Effect of Bilateral Trading Relationships on Execution Costs in Over-the-Counter Markets

George Issa*

Elvis Jarnecic**

Abstract

In over-the-counter markets, traders have a natural incentive to enter into relationships to avoid search costs. Using unique trade data from the Australian wholesale money, Treasury bond and semi-government bond markets, we provide an empirical investigation on the extent, duration and pricing-effect of such relationships. Consistent with the hypothesis that relationship counterparties provide immediacy at the expense of inferior prices, we find that relationship strength has a positive effect on execution costs. This effect is larger during stressed relative to normal interbank market conditions, which we attribute to greater variability in private values amongst traders.

Keywords: over-the-counter markets; relationship banking; market microstructure; debt markets

EFM Classification Codes: 340, 360, 550, 570

* Presenting author. Address: Room 444, H69, University of Sydney, NSW, 2006, Australia. E-mail: giss5076@uni.sydney.edu.au. Tel.: +612 8088 4200. Fax: +612 9232 4983.
** Address: Room 444, H69, University of Sydney, NSW, 2006, Australia. E-mail: elvis.jarnecic@sydney.edu.au. Tel.: +612 9351 8708. Fax: +612 9351 6461.

1. Introduction

Despite the prominence of over-the-counter (OTC) trading in financial markets worldwide, the market microstructure of OTC markets is not yet well understood, not only because it is difficult to conceptualise their opaque and disperse trading mechanism, but also because data has generally been unavailable.[1] Nonetheless, beginning with the seminal framework proposed by Duffie et al. (2005), a theoretical strand of literature has recently arisen with its primary focus being the role of search frictions in price formation: as there is no central meeting place, traders must actively search-and-bargain with potential counterparties to find the "best" price.[2] To model this iterative search process, traders are randomly matched with each other until the expected marginal benefit of continuing to search – in the form of a better price – is just outweighed by the marginal search cost.[3] *Inter alia*, this approach has been used to help explain liquidity premia and concentration (Vayanos and Wang, 2007; Duffie et al., 2007; Weill, 2008), the heterogeneity of asset positions (Lagos and Rocheteau, 2009), and the on-the-run effect in government bond markets (Vayanos and Weill, 2008). By ignoring learning effects and relationships, however, a potentially important shortcoming of this paradigm is its inconsistency with both anecdotal and empirical evidence of close trading partnerships in OTC settings.

In this paper, we provide empirical evidence aligned with an alternative hypothesis of OTC price formation that is consistent with both the existing search literature and with the common practice of stable trading relationships. The argument underlying this hypothesis is that traders have a choice to enter into either a *relationship-based trade*, which offers immediacy and a reliable trade price, or a *search-based trade*, which offers a superior trade

[1] Historically, most OTC markets did not have a central trade repository. Where data is available, confidentiality issues often preclude academic use. One notable exception is the U.S. corporate bond market, which has attracted significant research following the staggered implementation of the Trade Reporting and Compliance Engine (TRACE) in the early 2000s (see, for e.g., Bessembinder et al., 2006; Edwards et al., 2007; Goldstein et al., 2007).

[2] The concept of explicit search frictions in trading is not novel. Garbade and Silber (1976), for example, present a model of the U.S. government bond market in which the expected liquidity cost of transacting has a component that reflects the cost of contacting each dealer.

[3] These costs include delay, negotiation costs, and a loss of previous quotes that tend to be adjusted unfavourably upon repeated interaction (Zhu, 2011).

price at the expense of incurring search costs. In the empirical analysis, we use confidential data from the Austraclear system to test two primary empirical hypotheses that stem from this central hypothesis. This unique, comprehensive dataset includes trader identities and covers all secondary trades from the Australian interbank money, Treasury bond and semi-government bond markets between 16 August 2006 and 31 January 2014. Consistent with the first empirical hypothesis, we find that during normal periods the execution cost – measured by comparing the traded yield to a benchmark yield – paid by the bank initiating a transaction is positively related to the strength of its pre-existing relationship with the counterparty. In line with the second empirical hypothesis, we find weak to moderate evidence that the size of this execution cost effect increases during illiquid and stressed periods; we interpret this finding as being consistent with our central hypothesis on the basis that the benefits of search are greater during stress periods due to greater variability in the prices at which counterparties are willing to trade at.

The concept of relationships arising in the presence of search frictions is well-established and based on simple intuitive reasoning: to avoid the costs of random search, traders are incentivised to enter into ongoing bilateral relationships based on trust and mutual compatibility. In social psychology, Thibault and Kelley (1959) study the formation of groups and suggest that the expected costs of searching is an important factor for the continuance of relationships. In economics, matching theory has been extensively used to model how mutually beneficial relationships emerge over time in the presence of search costs, not merely within a labour market setting (see, e.g., Burdett, 1978; Mortensen and Pissarides, 1994), but also in personal interactions such as marriage (see, e.g., Becker, 1973; Shimer and Smith, 2000).[4] In perhaps a more relevant context, Weisbuch et al. (2000) model a supplier market and show that there exists a clear division between buyers that are loyal to certain sellers and those that continue to search, and that this division depends on the emphasis placed by the buyer on their past trades. In finance more narrowly, however,

[4] Indeed, Dale Thomas Mortensen, Christopher Antoniou Pissarides and Peter Arthur Diamond were awarded the 2010 Nobel Prize for their 'fundamental contributions to search and matching theory'. Petrongolo and Pissarides (2001) provide an extensive survey of this literature.

theories of endogenous relationships tend to be closely aligned with information frictions. The relationship banking literature, for instance, provides strong empirical evidence that banks tend to form relationships with both firms (Petersen and Rajan, 1994; Berger and Udell, 1995; Ongena and Smith, 2000; Ongena and Smith, 2001) and other banks (Cocco et al., 2009; Affinito, 2012; Hale, 2012) in loan markets.[5] According to the established view in Kane and Malkiel (1965), such relationships emerge as lenders are able to closely monitor borrowers to reduce moral hazard and information asymmetry, thereby decreasing borrowing costs as the relationship matures.[6] To the best of our knowledge, only several recent papers have proposed that relationships endogenously arise in financial markets to eliminate search costs (Afonso et al., 2014; Boualam, 2015).

The novel component of our argument lies in its *pricing prediction*: we predict that relationship traders pay a *higher* execution cost to initiate a transaction. Hence, it is important to first address the inconsistency between our prediction and the closely-connected relationship banking literature (see, e.g., Cocco et al., 2009). We propose that the crucial distinguishing point stems from the party that derives greater value from the relationship. In the loan markets that are studied in the relationship banking literature, the ability of the borrower to meet their obligations is material information to the lending bank. Hence, the relationship directly benefits the passive liquidity supplier (i.e., lender), rather than the initiating client (i.e., borrower);[7] relationship lenders will therefore be incentivised to provide better loan terms, including prices, than spot lenders. In a market with search frictions and no informational concerns, by way of contrast, the relationship directly benefits the initiating client, rather than the passive liquidity supplier. For this reason, in our empirical tests we study a narrower market setting that reasonably isolates the effect of search costs from information asymmetry costs. That is, we study a secondary asset market in which counterparty credit risk is virtually non-existent: the debt securities are issued by a third-party

[5] For a detailed survey of this literature, see Boot (2000) or Elyasiani and Goldberg (2004).

[6] Other key theoretical studies include Sharpe (1990), Diamond (1991), von Thadden (1995) and Petersen and Rajan (1995).

[7] Of course, search costs savings are also realised by the borrower, but their value is less than the informational value obtained by the lender.

to the trade, implying that no counterparty informational concerns persist following settlement; settlement risk itself is negligible due to the efficient and centralised settlement method used in Austraclear.[8]

Several papers present arguments that are closely linked to ours. In a similar spirit to Duffie et al. (2005), Lester et al. (2014) present a model of OTC markets with search frictions but instead allow for intermediation, with dealers competing by publicly posting their orders. The authors find that traders face a trade-off between execution speed and execution costs, which is similar to our conjectured trade-off, except that we attribute it to a latent relationship-based variable. Zhu (2012) presents a model of OTC quotation behaviour in which dealers are privately approached by a seller. Upon repeat contact, a dealer revises their offer downwards as they infer that the revisiting buyer has reduced outside options. If the seller approaches a subset of dealers first – analogous to relationship dealers – and the fundamental asset value is unknown to all dealers, then the favoured subset is more likely to offer a higher price: dealers in the disfavoured group infer that the asset value is likely to be low given that the buyer did not initiate a transaction with the favoured group. If the fundamental value is known, however, and the asset has a private value attached to it, then it is possible that relationships are associated with inferior prices.[9] Babus and Hu (2015) provide a model of OTC markets within which relationships endogenously form. They show that under the crucial assumption that investors have a low probability of repeated interaction, traders may develop a single long-term bilateral relationship, with one party implicitly acting as an intermediary. In an empirical study of trading relationships in the U.S. interbank lending market, Afonso et al. (2014) suggest that relationships may arise to reduce search costs, and that trading partners are selected for "liquidity hedging" purposes. Their liquidity hedging story is intuitive, since the viability of a long-term relationship (as well as its ability to reduce search costs) is greater when trading partners either have complementary liquidity needs or, as in Lester et al. (2014)

[8] After the agreed terms-of-trade are input by both banks in Austraclear, the necessary cash and securities are irrevocably and instantaneously transferred between the banks' reserve accounts via the Real-Time Gross Settlement (RTGS) system (Gallagher et al., 2010).

[9] To provide a rough isolation of our hypothesis from this alternative explanation, we implicitly control for private value in Section 5.3.

and Babus and Hu (2015), one party acts as an intermediary. Their argument is also connected to the general equilibrium model presented in Boualam (2015), who analyses bank lending relationships in an economy with search frictions and limited contract enforceability.

The rest of this paper is structured as follows. Section 2 briefly presents the intuition for our theoretical argument and stipulates the hypotheses to be tested. Section 3 describes the Austraclear data and outlines the measurement of key variables. Section 4 uses duration analysis to better understand the extent and stability of interbank relationships in the sample; in this section, we provide supplementary evidence consistent with the liquidity hedging story in Afonso et al. (2014). Section 5 presents the primary analysis examining the effect of relationships on execution costs, and Section 6 concludes.

2. Empirical Hypotheses

Our central hypothesis is intuitive and non-mathematical. Consistent with the prior OTC search literature, we first consider an opaque, single-asset market where the asset value is known by all traders and the only trading friction is costly search-and-bargaining (see footnote [2] for examples of these costs). In contrast, however, traders are able to learn from their interactions with other traders. Also, traders act rationally and exhibit exogenously different trading needs, including their preference for buying versus selling (as indicated by their net buying demand). Under this set of assumptions, traders are able to infer from repeated interaction whether their trading needs are more compatible with specific counterparties. Simple intuition then dictates that when traders have a greater need for immediacy (e.g., to capitalise on short-term profitable opportunities or to liquidate an open, undesired asset position), they will be inclined to circumvent the search-and-bargaining process by approaching a compatible counterparty and trading quickly. Implicit bilateral trading relationships will therefore emerge over time, and trades under these relationships will be characterised by their immediacy and less attractive prices. Hence, the essence of our argument is that traders are faced with two alternatives when looking for prices: (1) enter into a search-based trade, which requires shopping for the “best” price at the expense of a costly search process; or (2) enter into a relationship-based trade, which provides immediacy and reliability at the expense of an inferior price.[10]

To test our proposition, we construct two primary empirical hypotheses (indicated by “p”):

- **Hypothesis 1p**: *Relationship strength has a positive effect on execution costs during normal market conditions.*
- **Hypothesis 2p**: *The positive effect in Hypothesis 1p increases during stressed markets.*

These hypotheses are framed at a trade-level. The dependent variable, execution costs, is defined relative to the difference between the trade price and an appropriate benchmark, and aims to capture the cost of initiating the trade without accounting for search costs. The independent variable, relationship strength, refers to the past tendency for the two parties to trade with each other. It is framed as a quantitative variable, rather than a dichotomous variable that separates search-based versus relationship-based trades, because the concentration of trading activity with a specific counterparty has a positive effect on not only the likelihood that the trade is relationship-based,[11] but also the associated search cost savings, and, by inference, the execution costs paid (consistent with Hypothesis 1p).[12] We broadly define stressed markets as periods when markets are not functioning smoothly due to scarce liquidity and a substantial reduction in the willingness of traders to provide quotes when approached by others. Hypothesis 2p then contends that the positive effect in Hypothesis 1p increases during stressed markets as the variability of private values[13] amongst potential counterparties increases, thereby increasing the premium obtained from searching; also, distressed traders are more likely to enter into fire-sales with relationship counterparties due to their preference for immediacy.

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[10] Interestingly, this choice is similar to exchange-based, limit order book markets where traders decide to execute trades using either market orders (analogous to a relationship-based trade) or limit orders (analogous to a search-based trade).

[11] This points to another justification for using a quantitative variable: there is no economic definition for what constitutes a trading relationship and therefore any cut-off is arbitrary.

[12] In any case, we use alternative dichotomous variables in robustness checks.

[13] See footnote [6] in Zhu (2012) for a discussion of idiosyncratic factors that affect private value. Since market stress tends to be associated with turbulence in factors such as margining, leverage and inventory, the variability of private valuations should increase contemporaneously.

To further test our central argument, we propose two secondary hypotheses (indicated by "s"):

- **Hypothesis 1s**: *The positive effect in Hypothesis 1p is larger for traders that are more efficient at search-and-bargaining*.
- **Hypothesis 2s**: *Relative to search-based trades, relationship-based trades exhibit more stable execution costs during both normal and stressed markets*.

First, it is intuitive that traders that are better at search-and-bargaining (possibly due to faster access to counterparties, better negotiation skills, stronger negotiation power, etc.) should be able to obtain more superior prices when entering into a search-based trade. Consistent with Hypothesis 1s, it then follows that these traders should derive a larger price improvement when trading with counterparties that they have a weaker relationship with. Second, in line with Hypothesis 2s, the stability of execution costs should be higher for relationship-based trades as an important motive behind the formation of relationships is the reliability of offered prices; in comparison, random counterparties provide a broad range of prices and thus the "best" price obtained from random search is likely to be sensitive to many factors including market conditions, search-and-bargaining ability, and patience.

3. Data

3.1 Data

Our dataset covers all secondary trades in the Australian wholesale money (including Bank Accepted Bills and Certificates of Deposit), Treasury bond and semi-government bond markets between 16 August 2006 and 28 January 2014. The sample is obtained from Austraclear, the settlement facility used for most debt transactions in Australia. We only consider government-issued and bank-issued fixed-rate securities, however, as they are much more homogenous and cover the majority of total transactional activity; it follows then that execution costs can be more accurately measured and benchmarked in these markets, and relationships are more likely to play a prominent role.[14] For each trade, the dataset lists the trade date, face value traded, cash amount, ISIN code, and the numerical identities of the buyer and the seller. Linked to each ISIN code, the Austraclear dataset provides security characteristics including asset class, the name of the issuer, maturity date, issue date, and total face value issued; for Treasury bonds and semi-government bonds, the dataset also identifies the coupon rate, coupon payment frequency, and ex-coupon period. Finally, at the beginning of each three-month interval, the dataset lists the numerical identities for all registered Austraclear participants; these lists have been cross-referenced with data obtained from the Australian Office of Financial Management (2014) and the Australian Prudential Regulation Authority (2014) in order to distinguish domestic versus foreign banks (from the table of foreign banks with a local branch) and dealer versus non-dealer banks (from the table of government bond dealers).[15]

Table 1 presents summary statistics for trade activity in the raw dataset. In total, there are just over one million trades across 1,830 trading days. Despite obviously being much less active than equity markets, there is a moderate level of activity for analysis: on average, around 257, 180 and 110 trades are executed each day in the money, Treasury bond and semi-government bond markets. Also, activity in these three asset classes represents around 79% of total fixed-rate debt activity in Austraclear (1,269,916 trades), consistent with our reasoning for excluding other asset classes. Interestingly, although there are only 29 Treasury bonds and 203 semi-government bonds, over 270,000 money market securities are lodged in Austraclear – 14,253 of which trade at least five times – indicating thin trading at a security level; this is not problematic, however, as bills matched on maturity date are virtually identical and almost perfectly substitutable.

< INSERT TABLE 1 >

[14] By way of contrast, as corporate bonds and floating-rate securities are typically not substitutable, relationships will intuitively be less valuable as non-relationship banks may offer *both* competitive prices and individualised securities.

[15] Only a subset of Austraclear participants are classified as banks, as other authorised deposit-taking institutions (ADIs), funds, and trustees are also able to participate. Since banks participate in the vast majority of transactions (over 90%), however, we generally refer to traders in this market as banks.

Table 2 presents the distribution of trade activity in the raw dataset across individual banks and bank-pairs. There are 471 banks that participate during the sample, 17 of which act as dealers. Most banks do not actively participate in the market, with around 59% of participants trading less than 200 times. Nonetheless, a decent proportion of banks do trade fairly actively, with 86 participants (or approximately 18%) trading over 2,000 times. In line with expectations, the distribution for dealers is left-skewed while the distribution for non-dealers is right-skewed; 12 dealers trade more than 20,000 times and all-but-one dealer trade more than 2,000 times. Interestingly, despite the small number of foreign banks, unreported figures show that the average foreign bank trades almost twice as often as the average domestic bank, in line with empirical evidence (Cocco et al., 2009) and the intuition that banks tend to penetrate foreign markets only when they have the necessary scope of activity and funds required to understand and profitably participate in the market.

< INSERT TABLE 2 >

Despite being difficult to interpret, the distribution of bank-pairs provides some initial marginal evidence that some participants enter into bilateral trade relationships. First, although there are theoretically ${}_{454}C_2 = 110{,}685$ possible pairs amongst the 471 participants, there are only 5,138 bank-pairs that actually trade during the sample, suggesting that the average participant has around 12 trading partners over the course of the 7.5 year sample. Even though the maximum number of pairs that an individual bank can be a part of (470) exceeds the number of trades that most banks enter into, one would intuitively expect many more bank-pairs under a pure random matching market even after accounting for the greater likelihood of trading with more active participants. Second, and more persuasively, many bank-pairs trade a substantial number of times in the sample. For instance, although most bank-pairs appear to represent non-relationship transactional activity (almost 43% trade less than 10 times), 417 bank-pairs (or just over 8%) trade over 500 times within the sample, indicative of fairly active relationships. When we split the set of bank-pairs depending on whether the participants are dealers (D-D), non-dealers (ND-ND) or mixed (D-ND), the sub-population distributions are considerably different: reflecting the greater likelihood for both dealers and non-dealers to regularly interact with other dealers, the distribution density at the lower-end of the trade count is highest for ND-ND followed by D-ND and then D-D.

We apply two initial filters to minimise any bias in our analysis: first, we exclude all banks that trade less than 200 times in the dataset, and second, we exclude all banks that were not Austraclear participants at both the beginning and the end of the sample. The first filter is used as proportional measures of relationship strength will be significantly upwards-biased if we consider banks that tend to trade only a few times each month. By eliminating any censored cross-sectional units, the second filter reduces survival bias and delayed-start bias, both of which tend to underestimate relationship length and reduce the accuracy of relationship strength measures. After applying these filters, the majority of banks (307 from 471) are omitted while the total sample is only marginally reduced by 6.8% from 1,002,279 trades to 933,823 trades. As trade activity is fairly high amongst the included banks, activity-based variables used in the analysis can be more accurately measured.

3.2 Key variables

This section describes the key variables used in the primary analysis in Section 5. We first calculate the yield (y) for each trade by solving one of the following pricing formulas:[16]

$$P = \frac{1 + c}{1 + \left(\frac{d}{365}\right) y} \tag{1}$$

$$P = \frac{1}{\left(1 + \frac{y}{2}\right)^{2T}} + \sum_{i=1}^{n} \frac{c}{\left(1 + \frac{y}{2}\right)^{2t_i}} \tag{2}$$

where P is the price per \$1 face value and is obtained by dividing the cash amount paid by the buyer with the face value of the security purchased, y is the unknown yield to maturity, T is the time-to-maturity in years, c is the coupon rate divided by the number of coupons paid per year, n is the number of coupon payments remaining, d is the number of calendar days

[16] These formulas are consistent with the actual/365 day count convention in the Australian money market and with the formulas used by the Reserve Bank of Australia (RBA; 2014) to price Treasury bonds.

between the trade date and the maturity date, and t_i is the time in years until the i^{th} coupon payment excluding the next coupon payment if the bond is currently trading ex-coupon.

To calculate the yield for money market trades, and for bond trades that entitle the purchaser to only one future cash flow (i.e., at maturity), formula (1) is used, under which y has a closed-form solution and can be determined exactly. We set c equal to zero for money market securities and for the bonds trading ex-coupon. To calculate the yield for bond trades that entitle the purchaser to more than one future cash flow, the more general formula (2) is solved iteratively using the Newton-Raphson method, under which solutions are obtained for 99.99% of bond trades. We then exclude the top 1% and bottom 1% of traded yields as they represent extreme outliers that will likely bias our results.[17]

We measure the execution cost associated with each trade with reference to the difference between a benchmark yield (y^*) and the traded yield (y):

$$EC = (y^* - y)I$$

where

$$I = \begin{cases} 1 & \text{if buyer initiated} \\ -1 & \text{if seller initiated} \end{cases}$$

Holding y^* constant, EC is higher for initiating buyers paying a lower yield (and thus higher price) and initiating sellers receiving a higher yield (and thus lower price). Given there is no trade initiator variable in the dataset, however, we only consider trades between dealers and non-dealers (i.e., D-ND) as well-established practice and the definition of intermediation dictates that non-dealer clients will generally initiate transactions with dealers. Hence, I becomes:

$$I = \begin{cases} 1 & \text{if dealer} = \text{seller} \\ -1 & \text{if dealer} = \text{buyer} \end{cases}$$

This filter ensures that I can be accurately inferred at the expense of reducing the number of trades in the dataset by around 36.0% from 890,349 to 569,592.

[17] Almost all these yields are more than three standard deviations away from the mean. In any case, we also repeated the primary analysis by winsorising these extreme yields, and qualitatively similar results were obtained.

The benchmark yield y^* is calculated as the arithmetic average yield across all trades that belong to the same asset class and maturity group on the same trading day. For money market trades, four maturity groups are defined according to time-to-maturity: less than 30 days, 30-44 days, 45-89 days and greater than 89 days. For bond trades, however, it is often not possible to estimate an accurate maturity-matched benchmark yield as the much larger spread in time-to-maturity across securities implies that there will be an insufficient number of daily trades in most reasonably-narrow maturity groups. Hence, we use an aggregated benchmark yield for Treasury bonds and semi-government bonds, and later control for maturity effects in the regression specifications.

For each trade, a relationship index $Reln$ is calculated as the number of trades between the same D-ND pair during the previous 50 trading days as a proportion of the total[18] number of trades that the non-dealer bank participated in during the same period. Consistent with the intuition that the scope of relationships tends to be broad and not restricted to individual markets, $Reln$ is calculated using trades across all asset classes. This proportional-based measure is similar to metrics used in the interbank relationships literature (e.g. Furfine, 2001; Cocco et al., 2009; Affinito, 2012), and is constructed to both allow for comparison – it controls for the trading activity of the non-dealer and is naturally bounded between 0 and 1 – and to take the perspective of the initiating party. In order to provide an initial value for $Reln$, the primary analysis excludes observations in the first 50 trading days of the sample. Since there is no economic definition for what constitutes a relationship, however, we note the importance of conducting robustness checks across different metrics. Therefore, we also measured $Reln$ as the logarithm of the number of trades between the bank-pair during the previous 50 trading days, and we also examined different windows for robustness (30 and 120 trading days); across these different measures, the key results from the primary analysis remained similar.[19] In further analysis presented in Section 5.3, we also use alternative

[18] This includes trades between non-dealers.
[19] 30, 60, 90 and 120 day windows were examined. In terms of the first primary hypothesis, all the coefficients remained positive and significant at the 1% level, except for semi-government bonds using the 90 day (5% level) and 120 day (5% level) window. In terms of the second primary hypothesis, the sign of the coefficient generally remained in the same direction relative to the main reported results, but around a third either became insignificant or had a reduction in the statistical significance level (i.e., to 5% or 10%).

proportional-based measures, including a measure that controls for how active the dealer is in the market.[20]

To proxy for market stress levels, the spread between the 30-day BAB rate and the 30-day Overnight Indexed Swap (OIS) rate is calculated for each trading day, with the rates obtained from the RBA website. Such a spread is conceptually similar to the LIBOR-OIS spread that is more commonly used in the literature because the Australian-based BAB rate is affected by credit risk similarly to LIBOR.[21] We then define a dummy $Stress$ variable as being equal to one on trading days when the BAB-OIS spread is in the top decile of all trading days in the sample. In line with expectations, casual observation of the $Stress$ variable indicates that it is typically equal to one during the Global Financial Crisis (GFC), and zero during other times.

4. Nature of Interbank Relationships

Before examining our main hypotheses, we briefly use duration analysis to document key characteristics (including distributional features, persistence and asymmetry) of interbank relationships. As this technique requires a non-overlapping unit of time, we use the following definition to identify relationships: for each bank-pair and month, a relationship is assumed to exist if the bank-pair trades at least 10 times. In contrast to the proportional, initiator-perspective measure $Reln$, we use a nominal criterion here as it is more appropriate when considering relationships from the perspective of both parties; in any case, unreported robustness checks confirmed that the results in this section are broadly insensitive to two alternative criterions: (1) months where a bank-pair trades at least 5 times; (2) months where the trades between a bank-pair represent a combined average of at least 5% of the two individual banks' trades. We then define a relationship spell as the number of successive months during which a bank-pair meets the above criterion. To ensure a consistent unit of

[20] Our primary measure implicitly assumes that traders are equally likely to approach any specific dealer under random search; this alternative measure explicitly controls for different likelihoods (according to relative trade activity) to calculate an abnormal relationship metric.
[21] For instance, Frank et al. (2008) use the LIBOR-OIS spread as a proxy for liquidity pressure in interbank funding markets.

time, we only include months for which all trading days are included (i.e., 16-31 August 2006 is excluded). All bank-pairs (D-D, D-ND and ND-ND) are considered so that we can identify any differences between the sub-groups and hence infer whether our primary analysis, which is restricted to only D-ND pairs, might be a biased representation of all bank-pairs.

4.1 Distribution of Relationship Durations

Table 3 presents the distribution of the observed duration of relationships. Interestingly, the number of relationship spells (4,285) is fairly close to the number of bank-pairs (5,138). It does not follow that most trades are relationship-based, however, as bank-pairs can have multiple relationship spells over the course of the 89-month sample.[22] Indeed, for the less active bank-pairs, identifying multiple relationships is a natural outcome due to fluctuations in trade activity about the criterion. Unsurprisingly then, the number of relationship spells decreases significantly when we repeat the analysis using a longer, quarterly unit of time (not reported).

Casual observation of the marginal distribution indicates that most relationship spells end fairly quickly, with almost half ending after the first month and over 80% ending within five months; further, the mean (median) duration is only 4.97 (2) months. Although the shorter end of the distribution is more difficult to interpret due to random fluctuations about the arbitrarily-selected relationship criterion, these figures nonetheless provide some evidence that relationships tend to be transient, especially since the mean and median durations are only slightly affected when using other relationship criterions. At the other end of the marginal distribution, however, there is a small spike in the number of relationship spells: 48 bank-pairs (around 1.12% of relationship spells or 0.93% of *all* bank-pairs) meet the relationship criterion across the entire 89-month sample, suggesting that a small but meaningful proportion of relationships tend to persist over the long-run. Moreover, the distribution of average monthly trades indicates that a more persistent relationship is also

[22] As an example of how this can arise, if a bank-pair has the following series of trade counts across the 16 months (1, 3, 5, 4, 0, 6, 5, 7, 8, 3, 1, 0, 2, 1, 3, 4), then it will be characterised as having three relationship spells (months 2-4, months 6-10, and months 15-16).

more economically important in terms of trade activity: the average number of monthly trades almost monotonically increases as relationship duration increases, with a large spike for relationships lasting in the longest duration bracket.

< INSERT TABLE 3 >

Table 3 also presents the distribution of relationship spells for D-ND, D-D and ND-ND bank-pairs separately. Although the distributions for these subsamples are broadly similar to the aggregate distribution, thus suggesting the above comments equally apply to each of them, there are some slight differences that should be noted. In particular, the spike in the proportion of relationship spells within the highest duration bracket is fairly large for D-D relationships (3.82%), moderate for D-ND relationships (1.46%), and almost non-discernible for ND-ND relationships (0.44%). It follows then that a greater proportion of relationships with dealers persist over time, perhaps because their intermediary role suggests they make more useful trading partners given their greater willingness to provide immediacy when required.

Before proceeding with any further duration analysis, an important issue that should be considered is censoring: duration observations beginning from the start of the sample (September 2006) are right-censored as we are unable to identify whether these relationships actually began earlier in time, and duration observations concluding at the end of the sample (January 2014) are left-censored as we do not know whether these spells actually ended or whether they continued to exist. Across the full sample and the subsamples, Table 3 indicates that censoring affects between 5.7-10.2% of relationship spells, which is fairly low. Nonetheless, by underestimating the length of these observed spells, censoring may bias our inferences on relationship duration, and it is therefore necessary to control for them in the next subsection.

4.2 Value of relationships over time

In this subsection, we study duration dependence, similar to the approach used in Ongena and Smith (2001), in order to infer whether the value of a relationship tends to improve, remain constant, or decrease over time. We construct a non-parametrically estimated hazard function as follows:

$$\lambda(t) = \lim_{\Delta t \to 0} \left(\frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \right)$$

where $\lambda(t)$ refers to the instantaneous likelihood that a relationship spell will end, conditional on the spell having already survived to t. Thus, when $\lambda(t)$ is positively related to time t, the hazard function is said to display positive duration dependence, indicating that the value of a relationship decreases over the long-term (as a mature relationship has a greater likelihood of ending relative to a newer relationship). Similarly, $\lambda(t)$ exhibits negative duration dependence when it is negatively related to time t, and constant duration dependence when $\lambda(t)$ is not related to t. As we only conduct a preliminary analysis here, we have not estimated a more formal parametric regression model, although such an analysis would be interesting for future research.

< INSERT FIGURE 1 >

Figure 1 plots the empirical hazard function for interbank relationship spells.[23] The function is constructed using the nonparametric maximum likelihood estimator (Kaplan and Meier, 1958). The hazard function is corrected for both left- and right-censoring using the method outlined in Allison (2010). In the figure, the black line represents the estimated hazard function $\lambda(t)$ with surrounding 95% confidence limits represented by the shaded blue colour. To obtain a smooth and continuous hazard function, we graduate the relationship spells using a local polynomial method, and the Epanechnikov kernel is used for the weighting function due to its optimality properties (Ramlau-Hansen, 1983). Note also that in unreported graphs we examined the hazard functions for D-ND, D-D and ND-ND relationship spells separately; since the patterns are similar to those in Figure 1 (for e.g., the confidence bands tend to

[23] Note that hazard functions exhibit mathematical equivalence with their associated cumulative density function (CDF) and survivor function; including these other graphs would therefore be redundant.

overlap across the three subpopulations), the analysis below is broadly applicable to each subsample.

Overall, despite a sharp upwards trend in the first two months, the hazard function tends to decrease over time, consistent with negative duration dependence. This negative trend is time-varying, however, as the curve appears to decrease at a decreasing rate: initially, the curve exhibits a sharp decrease until around 12 months; from then, the curve slowly approaches a hazard rate of zero, albeit with some random fluctuations along the way.[24] It appears then that the likelihood of ending a relationship decreases as it matures over time, suggesting that long-term relationships are more valuable. Intuitively, when a relationship first begins, the bank-pair is in a discoverability phase where it is not yet known whether the arrangement is mutually beneficial for both parties. Thus, within the first six months or so, the likelihood that a relationship will terminate is fairly high as most bank-pairs will fairly quickly determine that it is not in their interests to continue a relationship. This explanation is reflected in the graph, which suggests that relationships that have just lasted 2 months are only expected to last for another 3.2 months ($= 1/\lambda(t)$). Given that the vast majority of relationship spells are of short durations, this result reinforces the important role of relationships, as it suggests that banks tend to regularly experiment with each other, consistent with a search for long-term relationships of value.

As the relationship matures and the bank-pair displays a proven track record of continued engagement, however, the hazard function quickly declines (suggesting that the discoverability phase is finalised fairly quickly) and the likelihood that the relationship will persist over time increases. For instance, when a relationship spell approaches 10 months, the hazard function estimates that it will survive for around 16 months; further, as the spell approaches 37 months, $\lambda(t)$ becomes so close to zero that the relationship can be expected to continue for around another 100 months. Interestingly, except for a few fluctuations, the

[24] In particular, although the temporary upturn in $\lambda(t)$ after 80 months is quite large, it is likely due to randomness rather than a meaningful change in relationship dynamics at this stage in a trading partnership.

confidence bands surrounding $\lambda(t)$ are fairly narrow, revealing greater confidence in the existence of negative duration dependence.

4.3 Symmetry of relationships

We next investigate whether interbank relationships tend to be symmetrical with respect to the buying and selling activity of each participant bank. For each relationship spell between bank-pair (A, B), we define a relative buying index, RBI, as the proportion of all relationship trades where A is the buyer and B is the seller. As RBI can be measured from either of two perspectives, we choose party A so that the index is less than or equal to 0.5 in order to allow for comparison (i.e., A is the less frequent buyer). Thus, an RBI close to 0.5 indicates that the bank-pair are in a more balanced and two-way relationship, while an RBI close to zero indicates an asymmetrical and one-way relationship under which one participant almost always buys from the other.

< INSERT TABLE 4 >

The distribution for RBI is shown in Table 4. Similarly to a U-shape, there are two peaks occurring at either end of the distribution; for obvious reasons then, we do not interpret the mean and median. Nonetheless, we can infer from this distributional pattern that most relationships tend to be either significantly symmetrical ($RBI > 40\%$) or significantly asymmetrical ($RBI < 5\%$). *Prima facie*, this pattern is consistent with the intuition that relationships tend to be most valuable in two scenarios. Frist, when at least one participant is sufficiently active to allow for the time-varying buying and selling needs of the other to be met, consistent with an intermediary role. Second, when the two participants have offsetting buying and selling imbalances, so that the net buyer tends to purchase securities from the net seller.[25] This latter scenario is analogous to the liquidity hedging role proposed in Afonso et al. (2014). When we observe the RBI distribution for dealer and non-dealer subsamples

[25] For example, a small bank that tends to buy and hold bills up until maturity (either on its own behalf or on behalf of its customers) would find it attractive to enter into a relationship with a dealer that regularly obtains inventory from primary market transactions and seeks to offload them in the secondary market.

separately, however, the U-shape does not exist for interdealer (D-D) relationships. Instead, a single peak occurs at the right-end of the distribution. This is not surprising as it is well-established that dealers tend to use interdealer markets to offload undesired inventory onto other dealers.

5. Interbank Relationships and Execution Costs

In this section, we examine the impact of relationship strength on execution costs during normal markets versus stressed markets. As explained in Section 2, we aim to test two primary hypotheses: first, that during normal markets, execution cost increases as relationship strength increases, consistent with the intuition that search-based trades are initiated at better prices to compensate for search-and-bargaining costs (Hypothesis 1p); second, that during stressed markets, the magnitude of this positive effect increases, reflecting the greater variability in private valuations amongst traders and the tendency for traders to enter into fire-sales with relationship counterparties (Hypothesis 2p). Our key variables, $Reln$ and EC, are constructed using the variable definitions in Section 3.

5.1 Unconditional analysis

As a starting point, we investigate the unconditional effect of relationships on execution costs. Since $Reln$ is a continuous variable, however, we present the summary analysis with reference to a dummy that distinguishes between a relationship-based trade and a search-based trade. In particular, we refer to a trade as being relationship-based if $1 \geq Reln \geq 0.1$ and search-based if $0.1 > Reln \geq 0$. Although the 0.1 threshold appears to be arbitrary, the results are broadly consistent across both different thresholds (0.05 and 0.2) and a qualitative variable with five categories that proxy for relationship strength.[26] We then analyse summary measures for EC across both asset type and normal versus stress days (distinguished based on the $Stress$ dummy variable).

[26] The dummy is used, rather than the multi-stage qualitative variable, for clarity and simplicity. The results using the multi-stage qualitative variable indicate a positive (but not necessarily linear) effect. As this positive effect is fairly monotonic, however, the linear form for $Reln$ in the primary regression remains reasonable.

The results are reported in Table 5. In Panel A, the summary measures are calculated using the set of all trades. On the one hand, these figures provide initial evidence consistent with Hypothesis 1p. During normal days, the average EC for relationship-based trades is higher than the average EC for search-based trades by roughly 6.9, 3.4 and 3.9 basis points (bps) in the money, Treasury bond and semi-government bond markets. Moreover, difference-of-means t-tests[27] indicate that each of these differences are statistically significant at the 1% level. Given that most trades in these markets are for large face values, these figures are potentially economically meaningful for interbank traders.[28] On the other hand, the figures provide conflicting evidence with respect to Hypothesis 2p. In the money market, the average execution cost premium for relationship-based trades is considerably higher on stress days than normal days (12.5bps relative to 6.9bps), consistent with our expectations. In the bond markets, however, the average execution cost premium is lower in magnitude on stress days – in contrast to our expectations – although this difference is either statistically insignificant or weakly statistically significant (10% level).

< INSERT TABLE 5 >

For robustness, Panel B presents similar summary measures for observations constructed at a daily frequency: on each trade day, the average execution cost ($\overline{EC}$) for relationship-based trades and search-based trades is estimated separately. To omit unreliable $\overline{EC}$ estimates, days with less than five relationship-based trades or less than five search-based trades are excluded. Overall, both the averages reported and the statistical significance of the difference-of-means t-tests are quantitatively similar to those reported in Panel A. To further supplement these figures, we also reported the percentage of days for which $\overline{EC}$ is greater for relationship-based trades relative to search-based trades. Interestingly, while this percentage is very high for the money market subsample (around 86% and 95% on normal days and

[27] All difference-of-means t-tests in this paper are conducted by estimating standard errors allowing for unequal variances between the two populations.
[28] For example, for a bill with a face value of $10 million and 90-day maturity, the incremental trading cost for a relationship-based trade (assuming a yield of 5% for search-based trades) is around $1,660.

stress days), it is only slightly high for the bond markets (around 60% and 57% on normal days and stress days for the Treasury bond market, with the corresponding figures being 55% and 54% for the semi-government bond market). At a broad level then, for Hypothesis 1p the unconditional analysis provides strong supportive evidence in the money market and moderate supportive evidence in the two bonds markets; for Hypothesis 2p, however, the results are mixed but provide some marginal support.

5.2 Regression analysis

To formally test our two primary hypotheses, we estimate the following regression models:

$$EC = \beta_0 + \beta_1 Reln + \beta_2 (Reln \times Stress) + e \quad (1)$$

$$EC = \beta_0 + \beta_1 Reln + \beta_2 (Reln \times Stress) + \beta_3 \ln(Size) + e \quad (2)$$

$$EC = \beta_0 + \beta_1 Reln + \beta_2 (Reln \times Stress) + \beta_3 \ln(Size) + \beta_4 Coupon \quad (3)$$
$$+\beta_5 OTR + \sum_{i=1}^{20} \beta_{i+5} Time_i + e$$

where EC, $Reln$ and $Stress$ are as defined in Section 3.1. Model (1) is an initial baseline specification that does not include any controls (similar to the unconditional analysis), model (2) is the primary specification for examining the money market, and model (3) is the primary specification for examining the two bond markets. All models are estimated using the ordinary least squares (OLS) technique with standard errors that are adjusted for heteroskedasticity and autocorrelation using the procedure suggested by Newey and West (1987). The effect of relationships on execution costs is estimated by β_1 for normal periods and $(\beta_1 + \beta_2)$ for stress periods. Hence, Hypothesis 1p contends that $\beta_1 > 0$ and Hypothesis 2p contends that $\beta_2 > 0$.

Control variables are included to address omitted variable bias. Analogous to the literature on upstairs equity markets (Keim and Madhavan, 1996), traders may prefer to search-and-bargain when initiating large trades. Hence, to control for any size effects, the total face value of the traded asset ($Size$) is included, with a logarithmic transformation to reduce the effect of extreme outliers. As bonds with higher coupons – and thus shorter durations – may be more attractive to a subset of investors, they might trade at a price premium. Hence, to account for the possibility that relationship strength is correlated with the coupon rate of the traded bond, $Coupon$ is included as a control.[29] In Duffie's (1996) model, which has received empirical support in Jordan and Jordan (1997), the most recently auctioned security – referred to as being on-the-run – should trade at a price premium. As traders might be inclined to search-and-bargain when trading a relatively inactive off-the-run security, a dummy variable that indicates whether a bond is the most recently auctioned within its asset class (OTR) is included. To control for time-to-maturity effects, we adopt different approaches across asset type. For the money market, we directly adjust for time-to-maturity when constructing EC (see Section 3 for an explanation). For the two bond markets, a set of 20 dummy variables are used for each half-year maturity bracket until 10 years (with maturities greater than 10 years serving as a benchmark), thus allowing a constant, long-run yield curve across the time-series.[30] Although these maturity dummies cannot accurately account for time-to-maturity effects, they provide a reasonable control so long as yield curves follow a similar pattern on most trading days (see, e.g., Finlay and Olivan (2012) for a typical curve structure in the Australian market). In any case, we test alternative approaches in Section 5.3, including controls that allow for time-varying yield curves. Finally, our results are unaffected by the inclusion of either an individual $Stress$ variable or day fixed effects; we have not included them in our model because EC is constructed to have a daily average of zero.

< INSERT TABLE 6 >

Table 6 reports the regression results. For each asset type, we first estimate the base regression specification in (1a), (1b) and (1c). As in Section 4.1, the results confirm that during normal periods, $Reln$ is unconditionally positively related to ECs at the 1% level.

[29] We also examined specifications that replaced $Coupon$ with a bond duration variable (using the Macaulay method), and the results were qualitatively identical to those reported here.
[30] We also repeated the analysis using a linear and quadratic time-to-maturity variable instead of a set of dummies, and obtained qualitatively identical results for the key variables. This method was not used in the primary specification, however, as it is more restrictive. For instance, it does not allow for a point on inflexion at some time-to-maturity, after which the rate of change in the curve decreases.

Compared to trades between bank-pairs that have not previously traded ($Reln = 0$), trades between bank-pairs that have an exclusive relationship ($Reln = 1$) are 14.6, 10.2 and 5.0 bps more costly to initiate within money, Treasury bond and semi-government bond markets.[31] Interestingly, across asset type the effect of $Reln$ on EC is twice as strong during stress periods, although this differential effect is statistically insignificant for semi-government bonds. Given the large average size of debt market trades, these figures are economically large and suggest that banks initiating trades via search-and-bargaining obtain significantly superior prices. In terms of the model fit, a small proportion of the variability in EC is explained by $Reln$ in the two bond markets (0.1%), while a moderate proportion is explained in the money market (2.3%); this is not surprising, however, as bond prices are affected by many other factors relative to bill prices.

The primary regression specifications are then estimated in (2a), (3b) and (3c). After controlling for other factors, the key results remain qualitatively identical to those outlined in the preceding unconditional analysis. First, $Reln$ is positively related to ECs at the 1% level during normal periods, consistent with Hypothesis 1p that stronger relationships incur higher execution costs. Also, the effect remains economically significant: the estimated cost premium for banks with an exclusive relationship ($Reln = 1$) is 14.5, 6.9 and 11.5 bps within money, Treasury bond and semi-government bond markets. Second, while the coefficient on the interaction term $Reln \times Stress$ is positive across asset type, it is strongly significant in the money market (1% level), moderately significant in the Treasury bond market (5% level), and insignificant in the semi-government bond market. This result is consistent with Hypothesis 2p, and suggests that relationships incur a larger cost premium during stress periods; our *ex ante* explanation is that the variability of dealer quotes is much wider during stress periods, and hence the expected benefit from searching for the dealer with the best quote is also larger. Perhaps surprisingly, the control variables are either insignificant (OTR) or inconsistent across asset type ($Size$ and $Coupon$); it is important to be aware, however,

[31] Note that the intercept estimates the expected EC for $Reln = 0$ trades.

that the dependent variable represents the relative cost of initiating a trade, and hence may be either positively or negatively related to the asset price depending on trade direction.

< INSERT TABLE 7 >

We next test our two secondary hypothesis. To test Hypothesis 1s, we assume that large, domestic banks are more efficient at search-and-bargaining, and are therefore expected to have a larger $Reln$ coefficient. This assumption is intuitive as large banks will tend to have greater negotiation power and better pre-trade information (by trading more frequently), and domestic banks have greater knowledge of local market conditions and are therefore better positioned to negotiate prices. Table 7 reports the estimated coefficient and significance level for the two key variables ($Reln$ and $Reln \times Stress$) for large versus small banks and domestic versus foreign banks. As it is not accurate to simply compare the size of the coefficients between the two subsets, Table 7 also reports whether the 95% confidence intervals are non-overlapping and hence statistically significantly different. The results provide moderate evidence supporting the hypothesis: β_1 is statistically larger for large banks relative to small banks in the money market, and domestic banks relative to foreign banks in the money and semi-government bond markets, while the other comparisons were all statistically insignificant. There is some evidence, however, that this gap declines (and possibly either reverses or ceases to exist) during stress periods for large versus small banks in the money market, and domestic versus foreign banks in the semi-government bond market. In any case, the results are broadly aligned with Hypothesis 1s, which states that traders that are better able to negotiate prices suffer from a larger execution cost increase when trading with counterparties that they have a strong relationship with. In addition, since the coefficient on $Reln$ is positive and significant across most of these regressions, the primary results in favour of our primary Hypothesis 1p are fairly robust across bank type.

Hypothesis 2s posits that despite the average price difference in Hypothesis 1p, relationship traders offer more stable prices. To test this conjecture, we measure $Var(EC_k)$ each trading week as the standard deviation of EC for all search-based trades and relationship-based trades separately (using the same distinction as in Section 5.1). We also construct a dummy variable, $Reln_{Dummy}$, to distinguish relationship-based trades from search-based trades, and identify stress weeks as trading weeks where $Stress = 1$ on at least three days. Across asset type and normal versus stress weeks, we then conduct difference-of-means t-tests and regressions of $Var(EC_k)$ on $Reln_{Dummy}$ and a control for average trade size.[32] The results, presented in Table 8, provide conflicting evidence on the effect of relationships on the variability of execution costs during normal weeks: although execution costs are more stable for relationship-based trades in the Treasury bond market, they are more volatility for relationship-based trades in the money and semi-government bond markets. While there is some evidence that relationship-based trades have more stable execution costs during stress weeks, it is not possible to make any reliable inferences due to the small sample size (31 or 32 observations). Overall then, apart from the Treasury bond market, the results do not support the conjecture that relationship-based trades are initiated at a narrower cost range.

5.3 Additional robustness tests

In this section, we conduct further tests to assess the robustness of the primary results. We first re-estimate the primary regression specification (model (2) for money market and model (3) for the two bond markets) using alternative definitions for relationship strength and execution costs. For relationship strength, we consider our primary measure $Reln^*$ as defined in Section 3.1 (provided for comparison); a directional[33] measure $Reln_{Direction}$ that only considers the non-dealer's trades that are in the same direction (i.e., buyer or seller) in calculating the proportion; an overall measure $Reln_{Overall}$ that calculates $Reln^*$ for *both* the non-dealer bank and the dealer bank, and then takes the average between the two; the same dummy variable $Reln_{Dummy}$ as in the unconditional analysis in Section 5.1, which proxies for relationship-based trades without accounting for relationship strength; a categorical variable that takes one of five values depending on relationship strength ($Reln^* < 0.02$;

[32] Although the only control variable included is the logarithm of the average value for $Size$, the results are qualitatively similar when we included other variables including the average coupon rate (bonds only) and the fraction of trades in on-the-run assets (bonds only).

[33] The use of a directional measure is analogous to the lender and borrower preference indices in Cocco et al. (2009).

$0.02 \leq Reln^{*} < 0.05;\ 0.05 \leq Reln^{*} < 0.15;\ 0.15 \leq Reln^{*} < 0.3$); and an abnormal relationship strength measure $Reln_{Abnormal}$ that controls for the *expected* proportion of trades going through a particular dealer bank, and is defined as the difference between $Reln^{*}$ and the proportion of all trades during the same 50-day window that the dealer bank participates in. For execution costs, in addition to our primary measure EC^{*} as defined in Section 3.1 (provided for comparison), we also consider a maturity-adjusted measure EC_{RBA} that is similarly defined except for the benchmark yield used: for the money market, we obtained daily bank bill rates from the RBA website, and for the two bond markets, we obtained daily government bond yields for all maturities up to 20 years in half-yearly steps; we then used linear interpolation to infer the corresponding-maturity benchmark yields,[34] and excluded the time-dummies from the primary regression specification.

< INSERT TABLE 9 >

For each variable definition, Table 9 reports the coefficient and significance level for the two variables of interest ($Reln$ and $Reln \times Stress$). Overall, the results are strongly consistent with the primary regressions, especially in terms of Hypothesis 1p. First, across all relationship measures, the coefficient on $Reln$ is positive and significant at the 1% level. Indeed, relative to $Reln^{*}$, the coefficient tends to increase for the alternative proportional-based measures (it is more difficult to compare the dummy and categorical variables), indicating that perhaps the effect of relationships on execution costs has been underestimated in the primary analysis. In addition, the maturity-matched dependent variable (EC_{RBA}) also produced a positive and significant $Reln$ coefficient, except that the significance level is only marginal (10%) for the Treasury bond market. Second, the coefficient on the interaction $Reln \times Stress$ is positive and statistically significant across all alternative measures in the money market and most alternative measures in the Treasury bond market, and positive

[34] We also used linear interpolation for bonds maturing in greater than 20 years, except that we first estimated the yields at the two endpoints of the half-yearly interval. Since yield curves tend to flatten towards the long-term maturities, we estimate these yields by assuming that the difference between the yields at $T = 19.5$ years and $T = 20$ years continues but at a declining rate (geometric series with $r = 0.5$). For instance, our estimate of the yield at $T = 22.5$ years would be $[r_{20} + (r_{20} - r_{19.5})(1 + 0.5 + 0.5^2 + 0.5^3 + 0.5^4)]$, which can be generally simplified using the geometric series formula.

but statistically insignificant across all but one alternative measure in the semi-government bond market. Interestingly, the sole discrepancy in the semi-government bond market (EC_{RBA}) produces a fairly large negative and statistically significant coefficient, which rejects Hypothesis 2p. Nonetheless, as this is an isolated result, the analysis provides marginal to moderate evidence supporting it.

Next, we add additional variables to control for endogeneity across several dimensions. First, fixed effects are included at the (1) dealer level; (2) non-dealer level; (3) bank-pair level; and (4) security level.[35] By controlling for the average execution cost for each relevant cross-sectional unit, these fixed effects ensure that the appropriate identification is isolated.[36] Second, under Zhu's (2012) model, it is possible that closer relationships are associated with inferior prices independently of search costs if an asset's fundamental component is known while each trader assigns their own private value to it:[37] if non-dealers prefer to approach relationship dealers first, then they will more likely accept their quotation when their private value is low; it follows then that relationship trades tend to arise when the selling non-dealers private value is low, and vice versa for trades with non-relationship dealers. To isolate our search-based hypothesis from this alternative explanation, we therefore must control for the private value of the non-dealer and the dealer. Given it is likely that a significant component of private value is time-invariant, we implicitly control for private value by including fixed effects at the non-dealer and dealer levels. Additionally, since private valuations are likely to be correlated with inventory positions (Zhu, 2012), we control for the prevailing security holdings using several variable definitions: $Holding^{*}$ is the logarithm of the security

[35] Time fixed effects are not included as our measure of execution cost (which relates the traded yield to a contemporaneous daily benchmark) effectively controls for time-variation and is on average zero for each trade day.
[36] We thank an anonymous reviewer for identifying the potential bias that arises if these cross-sectional units endogenously sort into stronger relationships. For instance, dealer connectedness may have an important effect on execution costs (Babus and Kondor, 2013) and is likely correlated with our measure of relationship strength. Also, given that relationship strength is likely overestimated for smaller non-dealers (due to lower transaction activity), it is possible that the primary coefficient on $Reln$ is positively-biased if smaller non-dealers are exploited with inferior prices.
[37] We thank an anonymous reviewer for identifying this link. The link is only a speculative extension, however, as Zhu's model is a one-shot quoting framework under which dealers dictate take-it-or-leave-it offers. From a trade perspective, it is static and does not accommodate dynamic activity. In any case, it is not possible to directly test or fully isolate Zhu's model as the data does not document the search process underlying each trade.

holdings of the non-dealer at the close of the day prior to the trade date; $Holding_{Dummy}$ is a dummy that indicates whether the non-dealer held a nonzero position in the security at the close of the day prior to the trade date; other unreported measures (for which the results are qualitatively identical) including an abnormal measure that divides $Holding^*$ by the nn-dealer's average daily holding position over the 30 days prior, an interaction variable with $Reln^*$, and the same holdings measures calculated from the perspective of the dealer.

As shown in Panel C of Table 9, the primary results are largely invariant to the use of these additional controls. In terms of Hypothesis 1p, the coefficient on $Reln$ remains positive and significant at the 1% level for 13 of the 17 additional regressions performed.[38] Of the remaining four regressions, three were significant at the 5% level and only one was insignificant (inclusion of non-dealer fixed effects in the semi-government bond market). In terms of Hypothesis 2p, the results supplement the moderate evidence of a positive link between stressed market conditions and the strength of the $Reln$-EC effect.

Third, we test the sensitivity of the results to trade direction by re-estimating the primary model for buyer-initiated and seller-initiated trades separately. As reported in Panel D of Table 9, the results are broadly consistent with the key results: across all six regressions, the coefficient on $Reln$ is positive and highly statistically significant, corroborating the evidence in favour of Hypothesis 1p; there is also strong (buyer-initiated) and marginal (seller-initiated) evidence that the relationship premium increases during stress periods, in line with Hypothesis 2p. A further result, however, is that the coefficient on $Reln$ is statistically larger for seller-initiated trades relative to buyer-initiated trades across all asset categories. This additional result can perhaps be linked to the different benefits obtained from searching when buying relative to selling: if a trade initiator needs to purchase a specific security, then some dealers may be unwilling to provide a prompt quote if they have zero inventory; hence, the

[38] Security fixed effects are not estimated for the money market: due to the large number of securities, most of which are extremely thinly-traded, there is insufficient variation within-security to allow for estimation. Nonetheless, security-group fixed effects where security-groups were identified using the four maturity groups used to calculate y^*, as outlined in Section 3.2. The results were qualitatively identical with both $Reln$ and the interaction term retaining the 1% level of significance.

benefits obtained from searching will be lower than when the trade initiator needs to sell a specific security and can obtain ready quotes from a larger set of dealers.

For our final robustness test, we estimate the primary regression specification (model (2) for money market and model (3) for the two bond markets) at a weekly frequency rather than across the entire time-series. The same variables are used, except that the interaction $Reln \times Stress$ is excluded and the weekly regressions are instead separated into two groups (normal and stress) using the same procedure for the analysis of $Var(EC_k)$ in Table 8; also, to ensure a sufficient sample size, weeks with less than 300 trades are excluded. One important benefit obtained from this robustness check is that it allows us to infer whether the aggregate result is supported across shorter sub-periods; another benefit is that it allows for maturity effects to be more accurately controlled for because yield curves generally remain fairly stable within a weekly period.

< INSERT TABLE 10 >

Table 10 presents summary statistics for the results obtained from these weekly regressions. Initially, the average and median coefficients appear to be quite large and positive across asset type and week type, consistent with our primary results. Indeed, the test statistics obtained from t-tests of the set of all coefficients (and also the set of significant coefficients) exceed their 1% critical value for all asset types during normal weeks, and the money market during stress weeks.[39] Further, the differences in the averages and medians across normal versus stress weeks are broadly aligned with our primary results. On closer inspection, however, the variability of the coefficients indicate that while the primary results are strongly robust in the money market, they are only weakly to moderately robust in the two bond markets. First, while the standard deviation of the $Reln$ coefficients is reasonable at just over 10 bps for the money market, it is quite large for the two bond markets, varying between around 34 to 52 bps. Second, for the money market, the vast majority of weekly regressions

[39] We do not place much emphasis on the stress week test statistics due to the small sample size (15 to 32 observations).

have positive and statistically significant $Reln$ coefficients, with almost none producing negative and statistically significant coefficients; for the two bond markets, in comparison, only around 8.5% to 13.3% have positive and statistically significant $Reln$ coefficients, with a small but comparable proportion being negative and statistically significant.

5.4 Summary of results

In our primary analysis, we showed that after controlling for other factors, the strength of the pre-existing relationship between the two trading banks is positively related to the execution cost paid by the initiator. The size of this effect is also fairly large, suggesting that banks can obtain considerably superior prices by search-and-bargaining for the best price, rather than relying on a relationship dealer. Moreover, this result is robust across asset type, bank type, other specifications (including an unconditional analysis, alternative variable definitions and the inclusion of further controls), and a set of multiple weekly regressions. Taken as a whole then, the results provide strong support in favour of Hypothesis 1p.

Looking at the second primary hypothesis, the relationship-EC effect increases during stress periods in the money and Treasury bond markets; while the coefficient is statistically insignificant in the semi-government bond market, it is also positive. These primary results are fairly robust across the unconditional analysis and the further tests. Interestingly, however, a negative and highly statistically significant coefficient is obtained when using an alternative EC metric in the semi-government bond market. Nonetheless, at a broad level, the results provide marginal to moderate evidence supporting Hypothesis 2p.

Finally, the results provide weak to moderate evidence with both secondary hypotheses (1s and 2s). First, during normal periods, large banks (relative to small banks) and domestic banks (relative to foreign banks) are subject to a larger cost premium for relationship-based trades. The opposite result applies in semi-government bond markets, however, and there is also some evidence that the opposite result applies across asset type during stress periods. Second, execution costs are more stable for relationship-based trades in the Treasury bond market during both normal and stress periods. The relationship-based execution costs have a higher variance than search-based execution costs, however, during normal weeks in the money and semi-government bond markets.

6. Conclusion

Using intuitive reasoning, we present the qualitative foundations for a construct of price formation in OTC markets that is consistent with both the prior search literature and evidence that institutions tend to interact via relationships. Assuming that traders face search costs – including delay, negotiation costs, and a loss of previous quotes – rational traders have an incentive to form implicit trading relationships to avoid these costs. Our central proposition is that traders can enter into one of two possible trade types: (1) a search-based trade, which requires shopping for the "best" price at the expense of a costly search process; or (2) a relationship-based trade, which provides immediacy and reliability at the expense of an inferior transaction price. Under this framework, our two primary testable hypotheses assert that stronger relationships have a positive effect on execution costs during normal market conditions, and that this effect increases during illiquid, stressed markets. For further examination, we also develop secondary hypotheses stating that the effect of relationships on execution costs is larger for traders with better search-and-bargaining skills, and that relationship-based trades are associated with more stable execution costs.

To test these hypotheses, we use a unique and confidential OTC dataset that identifies and thus allows us to track bank traders. This dataset covers all secondary trading in the Australian interbank debt market for several asset types – money market, Treasury bonds, and semi-government bonds – over an extended seven year period that covers the period before, during and after the GFC. As a starting point, we first use duration analysis and show that not only is there fairly significant inferential evidence of relationships, but also that the hazard rate of these relationships decreases over time, indicative of increasing value as the relationship matures. Our primary analysis then provides strong evidence that during normal market conditions the strength of the pre-existing relationship between two banks is positively associated with the trade initiator's execution cost, in line with our central prediction. We also find that the strength of this positive association increases during stressed markets, which corroborates our expectation that searching provides a greater payoff when the range of private values attributed to an asset is broader (which is likely the case during stressed markets). In further analysis, we obtain weak to moderate evidence in favour of our secondary hypotheses. Perhaps most persuasively, the primary results are particularly robust to trade direction and methodological changes including the use of fixed effects or indicators of private value. Hence, when taken as a whole, our results provide fairly strong evidence consistent with our central conception of OTC price formation.

Looking forward, our results underscore the need for incorporating relationships in our understanding of OTC markets, not only in terms of their effect on prices (as shown in our analysis), but also their effect on microstructural features more broadly.[40] Indeed, it would be especially useful to develop a general model that is motivated by our central hypothesis and empirical results, and captures the decision between entering a search-based or relationship-based trade, perhaps with reference to either matching theory or game theory from the field of economics.

[40] The limited literature in this area has focused on their role during crises. Afonso et al. (2014) empirically show that relationships may decrease the propagation of liquidity shocks in an interbank loan market due to the liquidity complementarity between most trading partners. In a general equilibrium model, Boualam (2015) shows that an important factor for the slow recovery of credit following a crisis is the severance of bank lending relationships.

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TABLES

Table 1

Descriptive Statistics of Trade Data

This table reports summary statistics for trade activity in the raw Austraclear sample (16 August 2006 to 28 January 2014). The statistics are reported separately for the aggregate sample and for each asset class. *Trades / Day* refers to the average number of daily trades in the market, obtained by dividing *Trades* by *Trading Days*. *Securities* refers to the total number of securities lodged in Austraclear, while *Active Securities* refers to the total number of securities that trade at least five times. *Trades / Security* refers to the average number of trades per security, obtained by dividing *Trades* by *Securities*; similarly, *Trades / Active Sec* is obtained by dividing *Trades* by *Active Sec*.

	All	Money Market	Treasury Bonds	Semi-Gov Bonds
Trading Days	1,830	1,830	1,830	1,830
Trades	1,002,279	470,722	330,283	201,274
Trades / Day	547.69	257.23	180.48	109.99
Securities	272,177	271,945	29	203
Active Securities	14,401	14,253	29	119
Trades / Security	3.68	1.73	11,389.07	991.50
Trades / Active Sec	69.60	33.03	11,389.07	1,691.38

Table 2

Distribution of Trade Activity across Banks and Bank-Pairs

This table reports the distribution of the number of trades in the raw Austraclear sample (16 August 2006 to 28 January 2014) across individual participants and bank-pairs. In the *Individual Banks* section, each row lists the number of banks that trade a particular number of times (according to the *No. Trades* bracket); D refers to a dealer bank, ND refers to a non-dealer bank, and *All* refers to all banks participating in the sample. In the *Bank-Pairs* section, each row lists the number of bank-pairs that trade a particular number of times (according to the *No. Trades* bracket); D-ND refers to a pair between a dealer bank and a non-dealer bank, D-D refers to a pair between two dealer banks, ND-ND refers to a pair between two non-dealer banks, and *All* refers to all bank-pairs participating in the sample. *Total* in the bottom row refers to the total number of bank or bank-pair participants in a particular column, and *Possible* refers to the maximum possible number of bank-pairs obtained using a simple combinations formula.

	Individual Banks			Bank Pairs			
No. Trades	ND	D	All	D-ND	D-D	ND-ND	All
<= 10	89	0	89	760	12	1,428	2,200
11-20	26	0	26	249	7	339	595
21-50	54	0	54	310	9	390	709
51-100	51	0	51	230	5	258	493
101-200	59	1	60	197	13	165	375
201-500	49	0	49	200	18	131	349
501-1,000	35	0	35	121	15	52	188
1,001-2,000	21	0	21	74	17	24	115
2,001-5,000	30	1	31	36	16	17	69
5,001-10,000	15	0	15	10	9	1	20
10,001-20,000	14	3	17	14	5	2	21
> 20,000	11	12	23	3	1	0	4
Total	454	17	471	2,204	127	2,807	5,138
Possible				7,718	136	102,831	110,685

Table 3

Distribution of Observed Duration of Relationships

This table presents the sample distribution for the duration of interbank relationship spells, where each relationship spell is defined as the length of time in months during which a particular bank-pair trades at least 10 times per month. The distributions listed include all bank relationships, relationships between a dealer bank and a non-dealer bank (D-ND), relationships between dealer banks (D-D), and relationships between non-dealer banks (ND-ND). The *Marginal* column refers to the proportion of relationships lasting for a particular duration, and the *Mean Trades* column refers to the average number of trades per month for relationships belonging to the same duration bracket. In the final four rows, *Mean* (*Median*) refer to the average (median) relationship length under the *Marginal* column, and the average (median) number of trades per month across all relationships under the *Mean Trades* column; *Censored Obs* states the total number of observations that are either left- or right-censored, and *Total Obs* states the total number of interbank relationship spells.

Observed duration (months)	Proportion of:							
	All Bank Relationships		D-ND Relationships		D-D Relationships		ND-ND Relationships	
	Marginal	Mean Trades	Marginal	Mean Trades	Marginal	Mean Trades	Marginal	Mean Trades
1	47.89%	17.16	47.04%	11.72	42.25%	6.68	51.31%	5.47
2-5	36.22%	17.73	37.00%	7.56	32.70%	11.52	35.58%	7.39
6-10	6.60%	21.03	6.89%	11.67	7.64%	10.71	5.59%	9.06
11-20	4.57%	27.86	4.27%	13.85	7.01%	25.41	4.55%	11.85
21-30	1.91%	34.96	1.91%	18.45	3.18%	23.29	1.40%	21.82
31-40	0.49%	33.98	0.37%	19.36	1.49%	20.10	0.35%	18.46
41-50	0.47%	46.31	0.41%	24.47	0.85%	36.82	0.44%	21.66
51-60	0.19%	41.52	0.19%	23.68	0.42%	27.48	0.09%	26.85
61-70	0.14%	45.21	0.11%	24.75	0.42%	24.21	0.09%	29.40
71-80	0.23%	43.85	0.34%	38.84	0.21%	31.91	0.17%	33.85
81-89 (max)	1.28%	125.16	1.46%	110.52	3.82%	78.61	0.44%	52.59
Mean	4.97	46.47	4.79	48.81	8.69	54.43	3.87	30.36
Median	2	24	2	22	2	33	1	19
Censored Obs	314		200		48		66	
Total Obs	4,285		2,670		471		1,144	

Figure 1

Estimated Hazard Function for Relationship Spells

This graph presents an estimated hazard function of interbank relationships (see definition of relationships in-text or in Table 3). Intuitively, the function plots the instantaneous probability at any time T that a bank-pair will cease their relationship given that their existing relationship has already survived for T months. For the graduation of the relationship data, the local polynomial method is used with the Epanechnikov kernel for the weighing function. Number of relationship spells: 4,285.

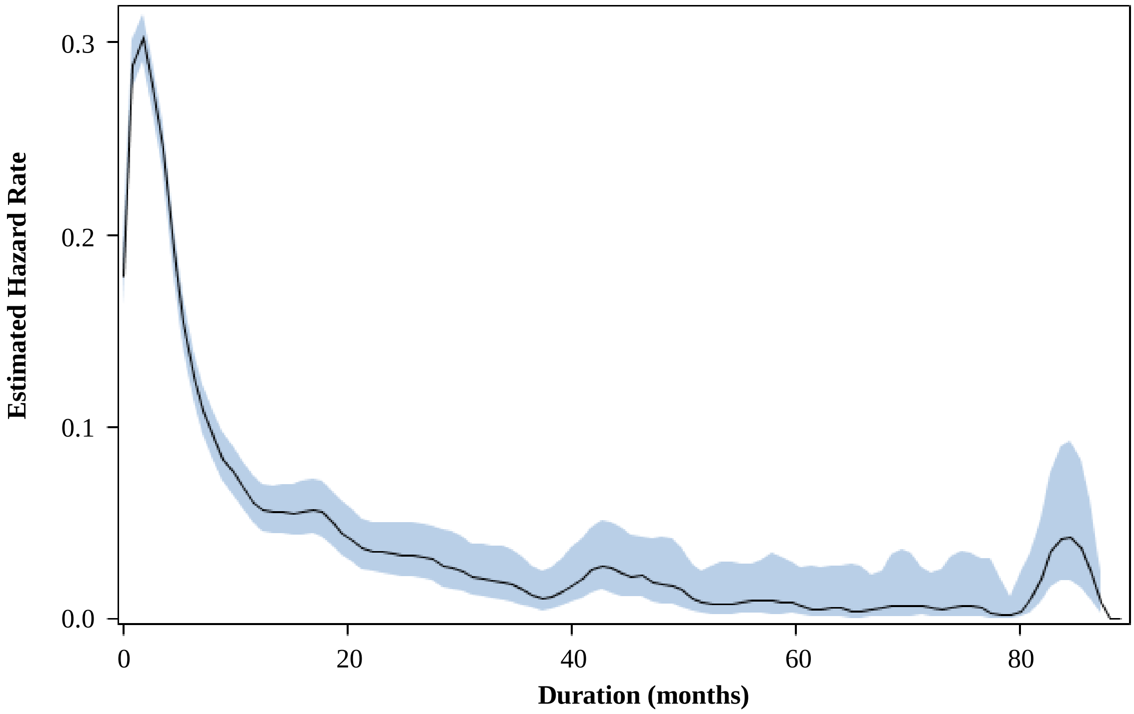

Table 4

Relative Buying between Banks in Relationships

This table presents the distribution of relative buying between banks that are in relationships (see definition of relationships in-text or in Table 3). The results are reported across all bank relationships, relationships between a dealer bank and a non-dealer bank (D-ND), relationships between dealer banks (D-D), and relationships between non-dealer banks (ND-ND). The key variable presented is the relative buying index (RBI): for each relationship spell, RBI is defined as the proportion of all trades during the relationship that bank B is the buyer, where bank B is the less frequent buyer in the relationship (that is, B is chosen so that $0 \leq RBI \leq 0.5$). In Panel A, the percentage of relationships within each RBI bracket is listed across different categories of bank-pairs. Panel B presents summary statistics of RBI observations across the same categories of bank-pairs; *Reln* refers to trades within relationship spells and thus uses the same sample in Panel A, while *Non-Reln* refers to all other trades for which the participating banks are not in a relationship.

Panel A: Percentage of Relationships in each RBI Category				
RBI (%)	All	D-ND	D-D	ND-ND
0-5	25.69%	29.83%	6.55%	23.80%
6-10	6.78%	7.47%	3.17%	6.63%
11-15	3.73%	3.50%	1.69%	5.06%
16-20	6.42%	6.15%	6.55%	6.97%
21-25	4.99%	4.95%	5.50%	4.89%
26-30	7.84%	7.28%	10.78%	7.96%
31-35	7.64%	7.43%	9.73%	7.30%
36-40	7.95%	7.79%	11.42%	6.97%
41-45	12.50%	11.36%	19.03%	12.52%
46-50	16.45%	14.24%	25.58%	17.91%
Panel B: Summary Statistics				
Reln				
- Mean	23.96%	22.13%	33.42%	24.43%
- Median	26.47%	23.00%	37.95%	26.09%
Non-Reln				
- Mean	16.04%	17.61%	34.41%	14.05%
- Median	8.65%	11.11%	39.46%	3.33%%

Table 5

Effect of Relationships on Execution Costs – Summary Analysis

This table presents a descriptive analysis of relationships and trade execution costs across asset type and day type (normal versus stress). Panel A reports the results from an analysis of all individual trades. *Ave Relation* EC refers to the average execution cost (EC) for relationship-based trades, *Ave Search* EC refers to the average EC for search-based trades, and *Difference* refers to the difference between the two. Panel B reports the results from an analysis of variables constructed at a daily frequency: on each trade day, the average EC ($\overline{EC}$) for relationship-based trades and search-based trades is estimated separately. Days with less than five relationship-based trades or less than five search-based trades are excluded. *Ave Relation* $\overline{EC}$ refers to the average relationship-based daily $\overline{EC}$, *Ave Search* $\overline{EC}$ refers to the average search-based daily $\overline{EC}$, and *Difference* refers to the difference between the two. *% days* $\Delta\overline{EC} > 0$ reports the fraction of trading days where the difference between the relationship-based $\overline{EC}$ and the search-based $\overline{EC}$ is greater than zero, and vice versa for *% days* $\Delta\overline{EC} < 0$. The test statistic obtained from a difference-of-means *t*-test with standard errors allowing for unequal variances is reported under each *Difference* figure in brackets. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Normal Days			Stress Days		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Individual Trades						
Observations	220,196	189,619	111,008	26,772	13,952	8,045
Ave Relation EC	7.695	2.462	1.108	13.374	2.722	1.446
Ave Search EC	0.771	-0.913	-2.771	0.826	1.095	-0.809
Difference	6.925***	3.375***	3.879***	12.548***	1.627*	2.254
	(57.06)	(9.01)	(5.19)	(25.53)	(1.73)	(1.04)
Panel B: Daily Variables						
Observations	1,551	1,244	1,223	155	91	63
Ave Relation $\overline{EC}$	8.194	2.333	1.284	12.899	2.356	0.166
Ave Search $\overline{EC}$	0.726	-0.930	-3.015	0.728	0.182	-0.162
Difference	7.469***	3.263***	4.299***	12.171***	2.174	0.328
	(40.32)	(5.92)	(4.38)	(16.08)	(1.19)	(0.10)
% days $\Delta\overline{EC} > 0$	86.33%	59.97%	54.66%	94.84%	57.14%	53.97%
% days $\Delta\overline{EC} < 0$	13.67%	40.03%	45.34%	5.16%	42.86%	46.03%

Table 6

Effect of Relationships on Execution Costs – Primary Regressions

This table presents a regression analysis of the effect of relationships on execution costs across asset type. A preliminary regression (see model 1) without any control variables is first estimated under (1a), (1b) and (1c). A primary regression is then estimated for money market trades (see model 2) and for Treasury and semi-government bonds (see model 3) under (2a), (3b) and (3c). The dependent variable used is the execution cost (EC) associated with initiating a particular trade, which is estimated with reference to the difference between a benchmark yield and the traded yield. The key variables of interest include: (1) $Reln$, which measures relationship strength; and (2) $Reln \times Stress$, which is an interaction term allowing for a different relationship effect during market stress periods. In terms of the control variables, $\ln(Size)$ refers to the logarithm of the security face value, $Stress$ is an indicator variable for market stress days, $Coupon$ is the bond coupon rate, $On\text{-}the\text{-}run$ is a dummy variable indicating whether the traded bond is currently trading on-the-run, and $Time_{1,2,\dots,20}$ refers to a series of dummy variables for 20 maturity groups. For each independent variable, the estimated coefficient and test statistic (in brackets) is reported. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: EC					
	Money Market		Treasury Bonds		Semi-Gov Bonds	
	(1a)	(2a)	(1b)	(3b)	(1c)	(3c)
Intercept	-0.393***	-11.118***	-1.403***	1.092	-2.714***	-36.191***
	(-6.20)	(-14.06)	(-6.99)	(0.82)	(-10.10)	(-15.41)
$Reln$	14.632***	14.474***	10.214***	6.890***	4.953***	11.536***
	(48.72)	(49.24)	(7.96)	(4.67)	(2.89)	(6.10)
$Reln \times Stress$	14.320***	18.659***	10.881***	9.096**	4.934	1.479
	(19.30)	(20.26)	(2.88)	(2.12)	(1.14)	(0.28)
$\ln(Size)$		0.662***		-0.421***		1.270***
		(13.46)		(-7.25)		(12.30)
$Coupon$				-0.269*		1.107***
				(-1.72)		(4.36)
$On\text{-}the\text{-}run$				-0.405		-0.055
				(-0.95)		(-0.08)
$Time_{1,2,\dots,20}$				x		x
$\bar{R}^2$	0.023	0.025	0.001	0.005	0.001	0.004
Observations	246,968	246,968	203,571	203,571	119,053	119,053

Table 7

Effect of Relationships on Execution Costs – Bank Size and Municipality

This table presents the results from estimating the primary regression model (as in Table 6) for different types of non-dealer banks. It aims to test whether the coefficients on the key variables of interest are sensitive to cross-sectional features of trade initiators. Panel A performs regressions for large non-dealer banks and small non-dealer banks separately, and Panel B performs regressions for domestic non-dealer banks and foreign non-dealer banks separately. For each regression, *Coefficient on* $Reln$ reports the coefficient on the variable $Reln$ while *Coefficient on interaction* ($Reln \times Stress$) reports the coefficient on the variable $Reln \times Stress$. Under each panel, *Sig. Diff* indicates whether the 95% confidence bounds for the two respective bounds are non-overlapping and thus statistically significantly different. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: EC					
	Coefficient on $Reln$			Coefficient on interaction ($Reln \times Stress$)		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Large vs Small Banks						
Large	23.703***	7.917***	12.977***	-3.611	9.018*	1.493
Small	12.995***	1.315	15.850***	14.681***	12.025	1.612
Sig. Diff	x			x		
Panel B: Domestic vs Foreign Banks						
Domestic	15.223***	7.128***	12.135***	15.213***	0.562	14.041***
Foreign	12.267***	9.172	-24.607***	-1.489	-56.986***	82.760***
Sig. Diff	x		x	x	x	x

Table 8

Effect of Relationships on Variability of Execution Costs

This table presents a descriptive analysis of the effect of relationships on the variability of execution costs across asset type and week type (normal versus stress). The variable of interest, $Var(EC_k)$, is defined uniquely for each trading week as the standard deviation of all execution costs belonging to one of two groups: relationship-based trades and search-based trades. Weeks with less than 50 relationship-based trades or less than 50 search-based trades are excluded. $Ave_{Relation}$ and Ave_{Search} refer to the average $Var(EC_k)$ across all weekly observations for the relationship-based trade group and the search-based trade group respectively. *Difference* lists the difference between $Ave_{Relation}$ and Ave_{Search}, with the test statistic obtained from a difference-of-means t-test allowing for unequal variances reported underneath in brackets. *Coefficient on* $Reln_{Dummy}$ provides the coefficient on the independent variable of interest ($Reln_{Dummy}$) obtained from a regression of $Var(EC_k)$ on a dummy indicating whether the weekly observation belongs to the relationship-based trade group ($Reln_{Dummy}$) and a set of variables that control for the average sized trade, the fraction of trades for which the non-dealer bank is large, and the fraction of trades for which the non-dealer bank is foreign. For these regressions, test statistics are reported underneath each coefficient in brackets, with standard errors estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: $Var(EC_k)$					
	Normal Weeks			Stress Weeks		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Summary statistics						
Observations	330	330	327	32	32	31
$\text{Ave}_{Relation}$	1.125	0.804	1.004	0.954	0.625	0.813
Ave_{Search}	0.951	0.994	0.968	0.984	1.025	0.998
Difference	0.174***	-0.190***	0.036	-0.030	-0.400***	-0.185*
	(8.06)	(-5.39)	(1.57)	(-0.45)	(-10.92)	(-1.69)
Coefficient on $Reln_{Dummy}$	0.165***	-0.103***	0.194***	-0.034	-0.296***	0.017
	(8.82)	(-3.78)	(2.91)	(-0.52)	(-6.50)	(1.08)

Table 9

Robustness of Regression Results to Main Variables and Trade Direction

This table tests the robustness of the primary regression model (as in Table 6). For each regression, the coefficients on the variables of interest $Reln$ and $Reln \times Stress$ are reported. Panel A lists the results obtained from replacing $Reln$ with a directional measure ($Reln_{Direction}$), a measure that considers the perspective of both the initiating non-dealer bank and the dealer bank ($Reln_{Overall}$), a dummy variable that indicates whether a trade is a relationship-based trade ($Reln_{Dummy}$), and a qualitative variable that takes one of five values depending on relationship strength ($Reln_{Category}$). Panel B lists the results obtained from replacing EC with an alternative measure constructed with reference to the difference between the traded yield and the daily corresponding-maturity bank bill rate (for money market) or yield rate (for Treasury bonds and semi-government bonds) derived from the central bank (EC_{Zero}). Panel C lists the results obtained from adding fixed effects (at the dealer, non-dealer, bank-pair, and security levels separately), an inventory measure that takes the logarithm of the security holdings of the non-dealer at the close of the day prior to the trade date ($Holding^{*}$), and a dummy inventory measure that indicates whether the non-dealer held a nonzero position in the security at the close of the day prior to the trade date ($Holding_{Dummy}$). Panel D reports the results from estimating the primary model for buyer-initiated and seller-initiated trades separately; an extra row, *Sig. Diff*, indicates whether the 95% confidence bounds for the respective bounds of the coefficients are non-overlapping and thus statistically significantly different. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: EC					
	Coefficient on $Reln$			Coefficient on $(Reln \times Stress)$		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Relationship measure						
$Reln_{Direction}$	19.772***	16.564***	17.482***	12.783***	11.314***	3.367
$Reln_{Overall}$	25.232***	6.435***	7.384***	23.860***	11.763***	7.588
$Reln_{Dummy}$	7.042***	2.364***	5.683***	5.701***	0.149	0.463
$Reln_{Category}$	2.233***	0.664***	0.868***	1.121***	1.068***	0.049
$Reln_{Abnormal}$	13.284***	8.557***	13.696***	16.972***	4.807	2.408
Panel B: Execution cost measure						
EC_{RBA}	21.901***	3.251*	5.494***	18.162***	3.780**	-13.552**
Panel C: Additional control variables						
Dealer FEs	18.331***	13.427***	9.345***	14.745***	9.336***	5.734
Non-dealer FEs	3.078***	4.197**	0.736	8.166***	11.569***	2.039
Bank-pair FEs	1.494***	13.873**	16.835**	8.990***	10.576**	4.101
Security FEs		9.124***	9.089***		6.309	3.276
$Holding^{*}$	14.852***	6.630***	10.868***	14.296***	10.930**	2.249
$Holding_{Dummy}$	13.668***	7.537***	9.591***	13.950***	10.022**	2.396
Panel D: Results split by trade direction						
Buyer-Initiated	13.131***	6.026***	9.338***	11.204***	15.061**	18.563**
Seller-Initiated	22.716***	24.655***	23.010***	12.573***	6.573	-16.605
Sig. Diff	x	x	x			

Table 10

Effect of Relationships on Execution Costs – Weekly Regressions

This table summarises the results obtained from estimating the primary regression model (as in Table 6) at a weekly frequency rather than across the entire time-series. Regressions are conducted across asset type and week type (normal versus stress); thus, the interaction $Reln \times Stress$ is excluded and $Reln$ is the sole variable of interest. For each set of weekly regressions, the count (*No. Regressions*), average, median and standard deviation of the estimated coefficients on $Reln$ are reported. *Test Statistic* reports the test statistic obtained from a one-sample t-test of the series of $Reln$ coefficients, while *Test Statistic (Alt)* reports the test statistic obtained from a one-sample t-test of the smaller series of significant (5% level) $Reln$ coefficients. *Positive and Signif* lists the number of weekly regressions (and the fraction of weekly regressions underneath in brackets) for which the coefficient on $Reln$ is positive and significant (5% level), and vice versa for *Negative and Signif*. Finally, *Ratio P:N* provides the ratio of *Positive and Signif* to *Negative and Signif*. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: EC					
	Coefficient on $Reln$					
	Normal Weeks			Stress Weeks		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Summary statistics						
No. Regressions	329	305	250	32	28	15
Average	16.055	10.353	13.186	30.905	15.403	9.052
Median	17.199	6.324	9.331	32.072	3.211	2.054
Standard Deviation	10.161	34.097	40.419	10.428	43.318	52.479
Test Statistic	28.66***	5.30***	5.16***	16.76***	1.88*	0.67
Test Statistic (Alt)	26.08***	3.23***	4.04***	14.41***	0.92	0.33
Positive and Signif	264 (80.2%)	26 (8.5%)	24 (9.6%)	30 (93.8%)	3 (10.7%)	2 (13.3%)
Negative and Signif	2 (0.6%)	9 (3.0%)	3 (1.2%)	0 (0%)	1 (3.6%)	1 (6.7%)
Ratio P:N	132	2.89	8	-	3	2