power? We showed in Section 5.2.2, that a client's reliance on Credit Suisse did significantly affect their activity with Credit Suisse declined post shock. However, in the context of search and bargaining frictions with persistent trading relationships, if a main outside trading option for more exposed clients was adversely affected, we expect these clients to have a reduction in bargaining power at other dealers and a greater difficulty substituting to alternatives—experiencing a greater worsening of trading conditions, paying larger spreads.

Analogous to the measure of client reliance on a dealer in Section 5.2.2, we define a client's exposure to the shock as the percent of the client's total notional traded in EURUSD over the out-of-sample pre-period that was with Credit Suisse, given by Equation 10.[59] The median value of E_i across exposed clients in the all $\leq$ 1y maturity sample is 5%.[60]

$$E_i = 100 * \frac{\sum_{t \in OutOfSample} NotionalTraded_{CS,i,t,EURUSD}}{\sum_{t \in OutOfSample} NotionalTraded_{i,t,EURUSD}} \tag{10}$$

We aim to document the implications of persistent trading relationships for client trading outcomes in this market. Our exposure measure is useful for studying client search and bargaining frictions and whether dealers exert market power over clients. In particular, as shown in Section 4, clients trade persistently with relationships they rely on more heavily, relationships are currency specific, and greater reliance on a dealer corresponds to higher premia on average. So, we expect clients that relied more heavily on Credit Suisse for EURUSD to have a larger reduction in bargaining power post shock and a greater difficulty substituting to alternative dealers.

5.3.1 Client-Level Trading Activity

We hypothesize, as stated in Hypothesis 7, that clients who were more exposed to Credit Suisse faced a relative increase in *client-level* spreads on average in the post-period compared to less exposed clients.[61] We expect more exposed clients to have more persistent relationships with Credit Suisse, since we showed in Section 4 that clients are more likely to trade with a dealer when they had greater reliance on that dealer. For example, these clients may search less efficiently across other dealers or "match" with Credit Suisse more frequently in their search process. Motivated by search and bargaining frictions as in Duffie *et al.* (2005),

[59] E_i corresponds to the relationship strength measure given by Equation 28 in Appendix C.2, where d is Credit Suisse.

[60] The distributions of E_i across clients with positive exposure in our all $\leq$ 1y maturity and maturity panel samples are in Appendix I.

[61] By "more exposed" we refer to clients that relied more heavily on Credit Suisse than the median client that had positive exposure to Credit Suisse.

because of their greater trading persistence, this adverse shock to a main outside trading option for more exposed clients may differentially reduce their bargaining power in trade negotiations with non-Credit Suisse dealers. So, other dealers can charge larger spread increases to these clients than less exposed clients, leading client-level spreads to differentially increase for more exposed clients. We expect client-level trading activity for more exposed clients to decline by more relative to less exposed clients if this is the case, as trading costs increase.

Furthermore, we showed in Section 5.2.2 that trading activity with Credit Suisse declined after the shock and this decline was not differentially larger for less reliant clients. If more exposed clients have greater search frictions due to their greater trading persistence with the shocked dealer, we would expect these clients to have greater difficulty trading with other dealers when their activity with Credit Suisse declines. Thus, we hypothesize their client-level trading volume will decline by more than less exposed clients in the post-period.[62]

Hypothesis 7 (Exposed Client Bargaining Power and Search Frictions) *Clients that relied more on Credit Suisse for EURUSD trading, "more exposed", have a relative increase in spreads and reduction in client-level trading activity compared to less exposed clients post shock.*

To test Hypothesis 7, we study whether this shock affected client-level activity differentially for more exposed clients compared to less exposed clients. Using difference-in-differences 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 have differential changes in notional trading volume or spreads relative to less exposed clients post shock. Equation 11 presents our regression equation, which we estimate on the sample of clients that were exposed to the shock and treat the set of more exposed clients as the treated group.[63] Specifically, we split the exposed clients by whether they more or less exposed to Credit Suisse, denoted by the indicator $\mathbb{I}[MoreExposed_i]$. A more exposed client refers to one whose exposure to Credit Suisse is above the median level

[62] Our sample includes all dealer-client pairs that traded a positive EURUSD notional in the pre-period and the client traded with Credit Suisse between January 1, 2022 and January 11, 2023. So, some exposed clients do not trade with Credit Suisse in the event pre-period. At the client-level, their activity catures their activity with only non-Credit Suisse dealers. This substitution component would be captured for clients that traded with Credit Suisse in the pre-period. For those that did not, we would expect a differential decline in the their client-level trading activity if they reduce trading quantities for example because they pay greater markups with other dealers that exert market power over them, making trading more costly than in the pre-period.

[63] To create the (client, date)-level panel, we take the set of (dealer, client, date) observations for dealer-client pairs where the client had positive exposure to Credit Suisse and the dealer and client traded a positive EURUSD notional in the pre-period. Then, we sum the notional values and trade counts across dealers for each (client, date). For spreads, we take notional weighted averages.

among exposed clients. Conversely, a less exposed client is an exposed client whose exposure is at or below that median.

$$Y_{i,t} = \beta_1 \mathbb{I}[Post_t] + \beta_2(\mathbb{I}[Post_t] \times \mathbb{I}[MoreExposed_i]) + \alpha_i + \alpha_w + \epsilon_{i,t} \tag{11}$$

The coefficient β_2 estimates the differential change in the outcome variable for clients that were more exposed relative to clients that were less exposed 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, to avoid removing a lot of variation as many clients do not trade every day.

Table 5 displays the results, where the outcome variables are % Notional Traded and % Trade Count by the client in EURUSD, an indicator $\mathbb{I}[Traded_{i,t}]$ denoting whether the client traded on date t, and the notional weighted average spread at the (client, maturity, date) level. $\%\ Not.\ Traded_{i,t}$ and $\%\ Trade\ Count_{i,t}$, as before, are winsorized at the first and 99th percentiles, but at the (client, date) level before restricting to the set of clients with positive exposure.

Focusing on the coefficients for the interaction term, $\mathbb{I}[Post_t] \times \mathbb{I}[MoreExposed_i]$, columns (1), (3) and (4) do not recover any significant differential changes in daily notional traded, probability of trading, or spreads paid by more exposed clients relative to less exposed clients post shock.[64] In column (2), we find that more exposed clients have a relative increase in client-level trade count relative to their active out-of-sample average compared to less exposed clients. Although the coefficient in the spread regression is positive, consistent with more exposed clients paying relative spread increases post shock, we do not identify a significant effect.

These results push against Hypothesis 7. They indicate that clients that were more reliant on Credit Suisse did not face significantly worse trading conditions at the client-level relative to less exposed clients, who may have had (i) a smaller shock to their bargaining power and (ii) fewer frictions in substituting to alternative dealers. We even see in column (2) that more exposed clients' change in average trade count, as a percent of their average active trade count in the out-of-sample pre-period, was more positive than that for less exposed clients post shock. So, more exposed clients seem to have resilient trading outcomes and perhaps even substitute to other dealers.

For example, we found in Section 5.2.2 that client reliance on Credit Suisse did not differentially affect clients' Credit Suisse-specific activity which declined on average from the

[64] Table 5 contains coefficients for $\mathbb{I}[Post_t]$ because the calendar week fixed effects do not fully absorb the post-period indicator in the week of the shock. We do not focus on this term as the coefficients for $\mathbb{I}[Post_t]$ are identified off of the variation only within that treatment week.

pre- to the post-period. Although our client-level specification does not only capture activity for clients that traded with Credit Suisse in the pre-period, our results suggest that these more exposed clients were able to substitute to other dealers. Additionally, our interpretation of the shock as one that may differentially harm more exposed clients' bargaining power when trading relationships are persistent applies to all of the more exposed clients, not just those that traded with Credit Suisse in the pre-period. Our insignificant client-level spreads results suggest that dealers did not differentially exert market power over more exposed clients post shock, where we expected this shock to affect more exposed clients' bargaining power.[65]

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

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]	(4) Spread
I[Post]	-2.606	-2.058	-0.012	-2.597**
	(4.779)	(2.568)	(0.017)	(1.042)
I[Post] × I[More Exposed]	1.359	4.863*	0.022	2.110
	(2.885)	(2.446)	(0.017)	(1.678)
Observations	22,400	22,400	22,400	8,362
Client Clusters	280	280	280	219
R^2	0.2236	0.3455	0.4819	0.0338
Adjusted R^2	0.2131	0.3367	0.4749	0.0040
Within R^2	0.0000	0.0008	0.0003	0.0005

Notes: This table reports results from difference-in-difference regressions at the (client, date) and (client, maturity, date) level that test Hypothesis 7, corresponding to Equation 11, where column (4) is at the (client, maturity, date) level and includes additional maturity fixed effects. Dependent variables are: *% Not. Traded* (*% Trade Count*), EURUSD notional traded (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 9, and winsorized at the first and 99th percentiles before dropping unexposed clients; $\mathbb{I}[Traded]$, an indicator equal to 1 if the client traded in EURUSD at t in the all $\leq$ 1y maturity; *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; $I[MoreExposed\_i]$, an indicator equal to 1 if the exposed client has exposure E_i above the cross-exposed client median exposure to Credit Suisse, and equal to 0 if E_i is positive but less than or equal to the cross-exposed client median. Exposure E_i is computed according to Equation 10. The samples aggregate the set of observations for dealer-client pairs where the client had positive exposure to Credit Suisse and the dealer and client traded a positive EURUSD notional in the pre-period. All specifications include client and week fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Exposed Clients' Trading Activity With Other Dealers

Next, as an extension to Hypothesis 7, we test whether there is a relative increase in non-Credit Suisse dealers' trading activity and spreads with more exposed clients compared

[65]It is worth noting that in our spread panel, most of the exposed client observations in the post-period are with non-Credit Suisse dealers. So, the client-level spreads are primarily capturing spreads with non-Credit Suisse dealers.

to less exposed clients post shock, within-dealer. That is, whether exposed clients have substitution patterns that are accommodated by other dealers. If this is an adverse shock to a trading alternative for exposed clients, non-Credit Suisse dealers have a greater increase in bargaining power over more exposed clients from the pre- to the post-period than over the less exposed clients they trade with. Thus, we expect a relative increase in spreads charged by these dealers to more exposed clients than to less exposed clients. In addition, it could be the case, as suggested by the results of Table 5, that more exposed clients substitute from Credit Suisse toward other dealers, trading a greater amount with non-Credit Suisse dealers relative to their typical bilateral trading activity with those dealers.[66] We test whether more exposed clients' potential substitution from Credit Suisse is accommodated by other dealers.

Hypothesis 8 (Exposed Clients With Other Dealers) *There is a relative increase in non-Credit Suisse dealers' activity and spreads with more heavily exposed clients post shock than less exposed clients, within dealer.*

Using variation across clients within the same (dealer, week), we document that the change in average trading activity from the pre- to the post-period with other dealers for clients that were more exposed to Credit Suisse, as a percent of their typical activity with that dealer, was more positive than that for less exposed clients. Additionally, they did not pay a significantly more positive change in spreads per notional dollar traded relative to less exposed clients. This is consistent with other dealers accommodating substitution by more exposed clients without charging them larger increased markups, even though these clients have a worsened set of outside options post shock because they relied more on Credit Suisse in the past.

We estimate Equation 12 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 effects allow us to control for dealer-by-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. The client fixed effects, for example, control for characteristics that may affect the average markup a client pays. The independent variable $\mathbb{I}[MoreExposed_i]$ is as specified in Section 5.3.1.

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

[66] Even for clients that did not trade with Credit Suisse in the pre-period, they may substitute any potential activity they would have had with Credit Suisse to alternative dealers post shock.

The results are presented in Table 6. The dependent variables % Notional Traded, % $Trade\ Count_{d,i,t}$, and $\mathbb{I}[Traded_{d,i,t}]$ are as described previously, but at the (dealer, client, date) level.[67] Notional weighted spreads are at the (dealer, client, maturity, date) level.

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

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]	(4) Spread
I[Post]	-0.203	-1.146	-0.022***	-2.494***
	(1.709)	(1.050)	(0.005)	(0.569)
I[Post] × I[More Exposed]	2.743**	2.069**	0.014*	1.841
	(1.318)	(0.941)	(0.008)	(1.460)
Observations	60,240	60,240	61,760	10,780
Client Clusters	233	233	240	208
R^2	0.1215	0.1429	0.1789	0.0745
Adjusted R^2	0.1103	0.1319	0.1683	0.0267
Within R^2	0.0001	0.0001	0.0001	0.0003
Dealer-Week FE	YES	YES	YES	YES
Client FE	YES	YES	YES	YES
Maturity FE				YES

Notes: This table reports results from difference-in-difference regressions at the (dealer, client, date) and (dealer, client, maturity, date) level that test Hypothesis 8, corresponding to Equation 12, where column (4) is at the (dealer, client, maturity, date) level and includes additional maturity fixed effects. Dependent variables are: % *Not. Traded* (% *Trade Count*), EURUSD notional traded (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 9, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs and unexposed clients; $\mathbb{I}[Traded]$, 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. 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; $I[MoreExposed]$, an indicator equal to 1 if the exposed client has exposure E_i above the cross-exposed client median exposure to Credit Suisse, and equal to 0 if E_i is positive but less than or equal to the cross-exposed client median. Exposure E_i is computed according to Equation 10. All specifications include dealer × week and client fixed effects, and column (4) includes additional maturity fixed effects. Standard errors are double clustered by client and date. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We find that, within dealer, the change in dealers' average bilateral notional trading activity with more exposed clients, as a percent of the dealer-client pair's typical active trading activity, was more positive than that with less exposed clients by 2.74 percentage points. There is also a more positive change in trade count and the probability of trading with the dealer. So, clients more exposed to the shock disproportionately increase the strength of their trading activity post shock relative to clients that were less exposed, at the same non-Credit Suisse dealer. Additionally, we do not find that more exposed clients pay a relative

[67]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 or the client is unexposed.

increase in spreads.

Our results are not consistent with Hypothesis 8—that the shock adversely affected the set of outside trading options for clients that relied more heavily on Credit Suisse, leading these dealers to exert greater market power over and increase their spreads by more to these clients. Instead, we showed in Section 5.3.1 that more exposed clients did not face a differential change in client-level notional trading activity, and in Section 5.2 that there was a reduction in Credit Suisse-specific trading activity. Thus, along with the results in Table 6 that show, within-dealer, more exposed clients had a relative increase in trading activity, our results suggest that these clients were able to substitute to non-Credit Suisse dealers and did not pay a relative spread increase. Our findings emphasize that search and bargaining frictions were not very costly for trading ability post shock.

It may be that the shock to Credit Suisse forced clients to search for or trade with alternative dealers and other dealers competed in the post-period to gain the business of these clients. Thus, we do not find results consistent with these dealers exerting market power over clients, as they want to gain or retain clients' business immediately post shock. Initially, dealers may offer favorable terms to attract persistent traders, but in the later post-shock period they may increase trading costs for the more exposed clients after securing this flow. As our post-period sample consists of the 40 trading days immediately following the shock, this remains to be tested.

Additionally, the results in Table 6 are conditional on clients having alternative non-Credit Suisse dealer relationships since we condition our sample on the set of dealer-client pairs that trade EURUSD in the pre-period. So, it could be the case that these patterns reflect the nature of clients' alternative trading relationships. For example, clients may pay a higher premium on average, or there may be additional terms of the trading relationship that adjust, such that that these dealers do not exploit their trading terms for these clients in these states of the world.

Moreover, our sample does not capture the extensive margin of substitution—clients' creation of new dealer relationships. However, it may be that the extensive margin of search, which requires paying fixed costs of relationship creation to substitute, is more frictional and results in worsened trading conditions for exposed clients after a shock to their dealer, particularly in the short run.

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

Finally, we examine how pre-existing relationship strength at non-Credit Suisse dealers affects trading outcomes for clients at these dealers post shock. We include client $\times$ week fixed effects to control for changes in client demand over time and ask whether a client's previous reliance on other dealers affects their substitution patterns and the spreads they pay. That is, we study whether more exposed clients had a relative increase in their trading activity and spreads at the non-Credit Suisse dealer that they relied on the most. 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.[68] 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 relative increase in trading activity and spreads post shock with the non-Credit Suisse dealer that they relied on more heavily than less exposed clients.*

We generate an indicator $\mathbb{I}[StrongRelClient_{d,i}]$ 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.[69] We use all seven currencies for this measure to capture a broader set of dealer relationships since the median client in our two-year data sample only had 1 dealer relationship.[70] We do not use our previous measure of a strong relationship here because the more exposed clients relied more on Credit Suisse and therefore less on other dealers. So, by construction, 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 trades with most persistently and therefore is most likely to substitute to.

We estimate Equation 13, where $\mathbf{X}'_{d,i,t}$ denotes the set of interaction terms that are not absorbed by the fixed effects, using the set of (d,i,t) observations where the dealer and client traded EURUSD in the pre-period, the clients were exposed to Credit Suisse, and the dealer is not Credit Suisse. As before, $\mathbb{I}[MoreExposed_i]$ denotes whether the client in the (d,i,t) observation was more exposed to Credit Suisse. We use the same dependent variables as in

[68] This is illustrated in Equation 25 of the model in Appendix B. For a given increase in market share, the average spread a dealer charges the client increases more due to markups if the dealer has a larger initial market share of the client's activity. So, when a client allocates activity away from Credit Suisse, we expect them to allocate an equal or greater amount of activity to dealers that they persistently trade with, proxied by composing a larger share of the clients activity. Therefore, we expect a relative increase in spreads for trades with dealers that had greater market power over the client.

[69] $\mathbb{I}[StrongRelClient_{d,i}]$ is computed using the out-of-sample relationship measure given by Equation 28 in Appendix C.2, computed over all seven currencies in our sample.

[70] See Appendix D.6 Table 10.

Section 5.3.2.[71]

$$
\begin{aligned}
Y_{d,i,t} = {} & \beta_1(\mathbb{I}[Post_t] \times \mathbb{I}[MoreExposed_i] \times \mathbb{I}[StrongRelClient_{d,i}]) \\
& + \mathbf{X}'_{d,i,t}\gamma + \alpha_{iw} + \alpha_d + \epsilon_{d,i,t}
\end{aligned} \tag{13}
$$

We are interested in the coefficient β_1, which gives the differential change in $Y_{d,i,t}$ for the dealer identified by $\mathbb{I}[StrongRelClient_{d,i}]$ relative to the other dealers in the client's dealer set for the more exposed clients versus less exposed clients. With the client × week fixed effect, we exploit cross-dealer variation, controlling for client demand, to test whether more exposed clients reallocated their trading activity relatively more to and paid a relatively larger increase in spreads at their main non-Credit Suisse dealer compared to the activity of less exposed clients with their main non-Credit Suisse dealer. Table 7 presents the results.

We note that the coefficients on $\mathbb{I}[Post_t]$ and $\mathbb{I}[Post_t] \times$ *More Exposed* appear in Table 7 because $\mathbb{I}[Post_t]$ is not constant within the week of the shock, March 8, 2023, but is for all other weeks. Otherwise, the variation would be absorbed by the client × week fixed effects.

We do not find any significant effect for β_1 across all columns of Table 7. That is, based on the triple interaction coefficients that are insignificant across columns (1)–(3), we do not identify that more exposed clients differentially changed their EURUSD trading quantities across their dealer set based on relationship strength. Specifically, more exposed clients did not significantly increase their activity to their main alternative dealer relative to other dealers, as a percent of their typical active relationship size with the dealer. Additionally, more exposed clients did not face a relative 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 less exposed group.

Overall, our analysis provides evidence against heavily reliant clients, due to their relationship persistence with the shocked dealer, face search and bargaining frictions that affect the resilience of their trading activity post shock. Instead, we show that these clients had a relative increase in their trading activity with non-Credit Suisse dealers than less exposed clients, as a percent of their typical bilateral relationship size, and did not differentially substitute to or pay relatively greater spread changes at their main non-Credit Suisse dealer relative to other dealers they traded with. This counters the hypothesis that, when the set of outside options for the more exposed client worsens, this main alternative dealer takes advantage of an increase in bargaining power that stems from their persistent trading relationship with the client, as they have a larger share of the client's trading activity.

[71] $\%$ $Not.\ Traded_{d,i,t}$ and $\%$ $Trade\ Count_{d,i,t}$ are winsorized at the first and 99th percentiles over all dealer-client pairs, before excluding (d, i, t) pairs where the dealer is Credit Suisse or the client was unexposed.

Table 7: Role of Client Reliance on Other Dealers

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]	(4) Spread
I[Post]	-0.235	-0.855	-0.021**	-4.709**
	(2.364)	(1.153)	(0.010)	(1.787)
I[Post] × I[More Exposed]	3.095	3.635**	0.045*	8.325**
	(4.212)	(1.729)	(0.025)	(3.900)
I[StrongRelClient_di]	3.248	10.432***	0.126***	-1.820
	(2.132)	(2.410)	(0.025)	(1.189)
I[Post] x I[StrongRelClient_di]	0.778	-2.560	-0.035**	0.683
	(1.952)	(1.915)	(0.016)	(1.290)
I[More Exposed] x I[StrongRelClient_di]	-1.117	-6.069*	-0.088***	7.126***
	(2.839)	(3.192)	(0.033)	(2.525)
I[Post] x I[More Exposed] x I[StrongRelClient_di]	-2.379	1.140	0.017	-3.038
	(3.215)	(3.085)	(0.027)	(2.427)
Observations	60,240	60,240	61,760	10,247
Client Clusters	233	233	240	176
R^2	0.1617	0.1887	0.2222	0.1706
Adjusted R^2	0.1022	0.1311	0.1667	0.0323
Within R^2	0.0007	0.0065	0.0107	0.0020
Client-Week FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Maturity FE				YES

Notes: This table reports results from regressions at the (dealer, client, date) and (dealer, client, maturity, date) level, which correspond to Equation 13, that test Hypothesis 9. Column (4) is at the (dealer, client, maturity, date) level and includes additional maturity fixed effects. 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 9, and winsorized at the first and 99th percentiles before dropping Credit Suisse pairs and unexposed clients; $\mathbb{I}[\textit{Traded}]$, 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; $I[MoreExposed]$, an indicator equal to 1 if the exposed client has exposure E_i above the cross-exposed client median exposure to Credit Suisse, and equal to 0 if E_i is positive but less than or equal to the cross-exposed client median, where exposure to Credit Suisse is measured as in Equation 10; $\mathbb{I}[\textit{StrongRelClient\_di}]$, 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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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—clients have a 32% higher probability of trading with a dealer if they had a relationship with the dealer, along with other dealers, in the last 4 weeks and this probability is higher if it was the only dealer the client had a recent relationship with. 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 they rely on more heavily, 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 relative reduction in client-level trading volume or relative increase in spreads in the EURUSD compared to less reliant clients. Instead, we find evidence that these clients were able to substitute to other dealers post shock and that dealers did not exert greater market power over more exposed clients. Specifically, heavily reliant clients have a reduction in Credit Suisse-specific activity post shock and less reliant clients, that we expect to be better able to substitute, do not experience a relatively larger decline in trading activity with Credit Suisse. Within dealer–week, more reliant Credit Suisse clients have a relative increase in notional and trade count with non-Credit Suisse dealers that they traded with in the pre-period relative to less reliant Credit Suisse clients, as a percent of their typical relationship size. These results, along with insignificant results for a differential change in spreads at these dealers, are consistent with more reliant clients substituting to existing dealer relationships without additional cost.

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 does not affect client trading outcomes by making trading relatively more costly for clients that were more heavily reliant on the shocked dealer. Instead, clients with other dealer relationships seem to be able to continue trading without additional cost. It could be that other dealers initially compete over Credit Suisse's clients' business immediately post shock and that trading costs increase once they have gained persistent clients' business, which we do not capture in our analysis. Additionally, clients without other relationships may face more adverse post-shock outcomes, which is worth further study.

For policy makers, our results underscore the resilience of this opaque market for clients' ability to continue trading when they have access to an alternative dealer. In addition, we do not find that clients are differentially affected based on their reliance on a dealer when dealer shocks occur. Policy makers can use this insight to evaluate the repercussions of dealer shocks.

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A Data Cleaning

A.1 Price Cleaning and Maturity Panel Generation

UK EMIR State Reports The UK EMIR trade repository data has two report types, activity and state reports. State reports contain trade-level information on all trades that are outstanding at the end of each date t. Activity reports contain information on all trades reported on each t. Since there is a 24-hour reporting requirement, some trades are executed on t, but reported the next day, $t+1$. These trades appear in the activity reports for $t+1$.

We use the UK EMIR state reports, which contain outstanding trades as of the end of each trading date, from January 1, 2022 through December 31, 2023 for seven currency pairs: AUDUSD, CADUSD, CHFUSD, EURUSD, GBPUSD, JPYUSD, and NZDUSD. The state reports are necessary to identify trading relationships as they contain all outstanding positions. They also allow us to capture daily trading activity—all trades that were executed on a date but are still outstanding the next day.[72] Our use of the state reports excludes intraday and very short-term newly executed trading activity. Since we wish to examine more persistent dealer-client trading relationships, these trades are not the focus of our analysis. In summary, 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 measure new trading activity on date t using these trade-level data in the following way. We load one reporting day t at a time, which contains trades executed at $t-1$ but reported at t, and 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. For outstanding positions, we use all trades that are outstanding at t with a residual maturity that is less than or equal to 1 year. Because UK legal entities have 24 hours to report their trades, if we only used those reported at t to capture new trades, we would miss those reported at $t+1$ and were executed at t.

Interpolated Bloomberg Benchmark Prices and Price Cleaning We use a (currency pair, maturity, date) (c, m, t) panel of spot FX rates, forward points, and settlement dates from Bloomberg to clean the trade-level price data, compute spreads, and generate our maturity panel.[73]

We start with the Bloomberg panel containing forward rates, computed from FX spot rates and forward points, and settlement dates for each (c, m, t) for maturities $m \in${1w,

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

[73] The spread computation is described in Section 3.2.

2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 7m, 8m, 9m, 10m, 11m, 12m} ("on maturities") 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. Then, we linearly interpolate the forward rate in units of $\frac{\text{USD}}{\text{Foreign Currency}}$ between adjacent "on maturities" with the same currency pair and date. For example, at date t for currency pair c and the 1-month and 2-month maturities, we have forward rates $F_{c,1m,t}$ and $F_{c,2m,t}$ and their associated settlement dates, $T_{c,1m,t}$ and $T_{c,2m,t}$, in the Bloomberg panel. We compute days to maturity as $T_{c,1m,t} - t$ and $T_{c,2m,t} - t$. Then, to compute a benchmark forward rate for this currency pair on date t with settlement date $T_{c,m,t} \in (T_{c,1m,t}, T_{c,2m,t})$, between those of the $1m$ and $2m$ "on maturity" observations, we linearly interpolate between $F_{c,1m,t}$ and $F_{c,2m,t}$.

For a (currency pair, date), the set of interpolated forward rates span from the days to maturity for the 1-week to the days to maturity for the 1-year forward from Bloomberg. So, any trade (outstanding position) with days to maturity (residual maturity days) below that implied by the corresponding 1-week forward's settlement date from Bloomberg will not be included in our maturity panel. That is, we are not extrapolating. These trades will, however, be included in the all $\leq$ 1y maturity bucket as long as they are in the $t + 1$ state reports that we use to define activity at t.

Once we have the interpolated (c, m, t)-level panel of Bloomberg forward rates, we have a benchmark forward price for all days to maturity between the 1w and 1y maturity for each (currency pair, date). We merge this panel into the trade-level data. Specifically, 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 interpolated forward rate panel. 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.[74]

We use the interpolated forward rates from Bloomberg as benchmark prices to compute spreads at the trade-level. The interpolated forward rates are in units of USD to foreign currency, computed using the FX spot rate and forward points for (c, m, t) observations. We interpolate these values across m, covering all maturities between 1w and 1y. So, all trades with the same currency, days to maturity, and date characteristics use the same Bloomberg benchmark price in their spread computation. We use the maturity panel for any analysis of spreads, which are measured according to the description in Section 3.2.

[74] We compute days to maturity in the trade data as the difference between the maturity date and trade execution date. The analogous computation in the Bloomberg panel, to correctly identify trades' maturity buckets, is to use the date and not the settlement date of the spot trade when measuring days to maturity.

Price Cleaning After interpolating Bloomberg forward rates across days to maturity for each currency pair and date, we clean the trade-level price data. 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 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 to be in units of USD to foreign currency. To do this, where m here denotes days to maturity, we take the interpolated 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 $Spread1 = \left| \frac{F\_format_\tau}{F^*_{c(\tau),m(\tau),t(\tau)}} - 1 \right|$ and $Spread2 = \left| \frac{F\_format_\tau^{-1}}{F^*_{c(\tau),m(\tau),t(\tau)}} - 1 \right|$
  2. If $Spread1 \geq 0.1$ and $Spread2 < 0.1$, so the F_format_τ is greater than 10 percent (1000 basis points) larger than the interpolated Bloomberg price but its inverse is less than 10% larger than the interpolated Bloomberg price, take the inverse 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 interpolated Bloomberg price, set the price column to NA.[75]

[75] 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).

5. If it is the case that both Spread1 and Spread2 are less than 10% larger than the interpolated Bloomberg price, we take F_format_τ or its inverse conditional on which is closer to the interpolated Bloomberg price.[76]

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 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 $\frac{\text{USD}}{\text{Currency}}$, to compute our spread measures and their notional weighted averages. To compute the notional weighted averages, we use a notional traded column associated with the observations for which we have cleaned prices and spreads.[77] This variable is used whenever we take notional weighted averages of spreads in our analysis. We also have the all $\leq$ 1y maturity bucket, which includes the notionals for all trades with maturity $\leq$ 1 year in our trade-level data and is not restricted to the spread maturity panel. Additionally, any maturity-specific quantities reported include total notional for the maturity bucket, which is not restricted to only the trades for which we have cleaned spreads. We note that we do not use these notionals to rescale and aggregate spreads. Instead, we use them and the all $\leq$ 1y maturity bucket to have greater coverage of quantities to measure relationships and gain a sense of data coverage.

To generate 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.

Relative to the transaction-level distribution of spreads for the EURUSD in Hau *et al.* (2021), our (d, i, c, m, t)-level distribution of EURUSD spreads has a similar 90th percentile value, but is more symmetric around zero.[78] This could be because we include more client sectors, while Hau *et al.* (2021) focus on non-financial firms with low financial sophistication. However, we do not see large systematic differences in symmetry when we split our EURUSD spread distribution by client sector. Alternatively, it may be due to differences in our datasets, where they use the set of EU dealers and classify firms into sectors using

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

[77]This notional traded variable equals the notional of the observations in our formatted price (spread) panel and missing for all other trades.

[78]See Appendix D.9 for our (d, i, c, m, t)-level distribution of EURUSD spreads.

Bureau van Dijk's Orbis data.

Finally, our resulting (d, i, c, m, t)-level spread distribution has large tails. For example, for the EURUSD over our 2-year sample period, the 5th and 95th percentiles are about 60 basis points in magnitude on average across maturities, but the extremes can reach magnitudes around 1000 basis points. To limit the influence of outliers in our regression analyses, we trim our (d, i, c, m, t)-level spread variable, across the 2-year sample and all currency pairs, at the 5th and 95th percentiles. For analyses that use our panel split by trade direction, at the (d, i, c, m, t, dir)-level, we trim the spreads at this level of aggregation.

Maturity Buckets We aggregate our trade-level data into a coarser panel using maturity buckets. We label maturity buckets according to the Bloomberg "on maturity" labels, with $m \in$\{1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 7m, 8m, 9m, 10m, 11m, 12m\}.

To assign trades to maturity buckets, for each trade τ with currency pair c, days to maturity DTM_τ, and execution date t, we take the days to maturity of the "on maturity" Bloomberg observations that are adjacent to τ with the same (c, t). Then, we compute the midpoint value for these adjacent "on maturities" by taking the mean of their days to maturity values. If DTM_τ is less than or equal to the midpoint value, τ is assigned to the maturity bucket for the adjacent "on maturity" with the lower days to maturity value. If DTM_τ is above the midpoint, τ is assigned to the maturity bucket for the adjacent "on maturity" with the higher days to maturity value.[79]

So, for a currency pair and date, our maturity buckets are non-overlapping and will span maturity dates between the "on maturity" 1-week and 1-year values. Each maturity bucket will aggregate information across all trades that were assigned to that maturity bucket.

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 corporations, 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.

[79] For example, suppose τ has currency pair EURUSD, days to maturity of 32, and execution date t. Suppose also that the Bloomberg panel "on maturity" observations for the EURUSD $1m$ and $2m$ on date t have days to maturity of 30 and 60. The midpoint is equal to 45. Since 32 is less than 45, τ is assigned to the 1m maturity bucket for the EURUSD at t.

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", 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 use 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.[80] 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.[81] We take the sum of the two measures. 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

[80] 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.

[81] 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.

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 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.[82] Additionally, we drop activity between counterparties that are identified as intragroup. Specifically, if a LEI pair reported a trade in our sample period, December 1, 2021 and December 31, 2023, as intragroup, we save the LEI pair. Then, we exclude activity in our panel, which aggregates LEIs for banks and dealers of the same parent, if the aggregated counterparty pair LEIs had any intragroup connections.[83] 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 8 to give a sense of data coverage.

[82]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.

[83]The aggregated LEIs are aggregated only among banks and dealers of the same parent when the parent has a dealer entity. Otherwise, the aggregated LEI columns are the original LEIs of the counterparties.

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 *et al.* (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

$$\mathbb{E}[u_{d,i,c,m,t,\tau}] = -\alpha_i spread_{d,i,c,m,t,\tau} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \xi_{d,i,c,m,t} + \epsilon_{d,i,c,m,t,\tau} \tag{14}$$

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

$$\mathbb{E}[u_{d,i,c,m,t,\tau}] = \underbrace{-\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \zeta_{d,i,c,t}}_{\overline{u_{d,i,c,t}}} + \epsilon_{d,i,c,m,t,\tau} \tag{15}$$

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 16.

$$P(Dealer = d) = \frac{\exp(-\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \zeta_{d,i,c,t})}{\sum_{d' \in \mathcal{D}_i} \exp(-\alpha_i \overline{spread}_{d',i,c,t} + X'_{d',i,c,t}\beta_i + \mu_{d',c,t} + \mu_{i,d'} + \zeta_{d',i,c,t})} \tag{16}$$

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

$$\ln(s_{d,i,c,t}) = -\alpha_i \overline{spread}_{d,i,c,t} + X'_{d,i,c,t}\beta_i + \mu_{d,c,t} + \mu_{i,d} + \mu_{i,c,t} + \zeta_{d,i,c,t} \tag{17}$$

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 17, 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 *et al.* (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 the marginal trading cost for 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. 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

$$N_{d,i,c,t} = N_{i,c,t} \times s_{d,i,c,t}\left(\overline{spread}_{d,i,c,t}, \overline{spread}_{-\mathbf{d},i,c,t}\right), \tag{18}$$

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 $N_{d,i,c,t}$

$$\max_{\overline{spread}_{d,i,c,t}} \left\{ N_{d,i,c,t} \times \overline{spread}_{d,i,c,t} - C_d(N_{d,i,c,t}) \right\} \tag{19}$$

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

$$\overline{spread}_{d,i,c,t} = -\frac{N_{d,i,c,t}}{\left(\frac{\partial N_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}}\right)} + \frac{\partial C_d}{\partial N_{d,i,c,t}} \tag{20}$$

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 18. Market size terms will cancel in the numerator and denominator and we are left with

$$\overline{spread}_{d,i,c,t} = -\frac{s_{d,i,c,t}}{\left(\frac{\partial s_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}}\right)} + MarginalCost_{d,i,c,t} \tag{21}$$

From client demand in Equation 16, the elasticity of the dealer's market share at the client with respect to the average spread the dealer charges the client is

$$\frac{\partial s_{d,i,c,t}}{\partial \overline{spread}_{d,i,c,t}} = -\alpha_i s_{d,i,c,t}(1 - s_{d,i,c,t}) \tag{22}$$

Combining Equations 21 and Equation 22, we recover an expression for the spread the dealer chooses to set for client i in market (i, c, t)

$$\overline{spread}_{d,i,c,t} = MarginalCost_{d,i,c,t} + \frac{1}{\alpha_i(1 - s_{d,i,c,t})} \tag{23}$$

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.

Note that the average spread is increasing in the market share that the dealer has in the client's trading activity, $s_{d,i,c,t}$. Additionally, the spread increases by more for a change in market share when the dealer has a larger market share of the client's activity. That is, assuming an increase in a dealer's market share doesn't affect the marginal cost of trading,

$$\frac{\partial \overline{spread}_{d,i,c,t}}{\partial s_{d,i,c,t}} = \frac{1}{\alpha_i(1 - s_{d,i,c,t})^2} \tag{24}$$

and

$$\frac{\partial \overline{spread}_{d,i,c,t}}{\partial s^2_{d,i,c,t}} = \frac{\partial}{\partial s_{d,i,c,t}} \left(\alpha_i(1 - s_{d,i,c,t})^2\right)^{-1} = \frac{2}{\alpha_i(1 - s_{d,i,c,t})^3}, \tag{25}$$

Both of these are positive for positive α_i and share $s_{d,i,c,t} \in (0, 1)$.

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 estimate 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 w, denoted by an indicator $\mathbb{I}[HasISDA_{d,i,w-1}]$. $\mathbb{I}[HasISDA_{d,i,w-1}]$ equals 1 if the dealer and client have a positive trade count or positive outstanding position, in any currency pair, at any week from January 1, 2022 through week $w-1$ and zero otherwise. We also construct an indicator $\mathbb{I}[Only1ISDA_{i,w-1}]$, which equals 1 if the client only had one dealer where the indicator $\mathbb{I}[HasISDA_{d,i,w-1}]$ 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 $\mathbb{I}[HasOut_{d,i,w-1}]$, 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 $w-4$ through week $w-1$, and zero otherwise. We also compute an indicator $\mathbb{I}[Only1Dealer_{i,w-1}]$ that equals 1 if the client, i, had only one existing dealer relationship in the last 4 weeks, measured by client i having $\mathbb{I}[HasOut_{d,i,w-1}]$ equal to 1 for only one dealer at week w. We use the indicator $\mathbb{I}[Only1Dealer_{i,w-1}]$ 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) $RelStrClientNDay_{d,i,w-1}$, 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, and (ii) $RelStrClientNOut_{d,i,w-1}$, 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. Let $NDay_{d,i,w}$ ($NOut_{d,i,w}$) denote the sum of notional traded (outstanding) between dealer d and client i across days and currency pairs in week w. The (dealer, client week)-specific measures are presented in Equations 26 and 27, respectively.

$$RelStrClientNDay_{d,i,w-1} = \frac{\sum_{l=w-4}^{w-1} NDay_{d,i,l}}{\sum_{l=w-4}^{w-1} \sum_{m \in \mathcal{D}} NDay_{m,i,l}} \times 100 \tag{26}$$

$$RelStrClientNOut_{d,i,w-1} = \frac{\sum_{l=w-4}^{w-1} NOut_{d,i,l}}{\sum_{l=w-4}^{w-1} \sum_{m \in \mathcal{D}} NOut_{m,i,l}} \times 100 \tag{27}$$

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 $\mathbb{I}[HasOut_{d,i,c,w-1}]$ to denote whether the dealer-client pair had an outstanding position from week $w-4$ through $w-1$, 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 $NetUSDPosition_{d,i,w-1}$, which is a categorical variable that denotes whether the dealer-client pair had a net outstanding position over all currency pairs from week $w-4$ through $w-1$ such that the client was (i) net selling USD, (ii) net buying USD, or (iii) neither.[84] 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

[84] 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 w for each direction. This gives us for each week w, 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 w. We then take the sum of the net position across weeks $w-4$ through $w-1$ and define the categories of $NetUSDPosition_{d,i,w-1}$ 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 19 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 pair, 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 pair, 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 $\mathbb{I}[Traded_{d,i,w}]$ 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 w, in any currency pair. For column (6), since the regression is at the (dealer, client, currency pair, date) level, the dependent variable is $\mathbb{I}[TradedCCY_{d,i,c,w}]$, 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 w, 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 January 1, 2021 and week w. Similarly, for column (6) of Table 1, we fill the set of dealers for each (client, currency pair, 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 pair, maturity, date), except column (5), which is at the (dealer, client, currency pair, maturity, date, direction) level. So, for example, the dependent variable in our (dealer, client, currency pair, 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

Relationship strength measures that we compute are presented in Equations 28 and 29 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, January 1, 2022 through January 11, 2023. Equation 28 (29) 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 28 and 29 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.[85] 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 $NEver$.

$$RelStrNDay^{(i)}_{d,i} = 100 * \frac{\sum_{t \in OutOfSample} NDay_{d,i,t}}{\sum_{t \in OutOfSample} \sum_{d \in \mathcal{D}} NDay_{d,i,t}} \tag{28}$$

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

From these relationship strength measures, we define indicator variables that identify whether a dealer-client pair (d, i) have a weak relationship. These indicators equal 1 for pair (d, i) when the corresponding measure of relationship strength is less than or equal to 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 30.

$$\mathbb{I}[WeakRel_{d,i}] = \begin{cases} 1 & \text{if } RelStrNDay^{(i)}_{d,i} \leq Median_{i \in \mathcal{J}_d}(RelStrNDay^{(i)}_{d,i}) \\ 0 & \text{otherwise} \end{cases} \tag{30}$$

for $\mathcal{J}_d = \{i \text{ s.t. } NDay_{d,i,EURUSD,t} > 0 \text{ for a t } \in PrePeriod\}$. If $\mathbb{I}[WealRel_{d,i}] = 1$, the interpretation is that the client relied less heavily on dealer d than other clients of d. When testing Hypotheses 5 and 6 in Section 5.2.2, these measures are computed specifically for when d is Credit Suisse.

[85] We also compute the relationship measure given by Equation 28 across activity in all seven currency pairs in our data for robustness and present the results for regression Equation 8 using this measure in Appendix H.

D Descriptive Statistics: Tables and Figures

D.1 Daily Average Notional Outstanding By Currency

Table 8: Average Daily Notional Outstanding for 2023S2 by Currency, All $\leq$ 1y Maturity

	(1) Daily Average Notional, USD Billions	N
USD	11,633.89	129
AUD	739.22	129
CAD	754.58	129
CHF	873.83	129
EUR	4,016.02	129
GBP	2,483.02	129
JPY	2,559.28	129
NZD	207.96	129

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 uses outstanding positions for all currency pairs since they are bilateral to the USD. The sample includes dealer-client and interdealer trades, but excludes client-client activity, activity between the same aggregated dealer entity, and intragroup activity. N denotes the number of days used in the daily average.

D.2 Statistics by Client Sector

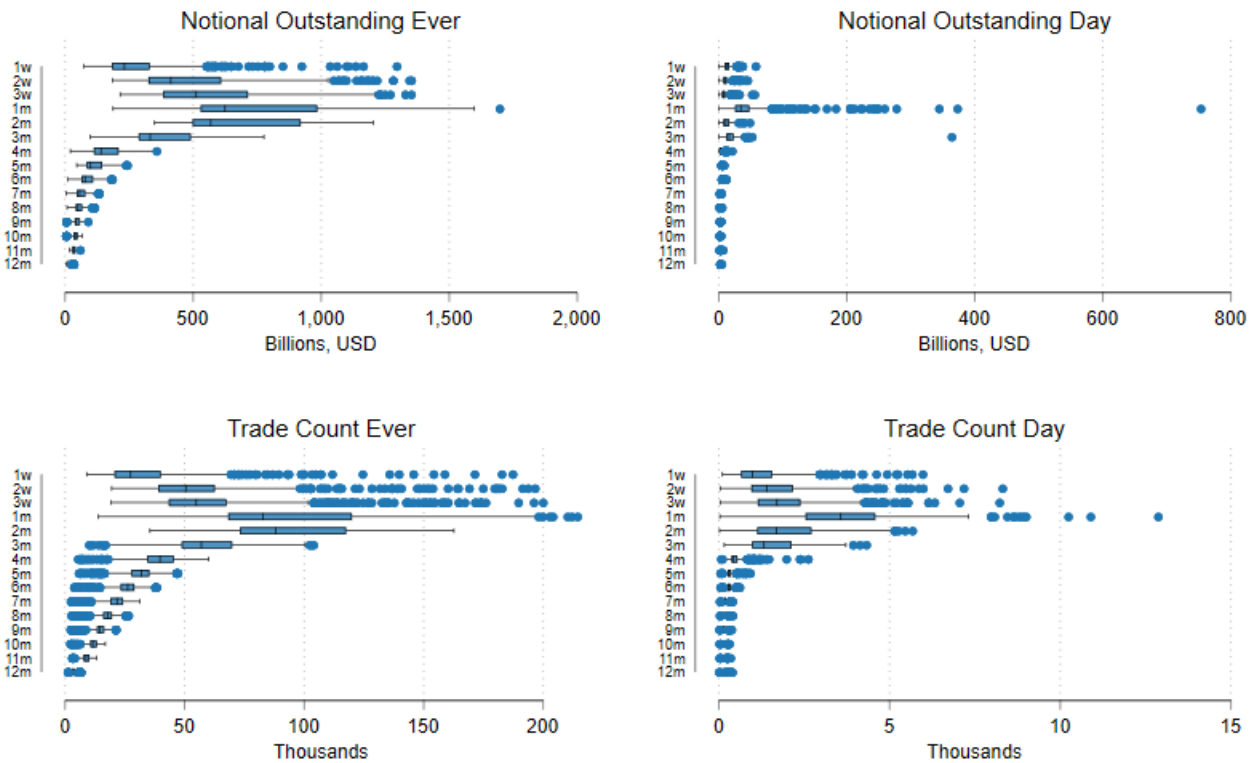
Table 9: Client-Sector Trading Activity Statistics, All $\leq$ 1y Maturity

	Client Count	% Notional Volume	X-Client Average % Days Traded
Asset Manag.	7,648.00	17.28	15.02
Bank	631.00	23.62	28.77
HF	448.00	27.18	34.80
Insurer	376.00	3.52	13.87
Non-Fin.	1,405.00	4.85	11.45
Other Fin.	389.00	4.66	22.66
PTF	11.00	0.67	30.91
Pension	1,037.00	5.33	16.48

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

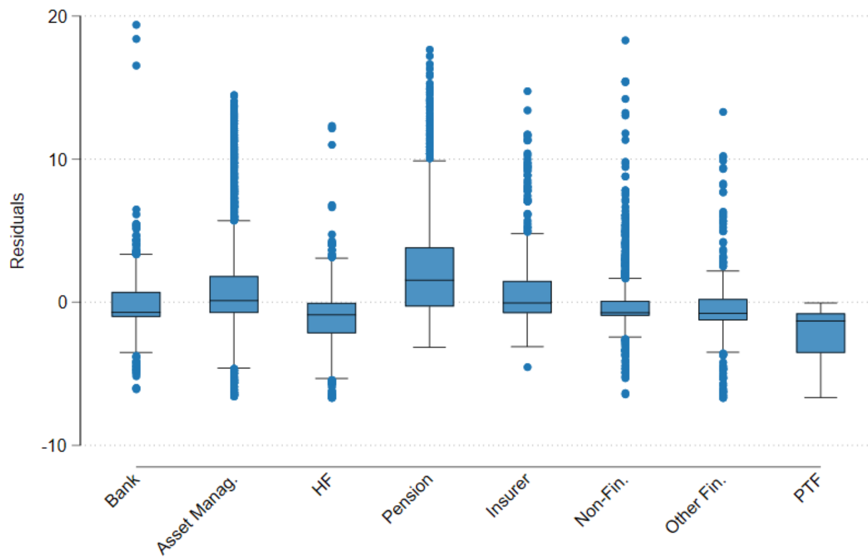
Figure 3: Distribution of Activity Variables Across Dates by Maturity



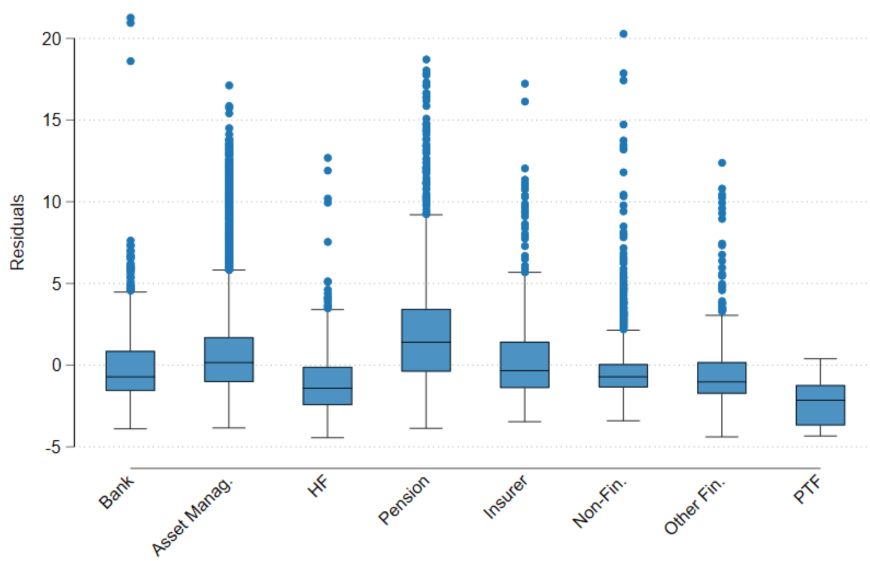
Notes: This figure plots the distributions of total dealer-client activity across dates by maturity, for four trading activity variables, for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.1. *Notional Outstanding Ever* is the total notional outstanding position across 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 bucket. The sample excludes intragroup activity.

D.4 Dealer Count Residual Plots

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



(a) $X_i = DaysTraded_i$

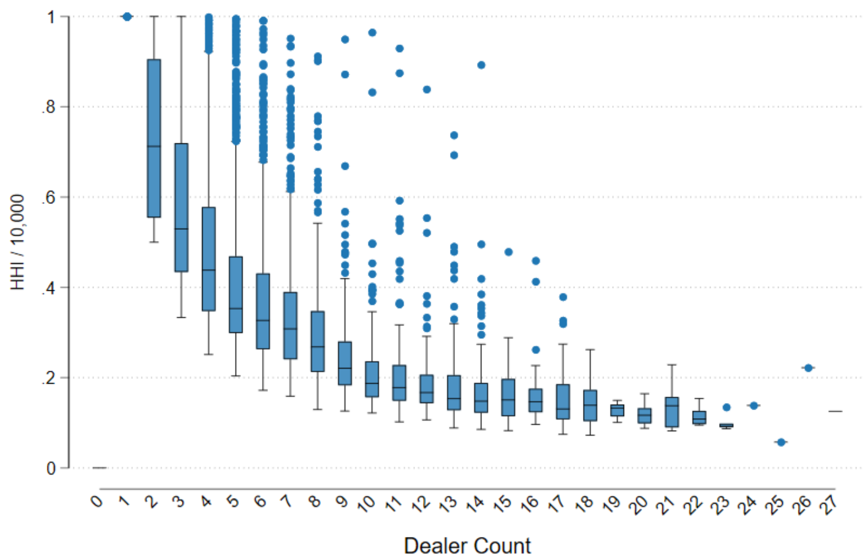


(b) $X_i = \ln(TotalNotionalTraded_i)$

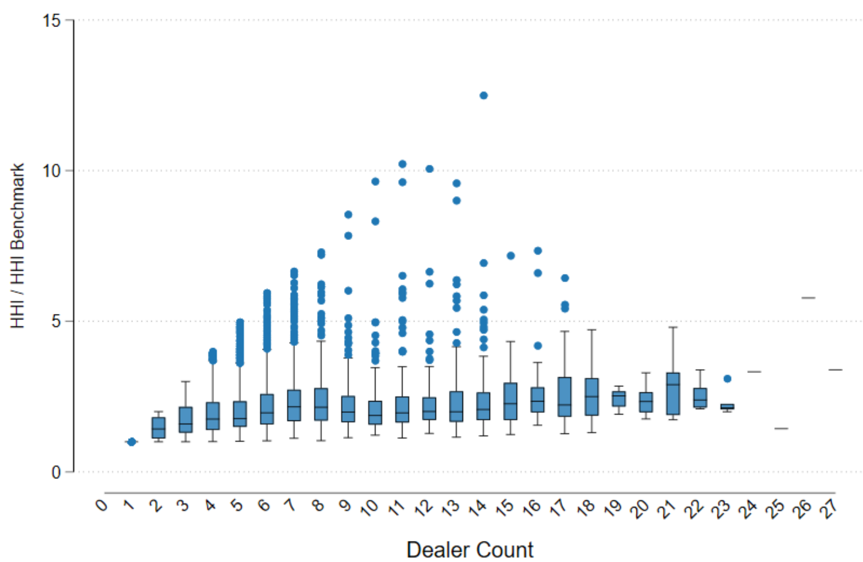
Notes: These figures plot the residual of a cross-client linear regression of dealer count on a control for client-level trading activity for the period of January 1, 2022 through December 31, 2023, referenced in Section 3.3. The cross-client regression is $DealerCount_i = \alpha + \beta X_i + \epsilon_i$. 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, $\ln(TotalNotionalTraded_i)$. Residuals are plotted by sector. The sample uses only dealer-client observations.

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

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	26892	4,963.77	58,299.41	0.46	4.63	58.37	583.83	3,596.00
Total Trade Count	26892	427.95	6,313.29	1.00	4.00	22.00	101.00	387.00
% Days Traded	26892	10.71	19.70	0.20	0.59	2.55	10.00	32.75
Currency Count	26892	2.25	1.92	1.00	1.00	1.00	3.00	6.00
Dealer Count	26892	2.40	2.51	1.00	1.00	1.00	3.00	5.00
% Notional With Main Dealer	26892	84.46	23.38	44.59	68.48	100.00	100.00	100.00
HHI, X-Dealer	26892	0.80	0.28	0.33	0.55	1.00	1.00	1.00
Average Dealer Count, Active Days	26892	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 510. *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 11: Client-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	21279	2,516.49	22,774.11	1.07	7.73	70.28	541.58	2,714.42
% Days Traded	21279	10.63	18.60	0.20	0.78	2.94	10.59	31.57
Currency Count	21279	2.29	1.93	1.00	1.00	1.00	3.00	6.00
Dealer Count	21279	2.45	2.48	1.00	1.00	1.00	3.00	5.00
Average Dealer Count, Active Days	21279	1.08	0.26	1.00	1.00	1.00	1.05	1.25

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* is the sum of notional traded 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 510. *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. *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 12: Dealer–Client–Date-Level Descriptive Statistics, All $\leq$ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	1958335	68.16	553.33	0.06	0.31	2.00	15.08	102.23
Total Trade Count	1958335	5.88	38.80	1.00	1.00	2.00	3.00	8.00
Currency Count	1958335	1.52	1.16	1.00	1.00	1.00	2.00	3.00
% Client's Previous Notional	1663087	53.87	40.10	2.36	12.36	50.68	100.00	100.00
% Dealer's Previous Notional	1663087	0.46	3.43	0.00	0.00	0.01	0.07	0.44

Notes: This table provides (dealer, client, date)-level statistics of trading activity in the all $\leq$ 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 13: Dealer-Level Descriptive Statistics, All $\leq$ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	46	2,901,863.34	7,184,180.83	6,451.83	22,349.42	129,929.16	2,337,094.60	6,614,568.49
Total Trade Count	46	250,181.78	692,371.67	50.00	1,946.00	7,973.00	127,401.00	602,077.00
Currency Count	46	6.33	1.78	2.00	7.00	7.00	7.00	7.00
Client Count	46	1,402.61	2,592.26	2.00	33.00	197.00	1,152.00	6,306.00
% Notional With Main Client	46	33.37	28.65	6.78	13.37	20.33	51.88	77.07
% Notional With Median Client	46	10.28	28.98	0.00	0.00	0.04	1.15	50.00
HHI, X-Client	46	0.23	0.29	0.02	0.04	0.09	0.34	0.60
Average Client Count, Active Days	46	83.82	176.25	1.00	2.27	6.64	52.51	324.41

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 14: Dealer-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Total Notional Volume, Millions USD	43	1,245,313.31	2,789,098.25	2,615.82	15,780.10	62,711.92	903,845.40	3,574,221.17
Currency Count	43	6.47	1.53	5.00	7.00	7.00	7.00	7.00
Client Count	43	1,210.58	2,113.37	4.00	29.00	204.00	1,389.00	5,256.00
Average Client Count, Active Days	43	68.61	139.30	1.00	1.88	5.95	45.78	243.11

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 15: 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)	257103	0.68	51.15	-48.89	-19.82	0.55	21.49	50.66
NW Spread, Client Buy USD	144432	-1.16	56.83	-55.25	-23.60	-0.25	22.26	53.04
NW Spread, Client Sell USD	140966	2.80	54.14	-48.49	-19.55	1.83	24.35	55.22
Total Notional, USD Millions	257103	12.85	57.68	0.02	0.14	0.87	4.89	23.17
Maturity Days	257103	50.93	58.34	14.00	21.00	30.00	60.00	90.00
# Observations Per Client	5471	46.99	125.74	1.00	3.00	10.00	37.00	106.00
# Observations Per Dealer	39	6,592.38	13,495.29	9.00	66.00	305.00	5,138.00	33,958.00
Panel B: CADUSD								
NW Spread (d,i,c,m,t)	166599	0.15	31.82	-30.04	-11.95	0.23	12.50	30.35
NW Spread, Client Buy USD	97494	0.21	36.09	-32.43	-12.51	0.86	14.44	32.16

NW Spread, Client Sell USD	85538	-0.01	30.36	-30.11	-13.17	-0.20	12.18	31.46
Total Notional, USD Millions	166599	16.34	90.28	0.03	0.20	1.12	6.30	28.83
Maturity Days	166599	56.33	63.95	14.00	21.00	30.00	60.00	120.00
# Observations Per Client	4513	36.92	114.52	1.00	3.00	8.00	26.00	71.00
# Observations Per Dealer	40	4,164.98	10,919.95	7.50	27.00	165.00	1,389.00	12,507.00

Panel C: CHFUSD

NW Spread (d,i,c,m,t)	154510	0.79	37.50	-36.05	-14.29	0.30	15.88	37.82
NW Spread, Client Buy USD	84275	0.39	44.59	-38.94	-17.32	-1.27	15.42	40.70
NW Spread, Client Sell USD	88221	1.51	37.36	-37.72	-13.48	2.37	19.14	39.93
Total Notional, USD Millions	154510	19.94	84.16	0.01	0.11	1.00	7.98	40.06
Maturity Days	154510	48.15	56.17	7.00	14.00	30.00	60.00	90.00
# Observations Per Client	3738	41.33	116.49	1.00	3.00	9.00	31.00	96.00
# Observations Per Dealer	37	4,175.95	8,662.57	16.00	32.00	153.00	2,303.00	16,483.00

Panel D: EURUSD

NW Spread (d,i,c,m,t)	927651	0.57	39.96	-38.18	-14.86	0.36	15.77	39.08
NW Spread, Client Buy USD	551296	-0.16	43.68	-41.03	-17.36	-0.49	15.92	41.09
NW Spread, Client Sell USD	506929	1.26	44.19	-40.23	-14.73	1.58	18.56	42.12
Total Notional, USD Millions	927651	21.10	138.05	0.04	0.18	0.99	5.78	31.79
Maturity Days	927651	59.11	68.73	14.00	21.00	30.00	90.00	150.00
# Observations Per Client	13160	70.49	310.96	1.00	4.00	14.00	53.00	158.00
# Observations Per Dealer	42	22,086.93	47,546.57	53.00	432.00	1,837.00	13,614.00	73,180.00

Panel E: GBPUSD

NW Spread (d,i,c,m,t)	792319	1.44	47.95	-41.31	-16.49	0.80	18.83	44.52
NW Spread, Client Buy USD	449403	2.29	52.56	-42.21	-17.16	1.15	20.44	48.08
NW Spread, Client Sell USD	429812	0.42	53.92	-45.01	-18.41	0.74	19.27	45.35
Total Notional, USD Millions	792319	18.89	118.25	0.02	0.12	0.71	4.70	27.18
Maturity Days	792319	60.19	69.11	14.00	21.00	30.00	90.00	150.00
# Observations Per Client	12111	65.42	232.65	2.00	5.00	16.00	50.00	150.00
# Observations Per Dealer	42	18,864.74	37,671.29	225.00	572.00	2,758.50	22,152.00	45,812.00

Panel F: JPYUSD

NW Spread (d,i,c,m,t)	256027	0.83	47.43	-44.68	-16.65	0.16	17.23	45.74
NW Spread, Client Buy USD	148180	-1.17	51.32	-49.72	-22.86	-2.03	15.30	48.91

NW Spread, Client Sell USD	139573	3.17	48.05	-44.98	-13.77	3.05	22.92	49.75
Total Notional, USD Millions	256027	34.87	159.59	0.06	0.32	1.97	12.78	66.33
Maturity Days	256027	53.15	59.81	7.00	21.00	30.00	60.00	90.00
# Observations Per Client	6825	37.51	123.78	1.00	3.00	9.00	26.00	70.00
# Observations Per Dealer	38	6,737.55	17,348.80	6.00	52.00	191.00	2,549.00	19,707.00
Panel G: NZDUSD								
NW Spread (d,i,c,m,t)	117011	-0.49	53.39	-50.50	-20.13	0.24	20.56	49.69
NW Spread, Client Buy USD	65707	-1.22	54.27	-54.00	-22.90	-0.69	21.22	51.45
NW Spread, Client Sell USD	63070	0.66	55.63	-51.92	-20.23	2.06	23.07	54.00
Total Notional, USD Millions	117011	8.36	34.68	0.05	0.19	0.85	3.94	15.65
Maturity Days	117011	44.77	47.11	14.00	21.00	30.00	60.00	90.00
# Observations Per Client	2811	41.63	94.58	1.00	3.00	9.00	31.00	97.00
# Observations Per Dealer	40	2,925.28	6,071.71	3.50	12.50	50.00	1,835.00	10,920.50

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 bucket 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 bucket 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 bucket 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 16: Client–Currency-Level Descriptive Statistics, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Panel A: AUDUSD								
NW Spread	5471	0.72	35.13	-23.68	-7.83	0.50	9.45	24.40
NW Maturity Bucket Days	5471	56.44	49.17	21.17	28.02	43.78	68.54	90.00
% of Days with Spread	5471	7.19	14.73	0.20	0.59	1.76	6.47	18.04

Maturity Count	5471	4.00	2.88	1.00	2.00	4.00	5.00	7.00
Dealer Count	5471	2.34	1.92	1.00	1.00	2.00	3.00	5.00
(d,i,c,m,t) Observations per (i,c)	5471	46.99	125.74	1.00	3.00	10.00	37.00	106.00
Panel B: CADUSD								
NW Spread	4513	0.57	17.76	-14.95	-5.59	0.21	6.46	16.19
NW Maturity Bucket Days	4513	50.02	38.67	21.00	28.68	38.57	61.64	89.04
% of Days with Spread	4513	5.54	12.87	0.20	0.59	1.57	4.51	12.35
Maturity Count	4513	3.90	2.83	1.00	2.00	3.00	5.00	7.00
Dealer Count	4513	1.98	1.45	1.00	1.00	1.00	2.00	4.00
(d,i,c,m,t) Observations per (i,c)	4513	36.92	114.52	1.00	3.00	8.00	26.00	71.00
Panel C: CHFUSD								
NW Spread	3738	0.28	21.53	-19.94	-7.14	0.22	7.35	19.11
NW Maturity Bucket Days	3738	51.20	39.44	21.00	28.21	37.84	66.31	90.00
% of Days with Spread	3738	6.51	13.94	0.20	0.39	1.57	5.29	17.06
Maturity Count	3738	3.80	2.76	1.00	2.00	3.00	5.00	7.00
Dealer Count	3738	2.20	1.71	1.00	1.00	2.00	3.00	5.00
(d,i,c,m,t) Observations per (i,c)	3738	41.33	116.49	1.00	3.00	9.00	31.00	96.00
Panel D: EURUSD								
NW Spread	13160	1.59	43.08	-17.24	-6.10	0.35	7.59	20.34
NW Maturity Bucket Days	13160	62.35	53.95	22.01	29.14	49.02	78.13	110.84
% of Days with Spread	13160	9.20	16.77	0.20	0.59	2.35	9.22	26.08
Maturity Count	13160	4.47	3.05	1.00	2.00	4.00	6.00	8.00
Dealer Count	13160	2.36	2.05	1.00	1.00	1.00	3.00	5.00
(d,i,c,m,t) Observations per (i,c)	13160	70.49	310.96	1.00	4.00	14.00	53.00	158.00
Panel E: GBPUSD								
NW Spread	12111	3.12	34.02	-18.31	-5.72	1.15	10.22	25.25
NW Maturity Bucket Days	12111	66.04	55.50	22.91	29.26	52.98	82.82	122.67
% of Days with Spread	12111	8.66	15.77	0.20	0.78	2.75	8.24	23.73
Maturity Count	12111	4.62	3.07	1.00	2.00	4.00	6.00	8.00
Dealer Count	12111	2.66	2.79	1.00	1.00	1.00	3.00	6.00
(d,i,c,m,t) Observations per (i,c)	12111	65.42	232.65	2.00	5.00	16.00	50.00	150.00

Panel F: JPYUSD

NW Spread	6825	2.03	34.91	-20.12	-6.83	0.42	9.33	26.14
NW Maturity Bucket Days	6825	55.63	50.85	21.00	28.32	41.82	70.05	90.00
% of Days with Spread	6825	5.46	12.24	0.20	0.59	1.57	4.71	11.96
Maturity Count	6825	3.81	2.79	1.00	2.00	3.00	5.00	7.00
Dealer Count	6825	1.83	1.39	1.00	1.00	1.00	2.00	4.00
(d,i,c,m,t) Observations per (i,c)	6825	37.51	123.78	1.00	3.00	9.00	26.00	70.00

Panel G: NZDUSD

NW Spread	2811	0.54	23.81	-20.78	-8.08	0.36	8.81	20.74
NW Maturity Bucket Days	2811	51.59	41.11	21.00	27.64	42.93	64.02	90.00
% of Days with Spread	2811	6.78	14.39	0.20	0.59	1.76	5.49	16.47
Maturity Count	2811	3.80	2.56	1.00	2.00	4.00	5.00	6.00
Dealer Count	2811	2.49	1.99	1.00	1.00	2.00	3.00	5.00
(d,i,c,m,t) Observations per (i,c)	2811	41.63	94.58	1.00	3.00	9.00	31.00	97.00

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.

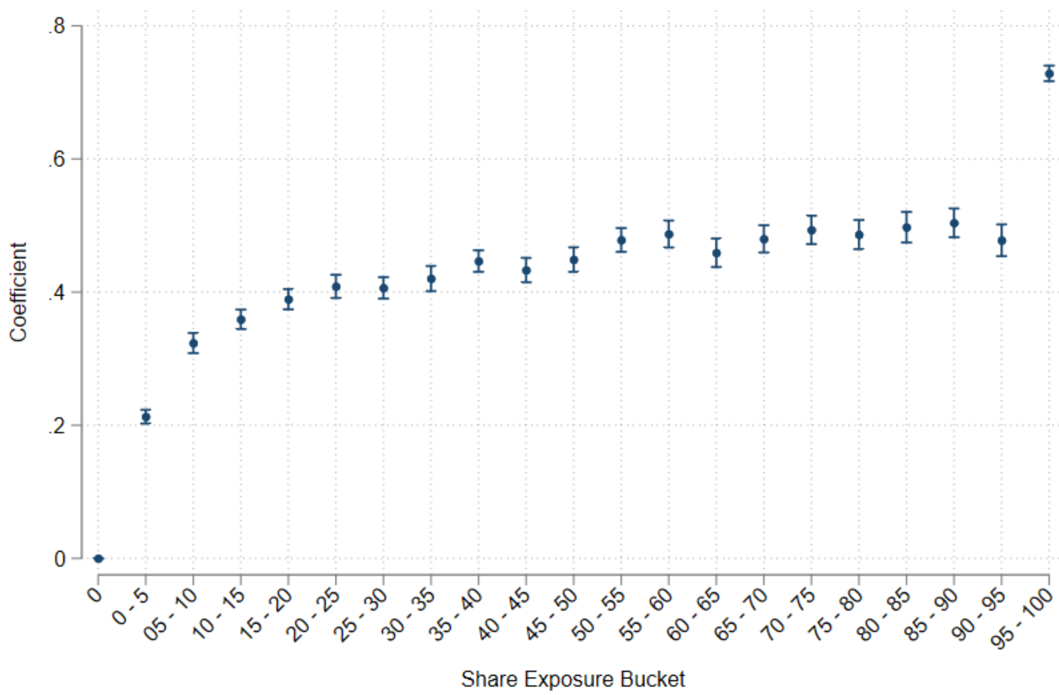
E Characteristics of Trading Relationships: Robustness

E.1 Trading Probability By Share Exposure Bucket

We estimate Equation 31 using the same data as the regressions of Table 1 in Section 4, with dealer $\times$ client sector $\times$ week fixed effects, $\alpha_{d,sec(i),w}$. We split the measure of client reliance on a dealer into a saturated set of indicators for 5% share intervals from 0 to 100%.

$$\mathbb{I}[Traded_{d,i,w}] = \sum_{b \in Buckets} \beta_b \mathbb{I}[RelStrength_{d,i,w-1} \in b] + \gamma \mathbb{I}[HasISDA_{d,i,w-1}] + \alpha_{d,sec(i),w} + \epsilon_{d,i,w} \quad (31)$$

Figure 6: Additional Trading Probability by Share Exposure Bucket



Notes: The coefficients plotted correspond to the β_b coefficients in regression Equation 31, which uses the sample for regression Table 1. Dependent variable $\mathbb{I}[Traded_{d,i,w}]$ is an indicator equal to 1 if the dealer and client trade at week w. The independent variables are: $\mathbb{I}[HasISDA_{d,i,w-1}]$, an indicator equal to 1 if the client and dealer traded or had an outstanding position between January 1, 2022 and $w-1$; $\mathbb{I}[RelStrength_{d,i,w-1} \in b]$, an indicator equal to 1 if the client's reliance on the dealer in the last 4 weeks, denoted by $RelStrength_{d,i,w-1}$, fell into share interval bucket b. $RelStrength_{d,i,w-1}$ is calculated using outstanding notional positions for the all $\leq$ 1y maturity across all currencies, measured by $RelStrNOut_{d,i,w-1}$ as defined by Equation 27 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 17: 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]	0.300***	0.089***	0.082***	0.077***	0.039***	0.062***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
I[Only1ISDA]	-0.009***	-0.004***				
	(0.001)	(0.001)				
I[HasISDA] × I[Only1ISDA]	0.558***	0.230***				
	(0.005)	(0.009)				
I[HasOut]		0.317***	0.244***	0.262***	0.015	0.049***
		(0.005)	(0.006)	(0.006)	(0.010)	(0.003)
I[Only1Dealer]		-0.001***				
		(0.000)				
I[HasOut] ×I[Only1Dealer]		0.296***				
		(0.011)				
I[HasOut] × %Outstanding			0.004***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.040***	
					(0.005)	
None					-0.111***	
					(0.010)	
I[HasOutCCY]						0.323***
						(0.005)
Observations	4928978	4928978	4818020	4534093	4928978	1.15e+07
Client Clusters	8942	8942	8047	7327	8942	8945
R^2	0.4470	0.5044	0.5192	0.5190	0.2063	0.4347
Adjusted R^2	0.4446	0.5022	0.5172	0.5170	0.2029	0.4295
Within R^2	0.2223	0.3030	0.3241	0.3209	0.0919	0.2667
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

Notes: This table reports results from the (dealer, client, week) and (dealer, client, currency, week) level regressions that test Hypotheses 1–2 for the period of June 25 to December 31, 2023, with client fixed effects. Dependent variables are indicators equal to 1 if the client traded ($I[Traded]$), net sold USD ($I[SellUSD]$), or traded in currency c ($I[TradedCCY]$) with the dealer that week. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client and dealer traded or had an outstanding position between January 1, 2022 and $w-1$; $I[Only1ISDA]$, 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 and dealer had an outstanding position 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 over the last month (*BuyUSD* is the reference group); $I[HasOutCCY]$, an indicator equal to 1 if the client and dealer had an outstanding position in the last month in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and week level in columns (1)–(5) and the client and (currency, week) level in column (6). Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: 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]	0.300***	0.088***	0.081***	0.075***	0.038***	0.061***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
I[HasISDA] × I[Only1ISDA]	0.558***	0.229***				
	(0.005)	(0.009)				
I[HasOut]		0.319***	0.246***	0.264***	0.014	0.049***
		(0.005)	(0.006)	(0.006)	(0.010)	(0.003)
I[HasOut] ×I[Only1Dealer]		0.297***				
		(0.011)				
I[HasOut] × %Outstanding			0.004***			
			(0.000)			
I[HasOut] × %Traded				0.004***		
				(0.000)		
SellUSD					0.041***	
					(0.005)	
None					-0.113***	
					(0.010)	
I[HasOutCCY]						0.325***
						(0.005)
Observations	4928028	4928028	4817127	4533275	4928028	1.15e+07
Client Clusters	8847	8847	7974	7265	8847	8904
R^2	0.4502	0.5082	0.5231	0.5231	0.2194	0.4382
Adjusted R^2	0.4367	0.4962	0.5114	0.5115	0.2003	0.4232
Within R^2	0.2242	0.3061	0.3270	0.3239	0.0940	0.2690
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

Notes: This table reports results from the (dealer, client, week) and (dealer, client, currency, week) level regressions that test Hypotheses 1–2 for the period of June 25 to December 31, 2023, with client × week fixed effects. Dependent variables are indicators equal to 1 if the client traded ($I[Traded]$), net sold USD ($I[SellUSD]$), or traded in currency c ($I[TradedCCY]$) with the dealer that week. Independent variables are: $I[HasISDA]$, an indicator equal to 1 if the client and dealer traded or had an outstanding position between January 1, 2022 and $w-1$; $I[Only1ISDA]$, 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 and dealer had an outstanding position 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 over the last month (*BuyUSD* is the reference group); $I[HasOutCCY]$, an indicator equal to 1 if the client and dealer had an outstanding position in the last month in currency c. Variables are defined in Appendix C.1. Standard errors are double clustered at the client and week level in columns (1)–(5) and the client and (currency, week) 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

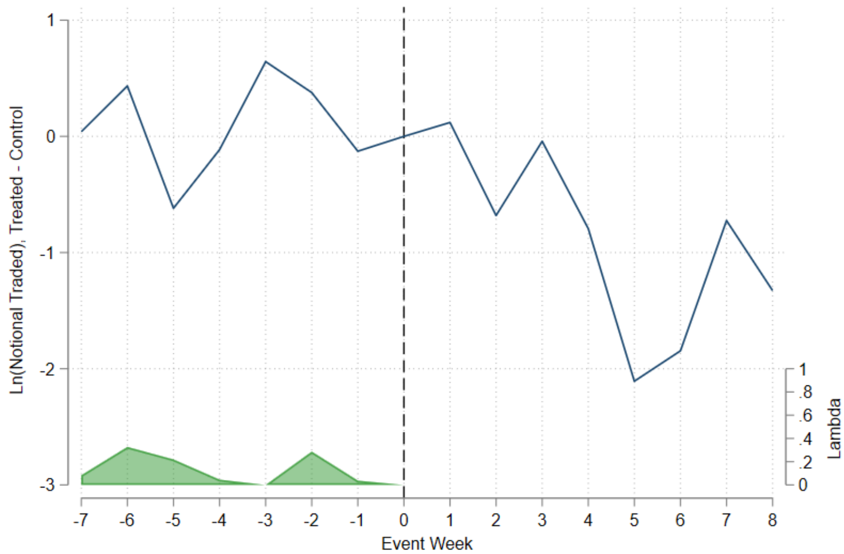
Table 19: Spreads and Dealer-Client Trading Relationships With Size Controls

	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread
I[HasISDA]	-0.054	0.001	0.285	0.290	0.268	0.294
	(0.443)	(0.449)	(0.431)	(0.431)	(0.414)	(0.433)
I[Only1ISDA]	-1.080	-1.079				
	(1.134)	(1.135)				
I[HasISDA] × I[Only1ISDA]	2.211*	2.088*				
	(1.149)	(1.152)				
Ln(Notional Traded)	-0.091***	-0.090***	-0.101***	-0.101***	-0.099***	-0.110***
	(0.026)	(0.026)	(0.029)	(0.029)	(0.030)	(0.031)
Trade Count	0.005	0.006	0.002	0.003	-0.010	0.007
	(0.009)	(0.009)	(0.010)	(0.010)	(0.026)	(0.010)
I[HasOut]		-0.173	-0.472*	-0.346	-0.030	0.115
		(0.287)	(0.265)	(0.258)	(0.248)	(0.309)
I[Only1Dealer]		0.002				
		(0.456)				
I[HasOut] ×I[Only1Dealer]		0.243				
		(0.469)				
%Outstanding			0.010***			
			(0.002)			
%Traded				0.008***		
				(0.002)		
I[NetUSDOut = dir]					0.022	
					(0.211)	
I[HasOutCCY]						-0.055
						(0.226)
Observations	1209305	1209305	1209305	1209305	3981549	1209305
Client Clusters	16,915	16,915	16,915	16,915	16,949	16,915
R^2	0.0878	0.0878	0.0876	0.0875	0.0642	0.0874
Adjusted R^2	0.0648	0.0648	0.0646	0.0645	0.0563	0.0644
Within R^2	0.0006	0.0006	0.0004	0.0003	0.0001	0.0002
CCY-Maturity-Date FE	YES	YES	YES	YES	YES	YES
Dealer-Date FE	YES	YES	YES	YES	YES	YES

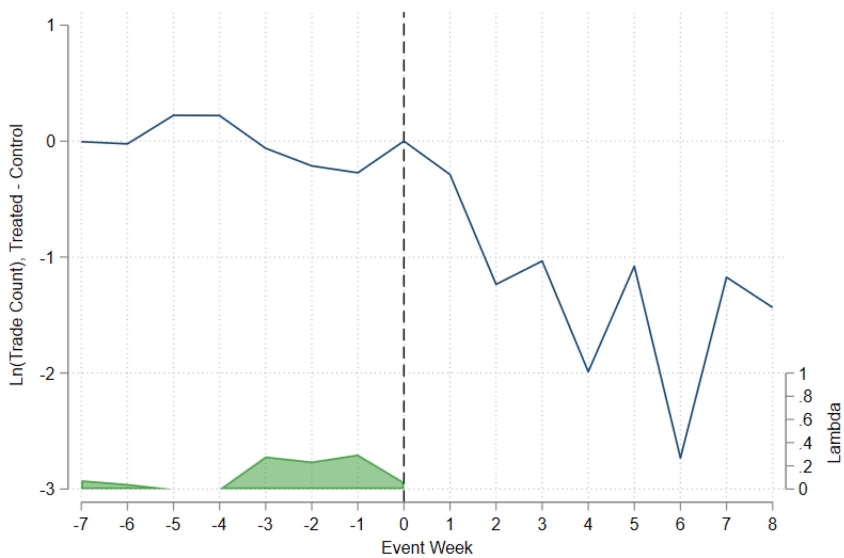
Notes: This table reports results from the (dealer, client, currency, maturity, date) and (dealer, client, currency, maturity, date, direction) level regressions, with controls for the size of trading activity, that test Hypothesis 3 for the period of January 1 to December 31, 2023, corresponding to Equation 6. The dependent variable is the notional weighted average spread across trades with the same dealer, client, currency, maturity bucket, 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 and dealer traded or had an outstanding position between January 1, 2022 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 and dealer had an outstanding position 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 and dealer had an outstanding position in the last month 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 Synthetic Difference-in-Differences: Dealer-Level

Figure 7: Difference in Outcome Over Time Between Credit Suisse and the Synthetic Difference-in-Differences Control Group



(a) $Y_{d,w} = Ln\big(Not.\ Traded_{d,w}\big)$



(b) $Y_{d,w} = Ln\big(Trade\ Count_{d,w}\big)$

Notes: This figure plots the difference in weekly log dealer-client EURUSD notional traded and trade count, $Ln(Not.\ Traded_{d,w})$ and $Ln(Trade\ Count_{d,w})$, between Credit Suisse and the weighted average of control dealers in the SDID implemented to test Hypothesis 4. Values are relative to that of event week 0, the week of March 8, 2023. Along the bottom of the figure, plotted against the right axis, are the lambda weights used to average pre-shock weeks, as in Arkhangelsky *et al.* (2021). The sample is a balanced dealer-week panel with the dealers that traded EURUSD every week of the sample. The first or last week of the daily sample are excluded if the week contains fewer than 4 trading days when aggregating to the weekly frequency.

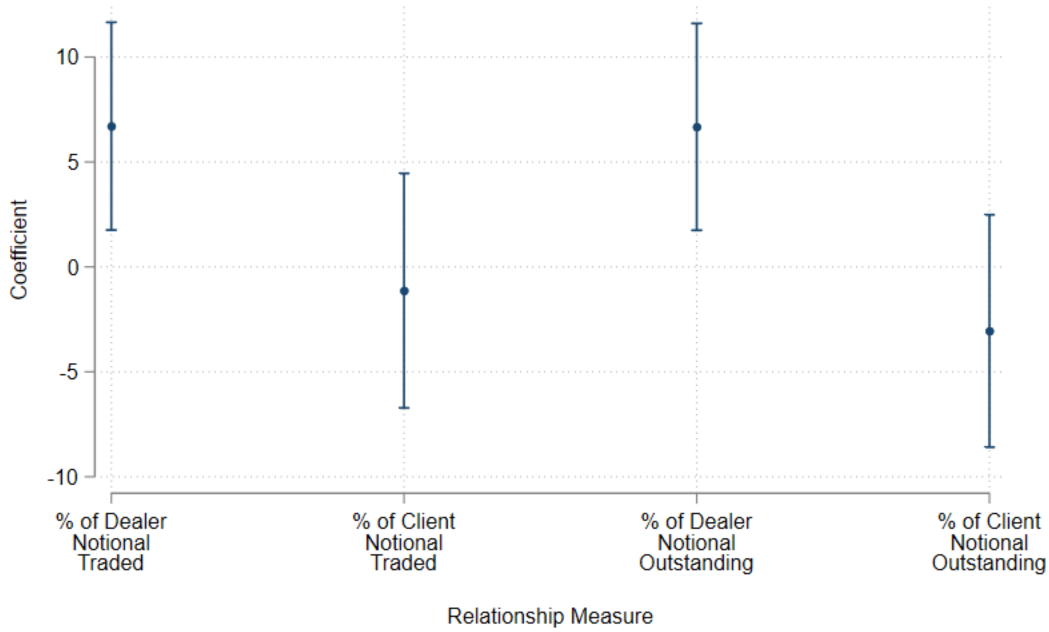
G Pre-Existing Relationship Strength and Credit Suisse Trading Activity: EURUSD

Table 20: Role of Client Reliance for Activity at the Shocked Dealer with Calendar Week Fixed Effects

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]
I[Post]	5.284**	4.557	0.025
	(2.615)	(3.149)	(0.024)
I[Post] x I[WeakRel_di]	-3.520	-1.132	-0.019
	(2.609)	(2.857)	(0.032)
Observations	5,360	5,360	6,000
Client Clusters	67	67	75
R^2	0.1021	0.1593	0.2193
Adjusted R^2	0.0878	0.1459	0.2071
Within R^2	0.0010	0.0006	0.0006

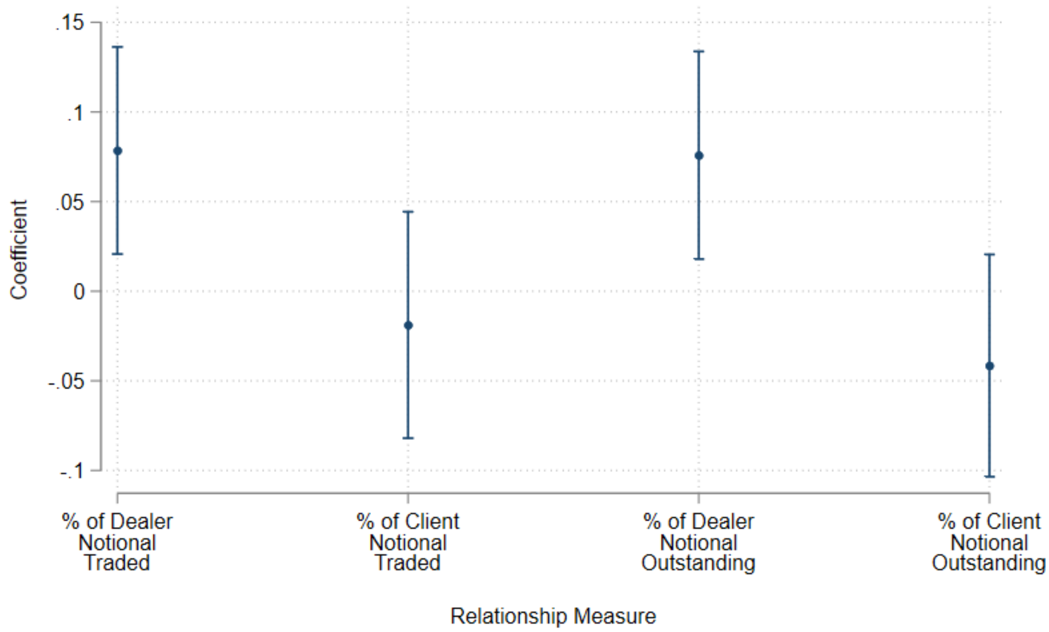
Notes: This table reports results from difference-in-differences regressions at the (client, date) level, given by Equation 8 and including calendar week fixed effects, that test Hypothesis 5. Dependent variables are: *% Not. Traded* (*% Trade Count*), EURUSD notional (trade count) traded by the client with Credit Suisse 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 9, and winsorized at the first and 99th percentiles before restricting to Credit Suisse observations; $\mathbb{I}[Traded]$, an indicator equal to 1 if Credit Suisse and the client trade in EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: $I[WeakRel\_di]$, an indicator equal to 1 if client was less reliant on Credit Suisse in EURUSD than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. Measurement details for $I[WeakRel\_di]$ are in Appendix C.2, which uses *RelStrNDay_i* as defined in that appendix. All specifications include client and calendar week fixed effects. Standard errors are double clustered at the client and date level. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 8: Effect of Relationship Strength on % $Trade\ Count_{d,i,t}$ at Shocked Dealer



Notes: This figure plots the difference-in-differences coefficient, β_2, from regressions at the (client, date) level that test Hypotheses 5 and 6. All columns correspond to Equation 8 with additional calendar week fixed effects, 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) and (4) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is % $Trade\ Count_{CS,i,t}$, EURUSD trade count by the client with Credit Suisse 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 9, and winsorized at the first and 99th percentiles before restricting to Credit Suisse observations. Independent variables are: $I[WeakRel]$, an indicator equal to 1 if client was had a weaker EURUSD relationship with Credit Suisse than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. X-axis labels denote the relationship strength measure used for $I[WeakRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[WeakRel]$. All regressions include client and calendar week fixed effects. Standard errors are clustered at the client and date level. Error bars plot $\pm 1.96 \times SE$.

Figure 9: Effect of Relationship Strength on $\mathbb{I}[Traded_{d,i,t}]$ at Shocked Dealer



Notes: This figure plots the difference-in-differences coefficient, β_2, from regressions at the (client, date) level that test Hypotheses 5 and 6. All columns correspond to Equation 8 with additional calendar week fixed effects, 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) and (4) test Hypothesis 5, and columns (1) and (3) test Hypothesis 6. The dependent variable is $\mathbb{I}[Traded_{CS,i,t}]$, an indicator equal to 1 if Credit Suisse and the client traded in the EURUSD in the all $\leq$ 1y maturity on date t. Independent variables are: $I[WeakRel]$, an indicator equal to 1 if client was had a weaker EURUSD relationship with Credit Suisse than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. X-axis labels denote the relationship strength measure used for $I[WeakRel]$. Appendix C.2 contains measurement details for the relationship measures and $I[WeakRel]$. All regressions include client and calendar week fixed effects. Standard errors are clustered at the client and date level. Error bars plot $\pm 1.96 \times SE$.

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

This appendix gives the regression table for Equation 8 where a weak relationship, $\mathbb{I}[WeakRel_{d,i}]$, is measured using the dealer's share of the client's notional trading activity across all seven currency pairs.

Table 21: Role of Client Reliance Over all Currencies for Activity at the Shocked Dealer

	(1) % Not. Traded	(2) % Trade Count	(3) I[Traded]
I[Post]	-2.997**	-4.875**	-0.048**
	(1.455)	(2.111)	(0.022)
I[Post] x I[WeakRel_di]	-3.520	-1.132	-0.017
	(2.601)	(2.851)	(0.032)
Observations	5,360	5,360	6,000
Client Clusters	67	67	75
R^2	0.0974	0.1529	0.2142
Adjusted R^2	0.0858	0.1421	0.2041
Within R^2	0.0061	0.0141	0.0188

Notes: This table reports results from difference-in-differences regressions at the (client, date) level, given by Equation 8, that test Hypothesis 5, but the relationship strength measure is computed across all currencies. Dependent variables are: % *Not. Traded* (% *Trade Count*), EURUSD notional (trade count) traded by the client with Credit Suisse 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 9, and winsorized at the first and 99th percentiles before restricting to Credit Suisse observations; $\mathbb{I}[Traded]$, an indicator equal to 1 if Credit Suisse and the client trade in EURUSD at t in the all $\leq$ 1y maturity. Independent variables are: $I[WeakRel\_di]$, an indicator equal to 1 if client was less reliant on Credit Suisse across all seven currencies than the median client at Credit Suisse, across clients that traded EURUSD with Credit Suisse in the pre-period; $I[Post]$, an indicator equal to 1 if the date is after March 8, 2023. Measurement details for $I[WeakRel\_di]$ are in Appendix C.2, which uses activity in all seven currencies. All specifications include client fixed effects. Standard errors are double clustered at the client and date level. Significance stars are denoted as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I Exposed Clients' Exposure To Credit Suisse

Table 22: Distribution of Exposure to Credit Suisse Across Exposed Clients, All $\leq$ 1y Maturity

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Exposure_i	280	26.78	36.64	0.04	0.39	4.98	44.81	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 10. 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.

Table 23: Distribution of Exposure to Credit Suisse Across Exposed Clients, Maturity Panel

	Observations	Mean	Standard Deviation	p10	p25	p50	p75	p90
Exposure_i	265	25.23	35.81	0.04	0.36	4.52	37.30	100.00

Notes: This table provides the distribution of client-level exposure to Credit Suisse across exposed clients that are in the spread maturity panel. 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 10. The distribution is across clients with a positive exposure to Credit Suisse, that traded a positive EURUSD notional amount in the pre-period, and exist in our spread sample.