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The Value of Professional Ties in B2B Markets*

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We study how a particular form of social ties (i.e., professional ties proxied by past employment) affects price and profitability in business-to-business (B2B) markets. While most of the work on social ties focuses on information diffusion in business-to-consumer markets, we ask: Do B2B buyers receive higher or lower prices from sellers with whom they have professional ties? Answering this question is challenging because it is difficult to observe B2B prices, the individual decision-makers (IDMs), and elements of differentiation that drive price variation. Moreover, potentially endogenous formation of social ties exacerbates the identification challenge. We resolve these challenges by leveraging proprietary data from the Federal Reserve on the repo market, the largest market for short-term loans with daily transactions of over $2 trillion. In addition, we use financial disclosure laws to unmask IDMs at sellers and use LinkedIn to reveal their ties. We leverage exogenous movement of IDMs in and out of decision-making positions to identify the effect of professional ties on price. We show that a seller IDM, who is the buyer's former employee, charges the buyer 1/4 basis points more than other buyers with no ties (i.e., 25 basis points relative to median price, or 13% of average cross-sectional price variance). The mechanism driving this price increase is "supply reliability." Sellers with a professional tie to the buyer act more reliably towards that buyer during supply-demand imbalances. We perform several robustness checks, including leveraging the Federal Reserve's monetary policy actions in response to the COVID-19 pandemic, to show that an exogenous increase in the aggregate cash supply diminishes the effect of professional ties, consistent with a supply reliability mechanism. Our work suggests professional ties can affect B2B prices beyond observable supply-demand dynamics and provide value for sellers and buyers.

Key words: professional ties, social ties, business-to-business marketing, B2B marketing, repo, individual connections, B2B pricing, pricing, decision-making in financial markets

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1. Introduction

We study whether and how professional ties, a particular form of social ties measured by past employment, influence prices and provide value for buyers and sellers in business-to-business (B2B) markets. Business relationships are usually defined between two organizations based on the history of their transactions. Consequently, the role of individual decision-makers (IDMs) and their social ties in shaping organizational relationships is often overlooked.[1] Yet understanding how IDMs' connections affect business relationships and transactions is crucial and has important practical implications (Acemoglu et al. 2016, Kim et al. 2019, Karolyi 2018, Kranton 1996, Palmatier et al. 2007, Rotemberg 1994, Wang et al. 2010a). Despite an extensive literature on social ties in business-to-consumer (B2C) markets, work on the role of social ties in B2B markets is scarce. While the B2C literature focuses on the role of social ties in resolving information asymmetries between businesses and consumers (e.g., the role of word of mouth and referrals in new product adoption), we show that in B2B markets, social ties can provide value through channels other than information.

Pricing decisions have a disproportionately large impact on firms' financial outcomes, compared to other marketing decisions (Hinterhuber 2004, Nijs et al. 2007, Rao 2005). In many B2B markets, sellers customize prices for buyers based on their relationship (Chen et al. 2018, Clopton 1984, Ghosh and John 2005, Kim and Kumar 2018, Lin et al. 2018, Rust and Chung 2006, Ulaga and Eggert 2006). Yet there are many unanswered questions about the effect of relationships and social ties on price: Is a seller more likely to give a discount to a familiar buyer? Or, charge the buyer more? Would a buyer be willing to pay a higher price to a familiar seller? If so, why? What are the potential mechanisms through which buyer-seller social ties influence prices in B2B markets? Do social ties provide value for buyers and sellers? If so, how? In this paper, we seek to answer these questions by focusing on a specific type of social tie between buyers and sellers: their professional ties. We consider an individual in the seller organization to have a professional tie to the buyer organization if that individual worked for the buyer in the past.

Answering questions about the effect of professional ties on marketing mix elements like price in B2B contexts is challenging. First, it is difficult to observe prices in most B2B markets; usually buyers and sellers in these markets are contractually obligated to conceal the

[1] About 3% of papers that study business relationships published in a sample of top marketing journals focused on the role of individuals. Please see Appendix A for more details.

terms of their transactions. Second, variations in price are usually driven by unobservable factors where the product or service is ambiguous (Bruno et al. 2012). Third, IDMs and their ties are usually unknown. Finally, in many contexts, social ties form endogenously where unobserved factors affect both the formation of ties and the outcome of interest (Aral and Walker 2011, Godes and Mayzlin 2004, Manski 1993). We address these challenges by leveraging proprietary data from the Federal Reserve on the largest market for short-term loans, the repo market. With at least $2 trillion of daily transactions in 2019, the broader Treasury repo market is the main source of funding for many financial intermediaries, including investment banks (henceforth referred to as banks). A repo is a short-term secured loan with buyers borrowing cash at an interest rate. In this market, cash is the commodity of exchange and the interest rate, price. We first consider a proprietary panel of daily transactions between buyers and sellers from the overnight tri-party Treasury repo market, a segment of the broader repo market collateralized by Treasury securities, with $450 billion/day of transactions in 2019. Details about each individual seller's professional ties are then obtained by matching their Securities and Exchange Commission (SEC) filings with LinkedIn and other publicly available data sources.

Taking into account an extensive set of control variables, we show that a decision-making individual at the seller organization charged a buyer firm they used to work for (i.e., has a professional tie with) 0.25 basis points more than buyer firms that the IDM did not work for (i.e., 25 basis points of the median price of 1%). This price increase represents 13% of the average cross sectional price variation or a 3% rise in the seller's profit margin.[2] We show the robustness of our results using a multitude of additional checks.

We examine several potential mechanisms for the effect. One mechanism explores whether the higher price paid to a *familiar* seller is a *reliability premium*: A buyer is willing to pay a higher price to a familiar seller, trusting that in the face of a market shock, the seller will continue providing the buyer with enough cash. In the repo market, as in many other B2B markets, trust and reliability are important factors in purchasing decisions (Bolton et al. 2006, Mancini et al. 2016, Wang et al. 2010a). Financial institutions, including investment banks, fulfill their needs for short term cash by borrowing in the

[2] Market experts we interviewed consider this figure a sizable effect given the extremely commoditized nature of this market and the large volume of transactions. Please see Appendix C for a back-of-the-envelope calculation of the incremental profit.

repo market. Reliable access to liquidity guarantees that the bank can always fulfill its obligations to its clients.[3]

We test the validity of the reliability premium mechanism in four ways. First, using data from another repo segment that focuses on longer-term funding deals (i.e., the evergreen market), we show that the importance of professional ties declines with the length of the deal, suggesting that formal contracts can substitute for professional ties as they provide more supply reliability.

Second, we use exogenous changes in the overall supply of cash in the US economy from the Federal Reserve's monetary policy actions in response to the COVID-19 pandemic. We show that the effect of professional ties on repo prices vanished when cash was abundant in the US economy following the COVID-19 pandemic. However, the professional ties' effect returned when cash became scarce again after the Federal Reserve tightened monetary policy to combat high inflation in March 2022. By establishing the relationship between supply and the importance of professional ties, these results provide further evidence for the supply reliability mechanism.

Third, we leverage a large supply shock that hit the repo market on September 16-17, 2019, to provide evidence in support of supply reliability. On September 16-17, 2019, buyers had far more demand for cash than sellers could supply. Indeed, prices increased over 200%. We find that a seller with a professional tie to a buyer (i.e., the individual seller used to work for the buyer) provided that buyer with more cash during this supply shock, in comparison to buyers without professional ties.

Fourth, we show buyers with no professional ties borrowed less in alternative markets (i.e., non-tri-party repo) than buyers with professional ties during the September 2019 supply shock episode. We conclude that buyers with professional ties were not reliant on outside options because they had access to more reliable supply in the tri-party market. Finally, we also explore other potential mechanisms for which we do not find strong evidence.

The Treasury repo market provides an excellent opportunity to study the role of IDMs in B2B transactions. First, players in this market—as in any financial market—are meticulous

[3] For example, investment banks borrow cash in the repo market and lend it to their clients. Reliable access to cash guarantees that the bank will be able to run its day-to-day business without interruption. Because turbulence in the banking system can affect other parts of the economy, reliable access to cash for banks is also important for regulators. As Mancini et al. (2016) note, "the search for a market design that ensures stable bank funding is at the top of regulators' policy agenda."

about recording the details of every transaction. Second—as Dwyer et al. (1987) note—in many B2B markets, duties and performance are relatively complex and occur over an extended period of time, making the task of defining and measuring the item of exchange difficult. Ambiguity about the item of exchange, in turn, makes teasing out the price effect of professional ties from product attributes challenging. In the repo market, however, transactions are completed overnight, and the characteristics of the exchange are perfectly defined by the amount of cash borrowed, the interest rate, and the collateral type provided by the buyer—all of which are observable in our data. Third, financial regulations require the sellers to disclose the details of not only their assets and transactions, but also the identity of the IDMs responsible for trades. Fourth, we observe the history of interactions and relationships among different organizations since 2014 in a panel setting. This rich panel structure allows us to identify the effect of professional ties using the movement of professionally-tied individuals in and out of decision-making positions over time within each buyer-seller pair. In this setting, the same IDM is in charge of selling to all the buyers who deal with a seller and each buyer constitutes a small share of the seller's business. Therefore, the movement of IDMs in and out of decision-making positions is presumably exogenous to the seller's relationship with any particular buyer. The panel also helps us control for factors otherwise difficult to address when using only cross-sectional data, including the history of transactions and changes in buyer and seller characteristics. Fifth, many individuals in financial markets, including the repo market, share information about their careers publicly (e.g., via LinkedIn) and some third-party platforms also collect and organize information about careers of IDMs in financial markets (e.g., Bloomberg and Capital IQ). Such information can be used to identify professional ties of IDMs in this market.

Our work contributes to multiple strands of literature. First, we contribute to the literature on social ties. The work on social ties spans multiple disciplines from sociology (e.g., Feld 1981, Granovetter 1973, McAdam and Paulsen 1993) to psychology (e.g., Cohen and Janicki-Deverts 2009, Riley and Eckenrode 1986), economics (e.g., Cohen et al. 2008, Currarini et al. 2009, Montgomery 1991), and marketing. Marketers have explored various aspects of social ties and networks: social ties and word of mouth (e.g., Kamada and Öry 2020, Kumar and Sudhir 2021, Shriver et al. 2013); social ties and diffusion of new products (e.g., Aral and Walker 2014, Jing and Xie 2011, Lobel et al. 2017, Tucker 2008); social ties and referral behavior (e.g., Biyalogorsky et al. 2001, Van den Bulte et al. 2018, Yang and Debo 2019); social ties and conformity (e.g., Miniard and Cohen 1983, Sun et al. 2019). Two common themes emerge across most of the work on social networks and ties in the marketing literature. First, scholars tend to focus on B2C settings. Second, they explore various mechanisms and implications of diffusion of information and influence.[4] The value of social ties in these cases arises from the reduced information asymmetry between customers and firms (e.g., credit scoring using social ties data) or among customers (e.g., diffusion of new products among peers). We contribute to this literature by showing that in B2B settings, social ties *can* provide value through channels other than diffusion of information and influence. While many B2C settings encompass such a large number of sellers and buyers that social ties can provide valuable information about each side by facilitating the flow of information, in many B2B settings both supply and demand sides are more concentrated (i.e., there are few agents on either side, each with a fairly large share of the total supply or demand). In such settings, the main role of social ties is not necessarily to facilitate the transfer of information about a new product, for example, but rather to provide a higher level of trust in the supplier's reliability. As a result, the buyer will be willing to pay more, trusting that the socially connected seller will reliably provide enough supplies in the face of supply-demand imbalances.

Second, we contribute to the literature on B2B relationships, the dominant lens for viewing commercial interactions in B2B contexts (Blocker et al. 2012). A significant portion of this literature uses analytical models, and most papers using empirical methods employ survey or other non-transactional data to study business relationships.[5] Considering the limitations of survey methods (Bernard et al. 1984, Bleek 1987, De Schrijver

[4] Some exceptions exploring social ties and pricing include: Ajorlou et al. (2018) develop a theoretical framework to study optimal dynamic pricing in social networks; Galbreth et al. (2012) explore implications of social sharing for firms' pricing and profit; Manchanda et al. (2015) study how customers' social ties in an online community can increase their engagement and spending; Momot et al. (2020) characterize optimal pricing strategies for selective selling of exclusive products considering consumers social ties. Examples of papers on social ties in B2B context include: Bolander et al. (2015) explore the effect of salespeople's intraorganizational ties on their performance; Iyengar et al. (2015) study the effect of peer influence on repeat prescriptions among physicians; Manchanda et al. (2008) study social contagion and adoption of pharmaceutical products among physicians.

[5] In our analysis of the literature using papers published in a sample of top marketing journals, only about 19% of papers on B2B relationships use transactional data. Moreover, among empirical papers that study business relationships, roughly a quarter collect data on both sellers and buyers and around the same ratio use longitudinal data, even though studying relationships by its nature requires observing buyer-seller interactions over time. Most papers in this literature do not use any data about IDMs, in spite of the fact that these individuals form and maintain these business relationships. Please see Appendix A for examples of topics on B2B relationships that have been explored in the literature and more details about our systematic analysis of the literature.

2012, Pinsonneault and Kraemer 1993, Salamone 1977), scholars have pushed to use transactional data (LaPlaca and da Silva 2016, Lilien 2016, Sheth 1996) mostly to no avail given difficulties of accessing such data within B2B contexts. Furthermore, studies that dive deeper into the nature of corporate relationships and consider IDMs have a limited share in this literature; some researchers have even questioned whether the term "relationship" is the correct metaphor in this context (Blocker et al. 2012). Scholars have developed theoretical frameworks for studying personal connections and reciprocal exchanges (Kranton 1996), examined IDM's satisfaction with suppliers (Bohlmann et al. 2006), researched moral hazard and adverse selection issues in personal loan decisions (Kim et al. 2019), and assessed salesperson-owned loyalty issues (Palmatier et al. 2007). Very few, however, have explored how individuals and their connections shape marketing mix decisions. Most empirical research in the B2B relationships literature considers a relationship as a history of transactions between two organizations, without considering IDMs involved (Cannon and Perreault Jr 1999, Cui and Mallucci 2016, Geylani et al. 2007, Jap 1999, Luo 2023, Shachat and Wei 2012, Sa Vinhas and Heide 2015, Wang et al. 2010b).[6] Our paper contributes to the literature on B2B relationships by using unique transactional data to show how professional connections of IDMs and the history of B2B relationships affect pricing in B2B contexts across multiple organizations.

Third, we contribute to the literature on pricing in B2B markets. Despite having a disproportionately large influence on a firm's financial results (Hinterhuber 2004, Nijs et al. 2007, Rao 2005), pricing is a particularly neglected area in the B2B literature (Cressman 2012). Our analysis of papers published in a sample of top marketing journals reveals that only 3% of papers studying B2B pricing touched on the role of IDMs in pricing. Most of the B2B pricing literature focuses on the role of bargaining, capacity constraints, and contract structure in pricing (44%) as well as auctions (21%). Moreover, B2B pricing papers generally use analytical modeling (56%) or survey data (18%) rather than empirical methods with transactional data (11%).[7] Expanding our understanding of individuals' roles in B2B pricing has important implications. Given the significant effect of pricing on profitability, for example, managers might want to consider the professional ties of

[6] For a notable exception from the finance literature please see Karolyi (2018), who uses data on personal connections.

[7] See Appendix B for a more thorough analysis of the literature on B2B pricing.

their team members (i.e., whether a current employee is an ex-employee of a client) when forming sales teams (Bruno et al. 2012, Khatami et al. 2016, Marin and de Maya 2013). Policymakers and legal scholars might want to consider the career history of individuals as a potential conflict of interest (for financial advisers with fiduciary duties, for example), similar to the conflict when an employee leaves to work for a competitor (Graves 2006, 2020, Newman 2002, Orsini 2000, Saulino 2002). Our paper expands the horizon on B2B pricing by explaining the role of an IDM's connections in pricing and detailing how individuals influence price.

Finally, we contribute to the literature on pricing in repo markets and the intersection of finance and marketing. The smooth functioning of the repo market is critical for both stability of financial markets and monetary policy implementation in the United States. Several papers in the finance literature show that the repo market contributed to financial instability during the Global Financial Crisis of 2007-2009 (see Copeland et al. 2014, Krishnamurthy et al. 2014, Gorton and Metrick 2012, Martin et al. 2014, Adrian and Shin 2011, among others). Adopting the perspective of the B2B marketing literature, we contribute to the finance literature by providing new insights about how professional ties among buyers (i.e., borrowers) and sellers (i.e., lenders) can shift prices beyond observable supply-demand dynamics.[8] By adding to the joint marketing-finance literature, we show that adopting a marketing perspective when studying financial markets can improve our understanding of these markets (Jacobson and Mizik 2009, Mizik 2014, Cao and Sorescu 2013, Sorescu et al. 2018).

The remainder of the paper is organized as follows. In Section 2, we explain the institutional background. Section 3 provides a description of our data and construction of control variables. Section 4 elaborates on our empirical strategy. Section 5 discusses our regression framework and presents the results. We discuss the mechanism in Section 6 and robustness checks in Section 7. Section 8 concludes the paper.

[8] Several studies in the finance literature find evidence for the importance of trading relationships in financial markets (Anbil and Senyuz (2022) and Han and Nikolaou (2016) for the repo market; Afonso et al. (2014) for the interbank market; and Chernenko and Sunderam (2014) for money market fund lending.) However, important characteristics of inter-organizational relationships, i.e., connections of IDMs, and their impact on asset prices have largely been overlooked.

2. Institutional Context

2.1. What is Repo?

A repo transaction is a short-term secured loan that involves the sale and future repurchase of a security between a buyer (i.e., borrower) and seller (i.e., lender). The cash buyer owns the security and seeks cash (repo being the commodity of exchange), while the cash seller receives the security as collateral. On the maturity date, the buyer returns the cash with interest to the seller, and the collateral is returned to the buyer.

In this paper, we focus on the overnight Treasury repo market. The collateral required for the repo transactions are Treasury securities, with the maturity of the trade being one day. These features make the Treasury repo market extremely safe, because the loan is extremely short-term and backed by arguably the safest securities in the world. Indeed, these features make the Treasury repo market the largest, safest, and most liquid type of financial repo market in the United States (Anbil et al. 2023).

The exact size of the overall Treasury repo market is unknown because of limited data visibility on all its segments. In 2019, $2 trillion of cash and securities changed hands in the broader Treasury repo market every day (Baklanova et al. 2019). In the tri-party overnight Treasury repo market, one of the segments of the broader Treasury repo market, volumes averaged around $450 billion a day in 2019.

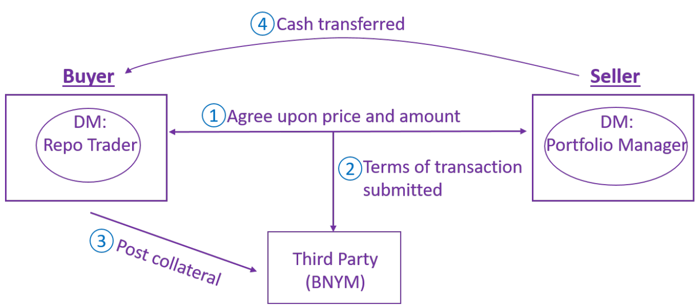
2.2. The Tri-party Repo Market

The tri-party Treasury repo market is part of the broader Treasury repo market. As the name reveals, three participants engage in each repo transaction: the buyer (i.e., borrower), the seller (i.e., lender), and the third party (i.e., the arbitrator). The buyers in this market are banks who use overnight repo to fund the assets on their balance sheet. The sellers in our data are money market mutual fund complexes (MMFs). MMFs are low-risk investment funds that invest in assets considered safe, including cash, commercial paper, certificates of deposit, Treasury securities, or Treasury repo. MMFs receive their cash from a broad range of investors. As cash under MMF management has more than doubled after the 2016 MMF reforms implemented by the SEC, MMFs have become important lenders of cash in the Treasury repo market.[9]

[9] Other sellers in tri-party Treasury repo that we exclude are asset managers, banks, Federal Home Loan Banks, and corporations. We exclude these sellers because it is difficult to identify their IDMs. Over our sample period, at least 75% of total volume is lent by MMFs.

Even though multiple people might be involved in repo transactions within both the buyer and seller organizations (i.e., influencers), one individual on either side makes the final decision about the repo transactions. The IDM at the seller is the portfolio manager.[10] The IDM at the buyer is the repo trader or repo desk manager. There is only one IDM at the seller who makes pricing decisions for all buyers at any given point in time. The third party, which acts as a neutral custodian offering back-office efficiencies like record-keeping, is the Bank of New York Mellon (BNYM). Importantly, BNYM, as the arbitrator, nearly eliminates all counterparty risk between the buyer and seller because it keeps the collateral of the buyer over the course of the repo transaction. In case the buyer defaults, the seller can easily retrieve the collateral from BNYM, sell it, and get their cash back (Martin et al. 2014).

Figure 1 The Tri-party Repo Transaction Process



This figure shows how repo trades are processed in the tri-party repo market. The IDM at the seller is the portfolio manager. The IDM at the buyer is the repo trader or repo desk manager. First, buyers and sellers agree upon the price and amount traded. Second, they submit the terms of the trade to BNYM, the arbitrator, for record-keeping and other back-office efficiencies. Third, the buyer delivers the Treasury bond collateral to BNYM for safe-keeping. The presence of the arbitrator and collateral nearly eliminates counterparty risk between the buyer and seller. Fourth, the cash borrowed is transferred to the buyer by the seller.

The flow chart of Figure 1 describes the process of a typical transaction in the tri-party repo market. IDMs at the buyer and seller (shown as ovals in Figure 1) agree upon the price and amount of cash exchanged, complying with volume limits set for risk mitigation purposes. The price is determined by the supply and demand for cash and will be affected by the Federal Reserve's monetary policy actions controlling the amount of cash in the

[10] For example, see the profile of a fund manager at JP Morgan Chase Asset Management who is responsible for several funds in the JP Morgan Chase complex. While the IDM sets the price, other individuals, usually know as "execution traders," assist in implementing the trade following the pricing policy set by the IDM.

economy. For example, when the Federal Reserve tightens monetary policy and decreases the amount of cash in the economy, the resulting higher demand to supply ratio creates upward price pressure. Besides changes in the Federal Reserve's monetary policy, other market-wide factors can affect repo prices. For example, corporate tax deadlines could affect repo prices by reducing the supply of cash. Buyer- and seller-specific factors like total assets under management (AUM) or short-term fund dependence (STFD), a measure of how desperate a buyer is for cash, can also affect transaction-level prices.

After the IDMs agree upon the price and amount, terms are submitted to BNYM by the administrative offices of the borrower and seller for record-keeping efficiencies. Then, the Treasury collateral is sent by the buyer to BNYM for the duration of the trade. A unique feature of this market is that collateral must meet predetermined general eligibility requirement. Indeed, the specifics of the collateral is not revealed at the time of the deal, as long as it meets the predetermined eligibility requirement. Therefore, all Treasury securities as collateral are valued the same, and the specifics of the security does not affect the price agreed upon between the buyer and seller. This feature is also known as "general collateral" (GC) and is important to our econometric framework because we do not need to worry about the value of the collateral affecting the price (Huh and Infante 2021). All trading is typically complete by 10 a.m. Eastern Standard Time.

In summary, the tri-party repo market is an excellent setting to study the importance of professional ties to pricing. First, we have almost complete product homogeneity. The product of exchange is cash, and the presence of the arbitrator, BNYM, nearly eliminates all counterparty risk between buyer and seller. As a result, counterparty risk does not affect prices; all deals are backed by identically valued Treasury securities held by the same third party. This uniformity of product (cash) across deals is important because in many B2B settings, the product or service is ambiguous or changes across deals (Bruno et al. 2012), which makes it difficult to study pricing over time. Second, we observe enough movement between the IDMs across buyers and sellers to enable us to study professional ties in this market. Typically, many professionals in finance start their careers in investment banking (i.e., working for the buyers in our market) and then move on to join MMFs (i.e., sellers in our market) later in their career. Working for the sellers in our market is considered more prestigious given higher salaries and better work-life balance. However, getting a job at the seller requires more work experience (Bond and Glode 2014, Siming 2013). Moreover, our interviews with professionals in the repo market revealed that buyers will most likely be aware if a seller IDM used to work for their organization; a repo desk manager described the repo market as "a world with a small pool of people."

3. Data, Control Variables, & Summary Statistics

3.1. Tri-party Proprietary Data

Our data set contains overnight (maturities of one day) repo transactions against Treasury security collateral in the tri-party repo segment. The daily data set includes transactions between August 22, 2014, and December 31, 2019, wherein we observe the price and amount agreed upon per transaction as well as the identities of the buyer and seller (in our robustness section, we extend this data set to December 31, 2022). We identify transactions where the seller is an MMF and drop transactions with non-MMF sellers, roughly 25% of transactions, because these sellers do not need to file regulatory documents disclosing their IDMs.

The raw data include transactions by each fund within an MMF complex. An MMF complex may have several MMF funds as part of its complex. The portfolio manager (the IDM at the seller) makes investment decisions at the complex level; the decisions are then relayed to each individual fund (Hu et al. 2021). Thus, we aggregate transactions to the complex-day level for each MMF seller instead of the fund level. For example, if we observe two funds such as "Fidelity Government and U.S. Treasury Fund" and "Fidelity Prime Money Market Retail Fund," we sum the transaction amount for the two and assign it to the complex, i.e., Fidelity Complex. That is, $MMFcomplex_{ijt} = \sum_{k \in J} MMFfund_{ikt}$, where $MMFcomplex_{ijt}$ is the transaction amount between buyer (bank) i and seller (MMF complex) j on day t, and $MMFfund_{ikt}$ is the transaction amount between buyer i and individual fund k, which is one of the funds at MMF complex j, on day t. J is the set of all the individual funds at MMF complex j. Our final dataset is collapsed to the buyer-seller-day level, with buyers being banks and sellers MMF complexes.

Table 1 displays summary statistics about buyers, sellers, and buyer-seller pairs during our sample period between August 22, 2014, and December 31, 2019. The buyers (banks) number 29, sellers (MMF complexes) 45. On average, each buyer trades with 10 MMF complexes. Sellers trade, on average, with 15 buyers.

Table 1 Summary Statistics about Buyers and Sellers

No. Buyers	29
No. Sellers	45
No. Buyer-Seller Pairs	535
Avg. Daily No. Buyer Partners per Seller	10
Avg. Daily No. Seller Partners per Buyer	15

This table provides summary statistics for buyer-seller pairs in the tri-party repo market between August 22, 2014, and December 31, 2019. Source: Bank of New York Mellon tri-party data.

3.2. Professional Ties Data

To construct our dataset of professional ties we need to (1) identify the IDM at each MMF complex, and (2) establish whether each IDM is a former employee of any buyer in the market. We use SEC filings to identify IDMs at seller organizations. We then use publicly available data on LinkedIn, Capital IQ, and Bloomberg to establish whether an IDM had a professional tie with any buyers in the market. Our data does not include the identities of IDMs at the buyer for two reasons. First, MMFs initiate the transaction with the buyer and provide the price and amount they are willing to trade. The IDM at the seller anchors the terms of the trade, making their financial decisions more important to study. Second, buyers do not need to reveal their IDMs in their regulatory disclosures. Thus, identifying the IDM at the buyer is challenging, if not impossible.

Since 2010, after the Dodd-Frank Act, the SEC requires that each MMF report their portfolio holdings and other information by submitting a monthly Form N-MFP.[11] Under the Investment Company Act of 1940, the form discloses information about each fund k that describes the composition of its portfolio of securities and investments. Each Form N-MFP covers one calendar month and must be filed by the MMF within five days after the end of the month. After 60 days, the filing is displayed publicly on the SEC's online database EDGAR (Electronic Data Gathering, Analysis and Retrieval).

We identify the IDMs at the seller as the individuals who sign Form N-MFP for the MMF fund. The Form must be signed by the individuals who act with legal authority for the fund per the Investment Act of 1940. Given that the Form N-MFP is submitted at the MMF level, we choose the individual common to all funds within a MMF complex. For example, we may observe three names on the Form N-MFP for "Fidelity Government and U.S. Treasury Fund" and the Form N-MFP for "Fidelity Prime Money Market Retail

[11] See the sample form provided by the SEC at `https://www.sec.gov/files/formn-mfp.pdf`.

Fund"; however, only one individual is common to both Form N-MFPs. We identify that individual as the decision-maker at the seller. (Also, recall that we aggregate all MMF funds to the complex level, i.e., Fidelity Complex using our example.)[12] If there is more than one individual who has signed all the N-MFP forms, we choose the individual whom we believe is the decision-maker, based on the individual's title (the title is usually CEO, CFO, Portfolio Manager). Individuals whom we believe to not be the decision-makers, although they sign multiple N-MFP forms, are usually the attorneys. We discuss this method of identifying IDMs and present robustness checks in Section 7.2.

Next, we identify the personal profile of each IDM on LinkedIn. For each IDM we match the most recent position on LinkedIn with the reported position on Form N-MFP to confirm that we have the correct profile. We then collect the full employment history of each IDM and compare resumes to our list of buyers to identify professional ties. We define $\textit{Professional Tie}_{ijt}$ to equal 1 when the IDM at seller j used to work for the buyer i and is in a decision-making position on day t (i.e., has signed the Form N-MFP for the seller for the month that includes day t.) If an IDM cannot be found on LinkedIn, we search for their Capital IQ and Bloomberg profiles.

We identify 163 IDMs at the seller. These individuals signed a Form N-MFP for a fund within a MMF complex. We discovered personal profiles for 155 individuals: 119 from LinkedIn, 27 from Capital IQ, and 9 from Bloomberg. Of the 163 IDMs at the seller, 55 worked for one of the 29 buyers in our data set. Of the 55 IDMs at the seller working for a buyer, 20 had a professional tie. That is, 20 IDMs at the seller used to work for the buyer they were trading with in the tri-party repo market.

A concern about using LinkedIn profiles is that they are controlled by the IDM, who may exaggerate or provide false information to attract more views. Although individuals might exaggerate their position or have an incomplete resume on LinkedIn, we believe they are less likely to report false previous positions. Nevertheless, to mitigate this concern, we do not use titles of current or past positions of IDMs in our analysis. Therefore, potential exaggerations of IDM titles on LinkedIn will not affect our analysis. Moreover, incomplete resumes would result in reporting fewer professional ties and would go against finding any significant professional tie effects (i.e., we will be estimating a lower bound for the

[12] We randomly checked 10 IDMs at the seller on the seller's website to verify that they were the decision-makers, that is the portfolio managers at the MMF.

effect). Furthermore, to alleviate concerns about misreported career histories on LinkedIn, we verify each resume provided on the LinkedIn profile using the IDM's Capital IQ profile. The profiles on Capital IQ are more difficult to manipulate by the IDM because the IDMs do not have any direct control over them. Of those IDMs at the seller who had Capital IQ profiles, we found that no LinkedIn profile had false information nor exaggerated.

Table 2 Summary Statistics about Professional Ties

Variable	N	Mean	Median	Std. Dev.
Professional Tie Variables				
Yrs. Worked at Buyer	155	3.1	0	6.0
Yrs. Worked btw. Buyer and Seller	55	6.1	8.4	15.8
Yrs. Worked at Seller	155	13.6	12.0	8.8

This table provides summary statistics about the career of the IDM at the seller. *Yrs. Worked at Buyer* is the number of years the IDM worked at the buyer. *Yrs. Worked btw. Buyer and Seller* is the number of years of experience gained between working for the buyer and seller. *Yrs. Worked at Seller while IDM* is the number of years as the decision-making individual at the seller. Source: SEC filings of Form N-MFP, LinkedIn, Bloomberg, and Capital IQ.

Table 2 presents summary statistics about *Professional Tie*. It shows, on average, that the IDM at the seller worked for the buyer 3.1 years (for those 100 individuals who never worked for a buyer, we set *Yrs. Worked at Buyer* to zero). Between working for the buyer and seller, the IDM at the seller gained a lot of experience: a median of 8.4 years. Finally, the IDM at the seller worked for the seller for 13.6 years. Note that we only observe the number of years the individual worked at the seller for 155 of the 163 IDMs at sellers (reflected in N).

Professionally-tied IDMs cover a sizable subset of the buyers and sellers in the sample. While only 12% (20 out of 163) of IDMs traded with their ex-employer, these IDMs worked for 31% (9 out of 29) of the buyers and 27% (12 out of 45) of the sellers, suggesting no concentration of ties among few buyers or sellers. Furthermore, between August 22, 2014, and September 13, 2019, professionally-tied IDMs handled transactions on 70,504 buyer-seller-days with a value of $61.9 trillion in total, out of which 6,662 buyer-seller-days with a value of $6.3 trillion were with professionally-tied buyers, indicating that our identification of professional ties is not reliant on few transactions.

3.3. Control Variables & Summary Statistics

Our specification includes buyer, seller, and buyer-seller fixed effects. Therefore, we use control variables to account for buyer, seller, or relationship-specific factors that could affect transaction price and change over time. In this section, we define and describe the role of these control variables.

3.3.1. Buyer and Seller Control Variables We use the buyer's size, measured by total assets on their balance sheet, and their market share of repo as proxies for the buyer's market power. Next, we calculate the buyer's short-term funding dependence (STFD), a measure created by banking regulators, to control for each buyer's reliance on the repo market to fulfill their liquidity needs.[13]

We use the quarterly Consolidated Report of Condition and Income Reports from the Federal Financial Institutions Examination Council, or Call Reports, to construct the two balance sheet measures (i.e., $TotalAssets_{iq}$, and $STFD_{iq}$) for each buyer (bank) i at quarter q.[14]

$$STFD_{iq} = \frac{(ST\ Noncore\ Funding)_{iq} - (ST\ Investments)_{iq}}{(LT\ Assets)_{iq}} \tag{1}$$

We calculate a buyer's market share by dividing the buyer's trade volume in the tri-party repo market by the sum of the trade volumes across all the buyers in the market as follows:

$$(BuyerMarket\ Share)_{it} = \frac{(Repo\ Volume)_{it}}{(Total\ Repo\ Volume)_{t}} \tag{2}$$

To construct control variables for the sellers (MMF complexes) that capture their preference for lending in tri-party repo versus buying Treasury securities outright, we use the SEC Form N-MFP to calculate MMF complex total assets under management (AUM), Treasury repo investments, and the amount of Treasury securities held. Recall that the

[13] STFD was developed by bank supervisors as a measure of banks' short-term funding dependence. For specific definitions of the numerator and denominator, see pages 3-6 of `https://www.federalreserve.gov/boarddocs/supmanual/bhcpr/UsersGuide13/0313.pdf` Total assets is item RCFD2170 on FFIEC 002 or FFIEC 031; or item RCON2170 on FFIEC 041 or FFIEC 051. Of the 29 buyers in the tri-party repo segment, 5 buyers do not have commercial bank entities in the US and therefore do not need to report regulatory ratios to the FFIEC such as foreign broker-banks.

[14] We follow the finance literature (such as Carlson et al. (2013), Anbil et al. (2023), and Anbil and Senyuz (2022)) in using quarterly STFD for daily analysis. Such application of quarterly data for more granular analysis is justified as the sellers who could use such data in setting prices when dealing with a buyer also have access only to quarterly data. For robustness checks about using quarterly data for STFD, please see Section 7.4.

Form N-MFP filings are at the MMF fund level. To aggregate to the MMF complex level, we sum all the seller control variables from the fund level to the complex level.[15]

3.3.2. Buyer-Seller (Relationship) Variables Finally, we include several variables to capture the strength of the relationship of each buyer-seller ij pair because this strength can affect prices and volumes in this segment (see, for example, Anbil et al. 2023, Anbil and Senyuz 2022, and Anderson and Kandrac 2018).

First, to capture the importance of the buyer (seller) to the seller's (buyer's) business, we define two daily variables for each buyer-seller ij pair. Buyer's (seller's) share of the seller's (buyer's) business is defined as follows:

$$(Buyer\ Share\ of\ Business)_{ijt} = \frac{(Repo\ Volume)_{ijt}}{\sum_{i\in I_j} (Repo\ Volume)_{ijt}} \tag{3}$$

$$(Seller\ Share\ of\ Business)_{ijt} = \frac{(Repo\ Volume)_{ijt}}{\sum_{j\in J_i} (Repo\ Volume)_{ijt}} \tag{4}$$

Where I_j is the set of all the buyers that trade with seller j, and J_i is the set of all the sellers that trade with buyer i. Since the share of business for the buyer and seller are contemporaneous, we create rolling averages of *Buyer Share of Business* and *Seller Share of Business*, respectively, from day $t-11$ to day $t-1$. Then, *Buyer Rolling Share of Business* and *Seller Rolling Share of Business* captures the history of the share of business for each buyer-seller pair, and these rolling variables are the two controls we use in our analysis.

Second, to capture the dynamics of buyer-seller relationships, we add measures of *Recency* and *Frequency* (Fader et al. 2005). We define *Recency* for each buyer-seller pair as the number of days since the buyer and seller last traded.[16] *Frequency of Trading* captures the rolling frequency of trading between a buyer and seller. It is defined as the number of times a seller j and buyer i transacted between day $t-11$ and day $t-1$. We choose this rolling window of 10 business days to reflect two weeks of trading. This window is long enough to capture the nature of buyer-seller relationships yet short enough to reflect the most recent changes in the relationship. In Section 7.4, we show evidence that our results are robust to various time windows used.

[15] We do not control for seller market share because MMFs have internal risk management limits that prevent them from being too exposed to a particular financial instrument, e.g. repo. Therefore, each seller's market share is stable over time with little variance. This effect is captured in our seller fixed effects.

[16] If the buyer-seller pair were trading before August 22, 2014, we use available Tuesday snapshots of our repo transactional data between January 2013 and August 22, 2014, to initialize *Recency*.

Table 3 Summary Statistics about Tri-party Repo Data and Control Variables

Variable	N	Mean	Median	Std. Dev.
Rate (in %)	277,762	1.10	1.01	0.89
Amount (in millions)	277,762	1000	500	1,294
Professional Tie	277,762	2.2%	0%	0.94%
Buyer Control Variables				
Buyer Market Share	277,762	0.07	0.05	0.05
Short-term Funding Dependence	251,896	0.28	0.06	3.9
Total Assets (in billions)	251,896	5.61	5.35	1.37
Seller Control Variables (in billions)				
Total AUM	233,689	16.2	16.4	1.97
Treasury Sec. Pos.	233,689	9.49	10.25	1.99
Treasury Repo Pos.	233,689	9.34	9.99	1.87
Buyer-Seller Control Variables				
Buyer Rolling Share of Seller Business	277,762	0.15	0.09	0.18
Seller Rolling Share of Buyer Business	277,762	0.1	0.06	0.15
Recency	277,762	2.0	1	13
Frequency of Trading	272,818	3.4	2	4.3

This table presents summary statistics about the independent and dependent variables in our analysis between August 22, 2014, and September 13, 2019. Rate is the amount charged between buyer i and seller j on day t. Similarly, Amount is the cash exchanged between buyer i and seller j on day t. "Buyer Control Variables," "Seller Control Variables," and "Buyer-Seller Control Variables" are defined in Section 3.3. Source: Bank of New York Mellon tri-party data.

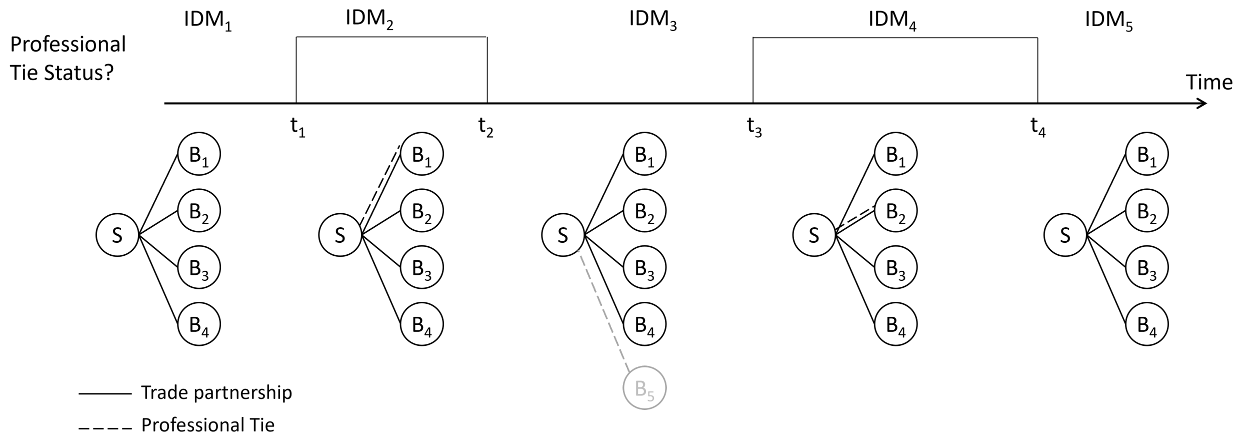
Table 3 presents summary statistics about the variables in our empirical specifications. The average price charged between buyers and sellers was 1.10% with an average amount of \$1 billion exchanged daily. On average, buyers have a "Short-Term Funding Dependence" of 28%, meaning for every \$1 of assets on their balance sheet, 28 cents is funded in the repo market. The average seller has \$9.3 billion of repo lending on its balance sheet ("Treasury Repo Position"). An average buyer has 7% market share ("Buyer Market Share") and accounts for 15% of its seller's business ("Buyer Rolling Share of Seller's Business"). Sellers, on average, account for 10% of their buyer's business ("Seller Rolling Share of Buyer's Business"). Buyers and sellers trade frequently; on average, trades occur every 2 business days and the two traded 3.4 times over 10 days.

4. Empirical Strategy

Our empirical strategy relies on the movement of individuals in and out of the decision-making position within the same selling organization over time to identify the effect of professional ties on price. Figure 2 presents a schematic example of our empirical strategy of IDMs moving in and out of the decision-making position at an example selling organization.

Before t_1, we observe no professional ties between S, the selling organization, and any of the buyers. Then, at t_1, IDM_2 who used to work for buying organization B_1 moves

Figure 2 **Schematic Example of Changes in Professional Ties for a Seller Over Time.**



into the decision-making position at the selling organization. Therefore, a professional tie exists between S and B_1, shown by the dotted line, during $[t_1, t_2)$. At t_2, IDM_3 replaces IDM_2 at S. IDM_3 is an ex-employee of B_5, but B_5 is not a trading partner of S, and therfore no professional tie is created between S and B_5.[17] Next, at t_3, when IDM_4 replaces IDM_3, her previous work experience for B_2 creates a professional tie between S and B_2. Finally, IDM_5, who was never an ex-employee of any buying organization, moves into the decision-making position at t_4. Now, S does not have a professional tie with any buying organization.

Overall, our empirical strategy addresses all three main obstacles in identifying the role of professional ties in B2B pricing: (1) lack of detailed transactional data and data about IDMs; (2) lack of clarity about the commodity of exchange, which makes separate identification of preference for the commodity of exchange from the buyer-seller relationship challenging; and (3) the endogenous formation of buyer-seller relationships.

We address the first issue by taking advantage of proprietary data in the context of the repo market. To address the second issue, we take advantage of absolute homogeneity of the commodity of exchange (i.e., cash) across transactions in our context. Moreover, the structure of transactions eliminates any meaningful variance in risk across transactions. The presence of BNYM as the entity that acts as the third party across all transactions nearly eliminates any counterparty risk between buyers and sellers.[18] Further, since the

[17] Professional ties between a buyer and seller do not affect the likelihood of their trading as shown in Table 6. Hence, IDM_3's movement into the decision-making position does not change the trading relationship between S and B_5.

[18] Even if we assume there is a meaningful risk of BNYM bankruptcy, such risk will be the same across all transactions between any buyer-seller pair and cannot explain any price differences across transactions.

maturity of all the trades in our sample is the same and very short (i.e., overnight) there is no variation in duration risk across trades. Next, because all the transactions are collateralized by US Treasury securities and all Treasury securities are equally valued because of the GC feature of the tri-party repo market, there is no variation in collateral risk across transactions. Finally, considering that we observe buyer and seller characteristics and the history of transactions for buyer-seller pairs, we can control for a myriad of factors that could potentially affect transaction prices.

To address the third issue, we use a fixed effect regression framework with daily time, buyer, seller, and buyer-seller fixed effects to identify the role of professional ties in pricing. In this framework, any unobserved time-invariant buyer, seller, or buyer-seller effect on price will be absorbed by fixed effects. We use the variation of professional ties across buyer-seller pairs over time to identify the effect of professional ties on price. Therefore, our main identifying assumption is that the movement of the IDM in and out of the decision-making position at the selling organization is exogenous to any time-varying buyer-seller specific unobserved factors. We provide some key evidence to justify this assumption below. Importantly, many of our justifications are based on our observations of the data, and are consistent with what we learnt from our extensive interviews with various repo professionals and market experts.

First, IDMs are not hired for their professional ties. 108 of 163 seller IDMs, a striking 66% of individuals, never worked for any buyer in our data set. Of the 55 that have worked for a buyer, only 20 ever traded with their ex-employer. In other words, only 12% of IDMs ever deal with their ex-employer. If professional ties with buyers were among determining factors for seller IDM hiring, we would expect to see a far higher percentage of IDMs having professional ties and dealing with their ex-employers.

Second, a seller organization does not assign an IDM (i.e., the same IDM who oversees trades across all the buyers) based on its relationship to any one buyer. As revealed in our interviews with market participants, sellers limit their exposure to any given buyer as a risk mitigation measure. While the default risk of any buyer is covered by Treasury securities held as collateral by the third party, sellers manage the risk of not having enough demand for their cash to fulfill their intended position by “not putting more than a certain number of eggs in each basket.” In addition, buyers manage the similar risk of not being able to borrow enough cash by distributing their trades across multiple sellers at any given point in time. We observe these behaviors in our data: the median share of any buyer from a seller's total business is about 9% (shown in Table 3). Moreover, professional ties do not predict the likelihood of trading between a buyer and a seller (Table 6 columns 1 and 2), which further confirms that IDMs' professional ties are not used by sellers to strengthen their relationships with certain buyers.

Third, we confirm that changes in unobserved status of commercial relationships between buyers and sellers over time do not drive IDM assignments. For example, if a stronger commercial relationship between a buyer and a seller (i.e., time-dependent relationship strength beyond the long array of observed factors for which we control) resulted in the seller assigning an IDM with a professional tie, we would expect to observe increased trade volume or increased share of business between the seller and the buyer with the professional tie. We found no evidence of changes in trade volume or the buyer's share of the seller's business being associated with assigning a professionally-tied IDM (see the analysis in the last two columns of Table 6).

Finally, due to their fiduciary duty, sellers must disclose information about IDM appointments to their investors. This information is typically publicized through fund prospectuses or announcements regarding IDM changes. Our research of 10 random fund prospectuses found that while expertise and experience were commonly cited as reasons for IDM appointments, relationship or work experience with specific buyers were never cited as reasons for hiring.

5. Regression Framework and Results

We examine the effect of professional ties on prices in the tri-party overnight Treasury repo market. We run the following fixed effect regression at the daily level from August 22, 2014, through September 13, 2019. We end at September 13, 2019, to avoid the stress episode in Treasury repo markets on September 16-17, 2019.

$$
\begin{aligned}
Price_{ijt} = \beta_0 &+ \theta_0 ProfessionalTie_{ijt} \\
&+ \theta_1 BuyerRollingShareofBusiness_{ij,t-1,t-11} \\
&+ \theta_2 SellerRollingShareofBusiness_{ij,t-1,t-11} \\
&+ \theta_3 Frequency_{ij,t-1,t-11} + \theta_4 Recency_{ij,t} \\
&+ \theta_5 Volume_{ijt} + \Delta_{ij} + \phi_t + \\
&+ \sigma_{1it-1} + \nu_{2jt-1} + \epsilon_{ijt}
\end{aligned}
\tag{5}
$$

Here, $Price_{ijt}$ is the interest rate agreed upon between buyer i and seller j on day t.[19] *Professional Tie* equals 1 if the IDM at seller j used to work for buyer i. The coefficient of interest is θ_0. A positive and significant θ_0 would suggest an association between a professional tie between the buyer and seller and higher prices. Besides Δ_{ij}, which indicates buyer-seller, buyer, and seller fixed effects and ϕ_t, which reflects daily time fixed effects, we include several control variables to account for any factors that the fixed effects might not capture.[20]

Including time fixed effects in our regression framework controls for macroeconomic factors that affect repo prices. For example, the monetary policy actions by the Federal Reserve and some seasonal events, such as quarterly corporate tax deadlines, can affect prices in the tri-party repo market. When the Federal Reserve increases its Interest Rate on Reserve Balances (IORB), that increase is passed through to prices in the tri-party repo market. In addition, on quarterly corporate tax deadline days, the supply of cash lent in the market declines because MMFs, the sellers in this market, lose cash as their investors withdraw funds to pay the Internal Revenue Service.

As proxies for the strength of buyer-seller relationships and to account for the dynamics of the relationship, we include the buyer (seller) rolling share of the seller's (buyer's) business (*Rolling Share of Business*) and the frequency of trading between the buyer and seller (*Frequency*). For each of these factors, we consider the rolling average from day $t-11$ to day $t-1$ as described in Section 3.3. We also include the trade volume (*Volume*). The

[19] Following Klee et al. (2016), we subtract the interest rate on reserve balances (IORB) from the tri-party interest rate to account for Federal Reserve changes to monetary policy. Our results are robust to not subtracting the IORB. Appendix Table D1 displays the results of Table 4 without the subtraction.

[20] We cluster our standard errors at the buyer-seller pair level, given that buyer-seller relationships are likely correlated (see Abadie et al. (2017) for more information on choosing the number of degrees of freedom for clustering).

number of days since the last trade between the buyer and seller (*Recency*) is included as another measure of relationship strength.[21]

Additionally, we include buyer-specific and seller-specific factors that could vary over time. Buyer-specific controls are reflected by $\sigma_{1i,t-1}$, which includes the buyer's overall share of the repo market (*Buyer Market Share*, defined in Equation 2), the buyer's last quarter total assets, and $STFD_{iq-1}$. $STFD$ captures the reliance the buyer has on the repo market. Seller-specific controls are reflected by ν_{1jt-1} and include the seller's last month total AUM, Treasury repo investments, and the amount of Treasury securities held. Total AUM controls for the amount of cash the seller could lend in the repo market. Because some sellers might have restrictions on their portfolio in terms of Treasury securities versus Treasury repo composition, including these variables controls for all potential investments the seller could make with their cash.

As shown in Table 3, on average, 2.2% of the transacting buyer-seller pairs on any given day are professionally-tied. This number varies over time (a standard deviation of 0.94%) as professionally-tied individuals arrive and leave decision-making positions. Moreover, professionally-tied IDMs covered a sizable subset of the buyers and sellers in the data set, and professional ties were not concentrated among few buyers or sellers. As mentioned before, 12 of 45 sellers (27%) and 9 of 29 buyers (31%) had professional ties.

5.1. Main Results

Table 4 displays the results of Equation 5. In Column 1, we observe that a *Professional Tie* between buyer i and seller j was associated with a 0.20 basis point relative increase in repo price charged in comparison with buyers and sellers without a professional tie. We observe this result after controlling for stable characteristics of buyer, seller, and relationship in addition to market trends (i.e., buyer, seller, buyer-seller, and daily time fixed effects). Once we add buyer, seller, and buyer-seller controls, accounting for their characteristics that might change over time, we observe that *Professional Tie* is associated with a higher price of 0.25 basis point (Column 2 of Table 4). Since the median price in this market is 1.01% (Table 3), this figure conveniently translates into 25 basis points price increase relative to the median, or 13% of the 1.97 basis points average cross-sectional variation in price. Only a select few buyer-seller controls are shown in Table 4 for brevity. Appendix Table

[21] We avoid using contemporaneous measures of the shares of business, and instead include the rolling averages of past shares of business to mitigate any concerns about endogeneity of these measures.

D2 presents the results of Equation 5 with the coefficients of all our controls. Overall, we find that professional ties between the buyer and seller significantly affected repo pricing.

What does this result indicate for sellers' profitability? Sellers in this market can also lend their cash at the Federal Reserve's Overnight Reverse Repo Facility (ON RRP). The ON RRP rate is set by the Federal Reserve and represents the outside option or the opportunity cost of participating in the repo market for the sellers. Therefore, we can assume the difference between the repo price and the ON RRP rate estimates the seller's profit margin, and for our sample, this difference is on average 0.0815%. Then, a professional tie raised a seller's profit margin for those professionally-tied trades by a considerable 3% (0.0025% / 0.0815%).[22]

To measure whether buy-side experience of IDMs could affect prices that an IDM charged overall (across all their buyers), we include an additional dummy variable, *IDM Buy-Side experience*, into the specification. IDMs with work experience as buyers could have more knowledge about the buy-side that they could use to their advantage in pricing. Column 3 of Table 4 shows that while the coefficient on *Professional Tie* remains positive and significant, the coefficient on *IDM Buy-Side experience* is insignificant, suggesting that buy-side experience does not drive repo prices.

[22] Such an assumption implicitly sets the seller's other costs of participating in the repo market (e.g., staff, logistics) to zero and therefore provides an upper bound for the seller's profit margin, underestimating the effect of professional ties on profitability.

Table 4 Effect of Professional Ties on Prices

	(1) Price	(2) Price	(3) Price
Professional Tie	0.0020***	0.0025***	0.0025***
	(2.60)	(2.75)	(2.75)
Buyer Rolling Share of Business		0.0065	0.0065
		(1.27)	(1.27)
Seller Rolling Share of Business		0.0053	0.0053
		(1.12)	(1.12)
Frequency		0.00013	0.00013
		(0.83)	(0.83)
Recency		-0.000022*	-0.000022*
		(-1.74)	(-1.74)
Volume		-0.00095	-0.00095
		(-0.45)	(-0.45)
IDM Buy-Side Experience			0.00016
			(0.08)
Buyer & Seller Controls	No	Yes	Yes
Buyer × Seller FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	277,762	212,028	212,028
Adjusted R^2	0.9727	0.9721	0.9721

This table displays the effect of professional ties on repo prices. Prices are the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. *IDM Buy-Side Experience* is a dummy variable that equals 1 if the IDM at the seller previously worked for *any* of the 29 buyers. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

6. Potential Mechanisms

In this section, we explore three different potential mechanisms whereby professional ties could affect repo pricing. We find strong evidence supporting one of the three mechanisms, for which we provide additional evidence and robustness checks in Section 7.3.

6.1. Description of the Potential Mechanisms

First, our interviews with various market participants and experts revealed the importance of *supply reliability* in the repo market.[23] Buyers must borrow cash every day to fund assets on their balance sheets. Thus, the reliability of sellers is essential to buyers so they can fund these assets regardless of market shocks. We hypothesize that buyers view professionally-tied sellers as more reliable and are willing to pay a premium for such reliability. This consistency of supply is critical in the overnight repo market because each trade lasts only one day. After the overnight trade expires and the buyer returns the cash, the seller has no formal or contractual obligation to provide cash to the buyer the next day. This lack of formal obligation becomes important particularly during a supply shock. A professional tie can provide an informal obligation for the seller to supply enough cash for the buyer. To test this mechanism, it is important to consider contracts that guarantee supply reliability by having longer maturity dates. In such contracts, professional ties should not affect prices as much because the longer maturity of the contract provides a formal vehicle for supply reliability. Of course, such supply reliability should come at the cost of higher prices for these longer maturity contracts.

Second, *internal signaling* could explain the premium charged by a buyer's ex-employee: an IDM in the selling organization with professional ties to the buyer charges the buyer more to signal to colleagues that no favoritism is involved. We can test for this mechanism using the number of years the IDM has been with the selling organization as a proxy for seniority. Since an IDM's confidence increases with tenure (Andreou et al. 2016, Banerjee et al. 2018, Serfling 2014) and higher confidence reduces the need for social signaling (Ali and Zhang 2015, Milbourn 2003, Shen 2003), we assume that more experienced IDMs need less signaling to their colleagues about fairness. Therefore, if the internal signaling mechanism is at play, we expect to observe lower prices the longer a professionally-tied IDM worked at the seller.

Third, the last potential mechanism we consider involves an *information premium*. To implement pricing negotiations, the seller must first diagnose and assess customer buying behavior and the customer's buying center (e.g., who is involved in the buying process and their relative level of influence). A more accurate assessment of the buying behavior

[23] We interviewed multiple individuals within this industry to gain insights about potential mechanisms. These individuals have a collective experience of over 70 years in the tri-party repo market.

and the influence involved in the purchasing process would position the seller to capture more of the value it creates for the buyer (Cressman 2012). The *information premium* mechanism suggests that an IDM for a seller who previously worked for a buyer leverages knowledge of the buying organization to charge the buyer more. While the *information premium* mechanism seems plausible, it is less likely to be the main driver of our results for two reasons. First, the buyer deals with multiple sellers simultaneously and is well aware if a seller charges other buyers less. In the long run, the buyer can choose to not trade with the seller that has superior information about the buyer. Indeed, the information premium mechanism cannot explain the buyer's willingness to pay more to a professionally tied seller given the buyer's outside options. Second, on average, 6 years pass after the IDM leaves the buyer and joins the seller, meaning that the IDM works for other employers in between. Thus, any information the IDM has about the buyer would be "stale." We empirically test for an *information premium* mechanism by using the number of years that an IDM worked for a buyer as a proxy for the level of information about a buyer. The more information the IDM has about the buyer, the higher the premium they can charge. [24]

We also rule out the possibility of *restricted search*; the buyer trusts the seller when borrowing from a professionally-tied seller and therefore is less likely to search for best prices. We note that the same individual at the buyer organization, the repo desk manager, is responsible for trading with multiple sellers daily (in our data, each buyer on average traded with 15 sellers each day). As confirmed in our interviews, the repo desk manager is incentivized to minimize the cost of funding and would be aware of price differences across different sellers. The cost of checking prices for the buyer is very low. The repo desk manager can check prices using messaging services on Bloomberg terminals, and we assume she does so given the average daily trade size in this market is large at $1 billion.

6.2. Testing the Potential Mechanisms

To test the three potential mechanisms simultaneously, we use an alternative data set from the evergreen tri-party market. The evergreen tri-party market differs from the overnight tri-party repo market in three ways: (1) there is a formal commitment between the buyer and seller to trade, therefore, by construction, all prices are observed for every buyer-seller

[24] We acknowledge that the "information premium" mechanism could potentially capture other aspects of personal relationships. For example, a buyer may be willing to pay a higher price when purchasing from an old colleague in the hope that the colleague will return the favor by offering a job at the seller in the future. We consider these alternative examples to be captured by our "information premium" mechanism.

pair in this market, and there are no "failed trades" because trading occurs every day; (2) the expiration duration of the deal is longer than one day; (3) the market is smaller ($200 billion/day worth of transactions). Under an evergreen deal, a buyer and a seller agree to trade a certain minimum amount each day for the foreseeable future (hence, the term evergreen). If one party decides to terminate the deal, there is a period before the parties stop trading, which is called the rolling length of the deal. For example, consider a buyer and a seller that decided to trade $3 billion every day under a 3-month evergreen deal. This deal's rolling length is 3 months, and if the seller chooses to exit the deal, the parties will trade the same amount daily for 3 months before they stop trading. But, so long as the seller or the buyer decide not to exit the deal, they trade under the terms of the deal indefinitely. Thus, the deal could continue for years before one party decides to exit, so the total implemented length of the deal is likely to be much longer than its rolling length.

Summary statistics about the rolling length of the deal versus the total implemented length are shown in Appendix Table D3. While the average rolling length of evergreen deals is 1.4 months, the average total implemented length of evergreen deals in our data is 23.6 months, with many deals in place for over three years.

Table 5 presents the results where we test for the presence of the three potential mechanisms. The coefficient on *Professional Tie* is positive and significant, as expected, across all 3 columns. The positive and significant coefficient on *Rolling Length of Deal* in Columns 2 and 3 indicates that prices increase with the rolling length of the deal. This increased price compensates for the seller's opportunity cost of using their cash in other, potentially more profitable, investment opportunities. Indeed, buyers are willing to pay higher prices for deals with longer rolling lengths, as the deal's longer length guarantees a more reliable supply of cash.

The negative and significant coefficient on *Professional Tie* $\times$ *Rolling Length of Evergreen Deal* suggests that the longer (i.e., more reliable) the formal evergreen deal, the less important professional ties become. This finding is consistent with the supply reliability mechanism, and we provide more evidence in support of this mechanism in Section 7.3.

The third column of Table 5 tests all three mechanisms simultaneously. The insignificant coefficient on *Professional Tie* $\times$ *Yrs. IDM Worked at Seller* and *Professional Tie* $\times$ *Yrs. IDM Worked at Buyer* suggests no evidence of the internal signaling nor information premium mechanisms, respectively.

From our interviews with repo market experts, we find that our results are consistent with their perspectives. Indeed, a veteran expert articulated such price differences stemming from professional ties as follows:

> *"The reason buyers pay more to sellers they know is that they are taking on an option [contract] that is not enforceable. You would do that only if you trust the other side. It's like if you buy home insurance without a formal contract. You want to know if your basement floods you can trust the seller and exercise that option [contract]."*

In summary, we find the strongest evidence in support of the supply reliability mechanism. Our results suggest that professional ties provide value for clients and increase a client's willingness to pay; in addition, they afford the seller the ability to extract more value from a client.

Table 5 Testing Potential Mechanisms Using The Evergreen Market

	(1) Price	(2) Price	(3) Price
Professional Tie	0.00166*	0.00214***	0.00376***
	(1.88)	(2.67)	(2.88)
Rolling Length of Evergreen Deal		0.00039**	0.00039**
		(2.10)	(2.13)
Professional Tie × Rolling Length of Evergreen Deal		-0.00041*	-0.00049*
		(-1.73)	(-1.81)
Yrs. IDM Worked at Seller			-0.00014
			(-0.28)
Prof. Tie × Yrs. IDM Worked at Seller			-0.00076
			(-1.17)
Yrs. IDM Worked at Buyer			0.00156
			(0.92)
Prof. Tie × Yrs. IDM Worked at Buyer			-0.00101
			(-1.03)
Buyer Rolling Share of Business	0.00697	0.00729	0.00728
	(1.34)	(1.40)	(1.40)
Seller Rolling Share of Business	0.00156	0.00135	0.00145
	(0.46)	(0.39)	(0.42)
Frequency	0.00013	0.00015	0.00015
	(1.23)	(1.44)	(1.45)
Recency	-0.00025	-0.00025	-0.00025
	(-0.78)	(-0.78)	(-0.78)
Volume	0.00020	0.00022	0.00021
	(0.27)	(0.29)	(0.27)
Buyer & Seller Controls	Yes	Yes	Yes
Buyer × Seller FE	Yes	Yes	Yes
Daily Time FE	Yes	Yes	Yes
Observations	175,520	175,520	175,520
Adjusted R^2	0.9705	0.9706	0.9706

This table presents a replication of our main result in Table 4 that tests three potential mechanisms, supply reliability, internal signaling, and information premium, using data from the evergreen tri-party repo market. *Price* is the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. *Rolling Length of Evergreen Deal* is the number of days until the deal expiration. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and December 31, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

7. Robustness Checks

In this section, we present various analyses to demonstrate the robustness of our results. First, we provide more evidence to mitigate any sample selection concerns. Second, we show the robustness of our definition of the individual decision-maker. Third, we provide more evidence in support of the supply reliability mechanism. We conclude with additional robustness checks for our main specification.

7.1. Selection

In this section, we provide empirical evidence to address concerns about a potentially selected sample.

We only observe transactions where the buyer and seller traded (i.e., rejected or failed trades are not observed). If professional ties affected the likelihood of trading between a buyer and seller, then inference based on a selected sample could result in biased estimates. Here, we explain why such sample selection is not a cause for concern and provide multiple robustness checks.

First, professional ties do not predict trading between a buyer and seller. Table 6 columns 1 and 2 estimate a probit model that predicts the probability of trading between a buyer and seller in a balanced panel and shows that professional ties cannot predict trading (a logit model yields similar results). Furthermore, professional ties do not predict trade volume or buyer's share of the seller's business (columns 3 and 4 of Table 6). In Heckman (1979) terminology, the expected value of the error term conditional on the sample selection rule is the same regardless of *Professional Ties*, and because we are seeking to measure the difference in the expected values for *Professional Tie = 1* and *Professional Tie = 0*, we do not need to correct for selection.

Second, we use proprietary data from the Federal Reserve that allows us to observe, and therefore, control for the $ volume of failed trades by each buyer across the broader Treasury repo market. These data are from the Form FR2004 Special Issues which requires 18 of the 29 buyers in the tri-party repo market to report their weekly positions, transactions, financing, and failed trades related to U.S. government securities as of every Wednesday at close-of-business.[25] These data are collected by the Federal Reserve to monitor U.S. government securities markets and conduct open market operations.[26]

[25] Some data in this article were obtained through a confidential survey of the Federal Reserve's primary dealers that require confidential treatment of institution-level data.

[26] Buyers required to file the FR2004 are primary dealers. As primary dealers, these buyers are required to intermediate in Treasury markets and, on average, conduct 80% of daily volumes in the tri-party repo market.

Table 6 Professional Ties, the Likelihood of Trading, & Trading Volumes

	(1) Trade	(2) Trade	(3) Buyer's Share of Seller's Business	(4) Volume
Professional Tie	-0.007	-0.0424	-0.0063	0.0666
	(0.11)	(-0.38)	(-0.71)	(0.78)
Buyer & Seller Controls	No	Yes	Yes	Yes
Buyer × Seller FE	Yes	Yes	Yes	Yes
Daily Time FE	Yes	Yes	Yes	Yes
Observations	534,125	369,340	212,028	212,028
Wald	0	119		
Adjusted R^2			0.7515	0.8130

The table presents the results of several robustness checks. The first two columns present marginal effects at the means of probit regressions for the likelihood of trading between a buyer and a seller as a function of whether there is a professional ties between them. We use a balanced panel for these two regressions with the dependent variable being a dummy variable set to one if a buyer and seller trade in a particular day and zero otherwise. Column 2 includes buyer and seller controls. Columns 3 and 4 display the effect of professional ties on the buyer's share of the seller's business and volumes (excluding trades on or after September 16, 2019). Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

Table 7 presents the results of our original specification after controlling for *Volume of Failed Trades*. We observe that *Professional Tie* remains positive and significant ensuring that our results are robust to any potential selection issues. Moreover, Column 2 shows the interaction between *Volume of Failed Trades* and *Professional Tie*. The interaction is insignificant and *Professional Tie* remains positive and significant. To the extent that *Volume of Failed Trades* provides a measure of likelihood of trade failure, this analysis demonstrates robustness of our results to potential selection.

Third, replicating the main results using the evergreen tri-party data (see Table 5) provides evidence that unobserved trades do not cause a selection problem. Because buyer-seller pairs participating in the evergreen market have a contractual obligation to trade a certain amount each day, we observe all the transactions in this market by construction. Although buyer-seller pairs might self-select to participate in the evergreen market, the share of evergreen agreements that were initiated by professionally-tied IDMs in our data was very small (1.7%). Moreover, what identifies the effect of professional ties on prices is the movement of professionally-tied IDMs in and out of decision-making positions usually

Table 7 Checking for Potential Selection Bias Using Volume of Buyers' Failed Trades

	(1)	(2)
	Price	Price
Professional Tie	0.0024**	0.0020**
	(2.50)	(2.10)
Volume of Failed Trades	0.00010	0.000099
	(1.37)	(1.35)
Professional Tie × Volume of Failed Trades		0.000066
		(0.53)
Buyer Rolling Share of Business	0.0075	0.0075
	(1.31)	(1.31)
Seller Rolling Share of Bus.	0.0048	0.0048
	(0.87)	(0.87)
Frequency	0.00016	0.00016
	(0.89)	(0.89)
Recency	-0.000025*	-0.000025*
	(-1.92)	(-1.92)
Volume	-0.0011	-0.0011
	(-0.44)	(-0.44)
Buyer & Seller Controls	Yes	Yes
Buyer × Seller FE	Yes	Yes
Daily Time FE	Yes	Yes
Observations	185,152	185,152
Adjusted R^2	0.9697	0.9697

This table presents a robustness check that tests for selection bias in our main result *Price* is the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. *Volume of Failed Trades* is the $ volume of failed transactions by buyer i during week w from the FR2004 Special Issues. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and December 31, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg, FR2004 Special Issues.

multiple months after an agreement has been signed. A professionally-tied IDM must honor the evergreen agreement signed by her predecessor which is arguably independent from the IDM's professional tie. Therefore, to the extent that selecting into an evergreen agreement by an IDM is independent of her successor's professional ties, Table 5 shows, through the positive and significant coefficient on *Professional Tie*, that our main findings are unlikely to be biased by sample selection.

7.2. Definition of IDMs

A potential concern of our procedure to unmask IDMs is that we might be identifying individuals other than the true repo pricing decision maker. In this section, we present robustness checks to alleviate this concern. We also note that there might be multiple individuals involved in repo decisions of a typical seller. We are trying to tease out the effect of professional ties of one individual involved in repo decisions whom we believe is responsible for pricing decisions. However, if other unobserved employees also affect repo pricing decisions, the influence of other unobserved employees would reduce the effect from our observed IDM. Therefore, our estimates would be the lower bound of the true effect of IDM's professional ties.

To show the robustness of our IDM choice, we performed a robustness check replacing the IDM with another signatory of the N-MFP filing of each seller whom we initially judged not to be the decision-maker for repo deals (whenever multiple signatories were available).[27] Following the professional ties of these new signatories, whom we call "pseudo-IDMs," we constructed a new variable for professional ties, *Pseudo-Professional Tie*, that equals 1 if an individual other than the IDM at the seller signed the Form N-MFP and used to work for the buyer. We replicate our main result of Table 4 using this alternative definition of professional ties and find no evidence that the professional ties of these "pseudo-IDMs" affect repo prices, shown in Table 8. Indeed, the effect of professional ties disappears when we insert the professional ties of the "wrong" individuals into our specification, making us more confident in our approach of choosing the individuals with decision authority on repo deals.

Another potential issue regarding identifying IDMs concerns the frequency of N-MFP filings. The N-MFP filings that we use to identify IDMs are filed once a month, whereas our

[27] Individuals whom we believed to be the IDM were titled as CEO, CFO, or Portfolio Manager. Individuals who signed multiple N-MFP filings whom we considered to not be the IDMs were attorneys.

Table 8 Effect of "Pseudo" Professional Ties on Prices

	(1)
	Price
Psuedo-Professional Tie	-0.00064
	(-0.22)
Buyer's Rolling Share of Bus.	0.0066
	(1.29)
Seller's Rolling Share of Bus.	0.0053
	(1.10)
Frequency	0.00013
	(0.82)
Recency	-0.000022*
	(-1.75)
Volume	-0.00097
	(-0.45)
Buyer & Seller Controls	Yes
Buyer × Seller FE	Yes
Time FE	Yes
Observations	212,028
Adjusted R^2	0.9721

This table displays the effect of "psuedo" professional ties on repo prices. Prices are the rate charged minus IORB. *Pseudo-Professional Tie* equals 1 if someone else signed the Form N-MFP on day t other than the IDM at seller j and used to work for buyer i. Our controls include the buyer rolling share of business, seller rolling share of business, frequency, recency and volume. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

analysis is performed using daily transactions. While our interviews with market participants confirm that when an IDM is assigned, she usually stays in her position for at least a few months (consistent with what we observe in the data), IDMs might change in the middle of the month. In such cases we might "mis-observe" the identity of an IDM at the start or end of her appointment. Assuming we mis-classify every IDM at the start and end of her appointment by 12 trading days (i.e., half a trading month), we might mis-classify at most 2.6% of the data, which reasonably could have very small effect on our results. We also note that mis-classifying buyer-seller pairs that do have a professional tie as ones that do not, and vice versa, because of not observing the exact IDM appointment dates would make it less likely to find any significant differences in prices owing to professional ties

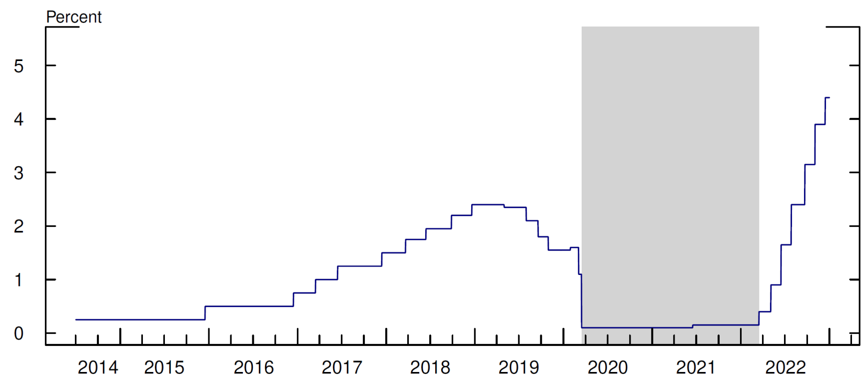


Figure 3 **The Federal Reserve's Monetary Policy Rate before, during, and after the COVID-19 Pandemic**

(i.e., would make our findings the lower bound of our effect as such mis-classification would attenuate any effect). Finally, the monthly analysis of the data yields similar qualitative results (see section 7.4), which further mitigates concerns about mis-classifying professional ties in the daily analysis.

7.3. The Supply Reliability Mechanism

This section provides further evidence in support of the *supply reliability* mechanism discussed in Section 6. We use long-term and short-term (and unexpected) exogenous supply shocks to provide additional evidence in support of the mechanism.

First, we leverage exogenous changes in the total supply of cash in the US economy resulting from the Federal Reserve's monetary policy response to the COVID-19 pandemic. On March 15, 2020, the Federal Reserve lowered the Interest on Reserve Balances (IORB) by 1.5 percentage points to 0.10%. However, due to accommodative monetary policy and the large supply of cash in the economy, inflation rose rampantly forcing the Federal Reserve to raise interest rates, and remove cash from the economy, beginning on March 16, 2022. Figure 3 presents the Interest Rate on Reserve Balances (IORB), one of the Federal Reserve's monetary policy rates between August 22, 2014, and December 31, 2022. The shaded region depicts when the Federal Reserve lowered IORB to 0.10% during the COVID-19 pandemic.

When the Federal Reserve tightened monetary policy before and after the COVID-19 pandemic, cash was more scarce, making it more difficult for buyers to borrow cash. However, when the Federal Reserve lowered interest rates for two years during the COVID-19 pandemic, cash was abundant, making it less difficult for buyers to borrow cash. If the supply reliability mechanism is at play, we would expect professional ties to matter when cash is more scarce, that is before and after the COVID-19 pandemic. During the pandemic, the effect of professional ties should be diminished since cash is abundant and supply reliability is not much of a concern for buyers.

To empirically test this hypothesis, we expanded the span of our data set through December 31, 2022, and Table 9 presents the results. In Column 3, we observe that the coefficients on *Professional Tie* × *Pre-COVID* and *Professional Tie* × *Post-COVID* are positive and significant, indicating that professional ties were important during times when cash was scarce. In addition, the coefficient on *Professional Tie* × *during COVID* is insignificant, indicating that the importance of professional ties vanished as buyers need not worry about supply reliability. These results are consistent with the supply reliability mechanism.

The lower significance level of *Professional Tie* in Table 9 during the pre-COVID era compared to our main specification in Table 4 is also consistent with professional ties becoming less important when cash is more abundant. The "Pre-COVID" period includes data between August 22, 2014, and March 14, 2020, as opposed to August 22, 2014, to September 13, 2019, in our main specification in Table 4. The Federal Reserve cut interest rates twice and increased cash in the economy between September 13, 2019, and March 14, 2020. Therefore, the pre-COVID era in Table 9 includes a longer period with lower interest rates and higher supply of cash compared to our main analysis.

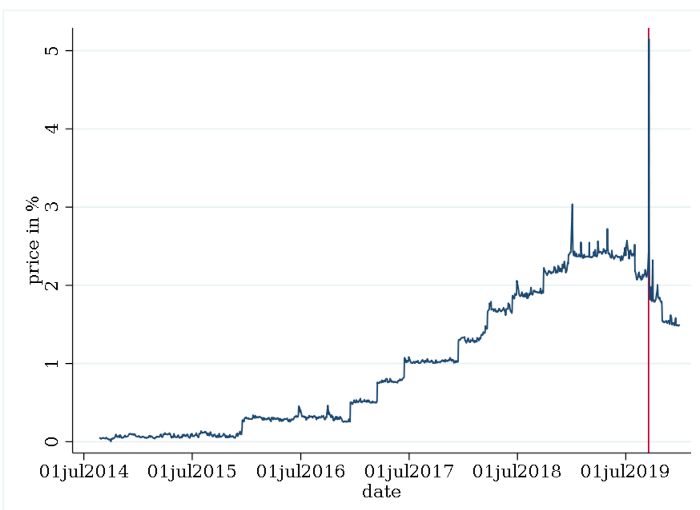
Table 9 The Effect of Professional ties Before, During, and After the COVID-19 Pandemic

	(1) Price	(2) Price
Prof. Tie × Pre-COVID	0.0019	0.0033*
	(1.08)	(1.65)
Prof. Tie (during COVID-19)	0.00074	-0.000032
	(0.56)	(-0.02)
Prof. Tie × Post-COVID	0.012**	0.014*
	(2.09)	(1.95)
Buyer Rolling Share of Business		0.0045
		(0.81)
Seller Rolling Share of Business		0.0050
		(0.95)
Frequency		0.00031*
		(1.87)
Recency		-0.0000095
		(-0.61)
Volume		-0.0025
		(-1.50)
IDM Buy-Side Experience		-0.00080
		(-0.51)
Buyer & Seller Controls	No	Yes
Buyer × Seller FE	Yes	Yes
Time FE	Yes	Yes
Observations	508,253	369,006
Adjusted R^2	0.9410	0.9325

This table displays the effect of professional ties on repo prices using an extended data set that includes the COVID-19 pandemic and exogenous changes in monetary policy by the Federal Reserve in response to the pandemic. Prices are the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. *Pre-COVID* and *Post-COVID* are dummy variables that equal 1 between August 22, 2014, and March 14, 2020, and between March 1, 2022, and December 31, 2022, respectively. *IDM Buy-Side Experience* is a dummy variable that equals 1 if the IDM at the seller previously worked for *any* of the 29 buyers. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. *ON RRP Take-up* is the logged $ amount of lending by seller j on day t at the ON RRP facility. *Unmet Demand Proxy* is the logged total repo borrowing for buyer i during week w to finance newly-auctioned Treasury securities. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

Second, to check the robustness of the supply reliability mechanism, we consider a short-term supply shock that occurred on September 16-17, 2019. During these two days, a supply-demand imbalance in the repo market resulted in many buyers scrambling to procure enough cash to fund assets on their balance sheet, and repo prices more than doubled unexpectedly while exhibiting significant volatility. Figure 4 illustrates the significance of movement in repo prices during this episode. We focus on the repo market shock on September 16-17, 2019, because the large price increases on these two days was completely unexpected and arguably one of the most important shocks to the repo market since the 2007-2008 Global Financial Crisis (Anbil et al. 2020, Correa et al. 2022).[28] Other smaller price jumps in this market were caused by changes in monetary policy by the Federal Reserve or expected seasonal factors such as year-end (where many buyers and sellers disappear from the market on the last trading day of the year) or corporate tax deadlines (where sellers lend less cash because their investors withdraw funds to pay the Internal Revenue Service). These smaller price jumps are well known to market participants and cannot be thought of as unexpected.

Figure 4 Repo Prices



This figure displays the average repo price between August 22, 2014, and December 31, 2019. Prices are in percentages and reflect the interest rate on a repo transaction. Source: Bank of New York Mellon tri-party data.

[28] The coincidence of a corporate tax deadline, the settlement of $54 billion Treasury securities, and quantitative tightening by the Federal Reserve resulted in the amount of cash in the US economy reaching its lowest level since the 2007-2008 Global Financial Crisis, creating an economy of cash scarcity, on September 16-17, 2019. For a more technical explanation of this stress episode see Anbil et al. 2023 or Afonso et al. 2020.

If the supply reliability mechanism is at play, we would expect buyers with professional ties to procure significantly more from their ex-employees on September 16-17, 2019. Table 10 presents the results of testing this hypothesis. The dependent variable is the logged volume of cash exchanged between buyer i and seller j on day t. Table 10 shows that the coefficient on *Professional Tie* × *Sept. 16-17* is positive and highly significant.[29] This result indicates that buyers borrowed about 7 times *more* cash from a seller with professional ties on September 16-17, 2019, despite higher prices. In other words, sellers with a professional tie to a buyer acted more reliably towards the buyer in the face of market volatility and were willing to provide the buyer with more funding. To the extent that buyers valued supply reliability, professional ties provided value for them.

Finally, we examine buyers' unmet demand during the supply shock in the repo market on September 16-17, 2019, to show the validity of the supply reliability mechanism. If professional ties can provide higher supply reliability, professionally-tied buyers should have less unmet demand for cash in the tri-party repo market during this shock. To test this hypothesis, we use data from the Federal Reserve's Form 2004 Special Issues, given that 18 of the 29 buyers in the tri-party repo market must report their total repo borrowing to finance newly auctioned U.S. government securities across all repo markets. These securities are a representative sample of the securities buyers finance in the tri-party repo market; thus, these data provide a reliable proxy for the buyer's total repo borrowing across all outside options.

Table 11 presents the results for regressing the log of this outside option proxy, total logged $ borrowing across all repo markets to finance newly-auctioned U.S. Treasury securities for each buyer every Wednesday, on the interaction between *Professional Tie* and a dummy variable that equals 1 on September 16-17, 2019, *September 16-17*. We run the regression weekly for 18 buyers between August 22, 2014, and December 31, 2019, as we observe total repo borrowing every Wednesday, and control for tri-party borrowing on that Wednesday among other factors. We find that the coefficient on the interaction term is negative and significant, suggesting that professionally-tied buyers have significantly less

[29] Table 10 also shows that higher buyer's and seller's share of business and higher frequency of trading are associated with higher cash volumes exchanged between the buyer and seller. We argue that the significance of these control variables when the dependent variable is volume, unlike when the dependent variable is price, provides evidence that typical relationship strength measures can only predict volumes in this market. These measures are unable to predict prices.

Table 10 Effect of Professional Ties on Prices
Testing The Robustness of the Reliability Mechanism

	(1) Volume
Professional Tie	0.0137
	(0.16)
Prof. Tie × Sept. 16-17	1.9400***
	(3.56)
Buyer Rolling Share of Business	2.2790***
	(6.14)
Seller Rolling Share of Business	2.3281***
	(3.13)
Frequency	0.0564***
	(5.73)
Recency	-0.0021***
	(-5.12)
Price	-0.6683
	(-0.74)
Buyer & Seller Controls	Yes
Buyer × Seller FE	Yes
Time FE	Yes
Observations	226,464
Adjusted R^2	0.8460

This table tests the *supply reliability* mechanism for the effect of professional ties on repo prices. The dependent variable in this regression is the log of the cash exchanged on day t between a trading buyer-seller pair. *Price* is the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. *Sept. 16-17* equals 1 if t equals September 16-17, 2019. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and December 31, 2019. t statistics are shown in parentheses. Statistical significance: *** p ≤ .01, ** p ≤ .05, * p ≤ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

unmet demand, and therefore use their outside options much less, during this important shock to cash supply in the repo market. This result is consistent with the supply reliability mechanism; in the face of a supply shock, buyers with professional ties were able to fulfill their funding needs in the tri-party repo market, rather than depending on outside options.

Furthermore, this analysis is not prone to selection of successful trades. Because we observe the demand for both the focal market, tri-party repo, and all outside options, non-tri-party repo, this analysis provides an additional robustness check for potential selection issues discussed in Section 7.1.

Table 11 The Effect of Professional Ties on Buyers' Unmet Demand During September 16-17, 2019

	(1)	(2)
	Total Repo Borrowing	Total Repo Borrowing
Any Prof. Tie	0.051	
	(0.51)	
Share of Business with Prof. Tie		-0.28
		(-1.19)
Prof. Tie × Sept. Shock	-1.48***	
	(-2.91)	
Share of Business with Prof. Tie × Sept. Shock		-1.99***
		(-3.46)
Repo Volume in Tri-party Market	0.27***	0.24***
	(6.66)	(5.63)
Buyer Controls	Yes	Yes
Buyer FE	Yes	Yes
Week FE	Yes	Yes
Observations	3,396	3,396
Adjusted R^2	0.6870	0.6875

This table tests whether a buyer's unmet demand drives the effect of professional ties on repo prices. The dependent variable is the logged total repo borrowing across the broader Treasury repo market to finance newly-auctioned US government securities for buyer i during week w. *Any Professional Tie* equals 1 if buyer i had a professional tie with any seller during week w in the tri-party repo market. *Sept. Shock* is a dummy variable that equals 1 if w is during September 16-17, 2019. *Share of Business* is the buyer's share of business and defined in Section 3.3. Other buyer controls include market share, total assets, STFD, and the amount of Treasury securities held on the buyer's balance sheet. We include buyer FE and week FE. Data are weekly Wednesday close-of-business snapshots between August 22, 2014 and December 31, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg, FR2004 Special Issues.

7.4. Other Robustness Checks

To ensure the robustness of our results to changes in the frequency of observation, we replicated the main analysis using data aggregated at weekly and monthly levels. As Table 12 shows, our results are robust to changing the frequency of analysis.

In our main analysis, for each of our control variables we used rolling averages from day $t-11$ to day $t-1$. To make sure our results are not sensitive to the choice of the time window for the rolling average, we replicated our analysis using various time windows. Table 13 shows that our results are robust to changing the time window for the rolling average of our control variables.

In repo markets, buyers usually have an internal mechanism to limit their exposure to any particular seller. Considering this mechanism, endogeneity of volume or buyer (seller) share of the seller (buyer) business is not a concern. Nonetheless, to ensure the robustness of our results, we re-estimated our main specification using a 2SLS framework. We instrument for volume using the average trade volume of a seller with all other buyers. In addition, we instrument for the buyer's (seller's) share of the seller's (buyer's) business using the average share of the seller's (buyer's) business from all other buyers (sellers). Both instrumental variables are calculated at the buyer-seller-day level. As Table 14 shows, our results remain unchanged. Additionally, column 1 shows that dropping *Volume* from the analysis does not change our estimate of the *Professional Tie* coefficient, providing further reassurance that endogeneity of the volume is not an issue.

Table 12 Effect of professional ties on Prices - Weekly & Monthly

	(1) Weekly	(2) Monthly
Professional Tie	0.0032**	0.0051**
	(2.11)	(2.39)
Buyer Rolling Share of Business	0.0030	-0.0044*
	(0.68)	(1.64)
Seller Rolling Share of Business	0.0009	0.0046
	(0.25)	(1.39)
Frequency	0.0000	-0.0000
	(0.29)	(-0.45)
Recency	-0.0000	0.0000
	(-0.69)	(1.41)
Volume	0.0014	0.0029***
	(1.24)	(7.18)
Buyer & Seller Controls	Yes	Yes
Buyer × Seller FE	Yes	Yes
Time FE	Yes	Yes
Observations	47,870	11,848
Adjusted R^2	0.9692	0.9584

This table displays the effect of professional ties on repo prices collapsing to weekly data (Column 1) and monthly data (Column 2). *Price* is the rate charged between the buyer and seller. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP at time t. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and time fixed effects (week fixed effects in Column 1 and month fixed effects in Column 2). Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

Table 13 Effect of Professional Ties on Prices Using Different Time Lags for Control Variables

	(1) 1 wk.	(2) 3 wks.	(3) 1 mo.	(4) 2 mo.
Professional Tie	0.0020***	0.0020***	0.0020***	0.0020***
	(2.64)	(2.64)	(2.64)	(2.65)
Rolling Buyer Share of Business	0.0060	0.0058	0.0057	0.0054
	(1.23)	(1.23)	(1.23)	(1.24)
Rolling Seller Share of Business	0.0048	0.0037	0.0037	0.0044
	(1.04)	(0.78)	(0.75)	(0.83)
Recency	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.84)	(-0.82)	(-0.82)	(-0.81)
Frequency	0.0001	0.0001	0.0001	0.0001
	(0.85)	(0.86)	(0.88)	(0.98)
Volume	-0.0009	-0.0008	-0.0008	-0.0008
	(-0.45)	(-0.42)	(-0.41)	(-0.39)
Buyer & Seller Controls	Yes	Yes	Yes	Yes
Buyer × Seller FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	214,784	214,784	214,784	214,784
Adjusted R^2	0.9708	0.9708	0.9708	0.9708

This table displays the effect of professional ties on repo prices where our "rolling share" control variables are measured across different lags. Prices are the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency Recency, and Volume are defined in Section 3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. Column 1 displays the results when these "rolling variables" are measured over 1-week; Column 2 when measured over 3 weeks; Column 3 when measured over 1 month; and Column 4 measured over 2 months. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

Table 14 Effect of Professional Ties on Prices after Instrumenting for Volume and Share of Business

	(1) OLS	(2) OLS	(3) 2SLS
Professional Tie	0.0024***	0.0025***	0.0023**
	(2.76)	(2.75)	(2.53)
Volume		-0.00095	0.0033**
		(-0.45)	(2.56)
Buyer Rolling Share of Business	0.0043	0.0065	-0.0028
	(1.30)	(1.27)	(-0.52)
Seller Rolling Share of Business	0.0031	0.0053	0.0024
	(0.72)	(1.12)	(0.32)
Frequency	0.000082	0.00013	-0.00015
	(0.81)	(0.83)	(-0.92)
Recency	-0.000019*	-0.000022*	-0.000012
	(-1.75)	(-1.74)	(-1.12)
Buyer & Seller Controls	Yes	Yes	Yes
Buyer × Seller FE	Yes	Yes	Yes
Daily Time FE	Yes	Yes	Yes
Observations	212,028	212,028	211,524

This table displays the effect of professional ties on repo prices where we use 2SLS to instrument for trade volume, buyer's share of the seller's business, and the seller's share of the buyer's business to account for any potential endogeneity effects. Prices are the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. Columns 1 and 2 shows the results of the OLS specification while Column 3 shows the results of the 2SLS. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

8. Conclusion

Using proprietary data from the tri-party Treasury repo market, we study how professional ties affect prices and create value for buyers and sellers in B2B markets. The characteristics of the tri-party repo market and the attributes of professional ties (i.e., the way we define them based on IDMs' past employment) allow us to explore fundamental yet rarely studied questions previously unaddressed within the marketing literature. We find that professional ties affect pricing in B2B markets; in the tri-party repo market, an individual with a professional tie to a buying organization charges the buyer a higher price.

The particular context of the repo market allows us to isolate the effect of professional ties on market outcomes. Nonetheless, there are many other contexts in which our findings could apply. For example, in the pharmaceutical industry, consistent access to raw materials is critical. Manufacturers often forge long-standing relationships with trusted suppliers to ensure access. Procurement managers often prioritize supply reliability over cost reduction (Makowski and Clauß 2011) by paying more to a reliable supplier over a cheaper one. Similarly, in many cases, physicians or surgeons leave their job to work for pharmaceutical or medical device companies as Medical Science Liaisons (MSLs) indirectly involved in product sales; hospitals' procurement managers move on to work for medical device sales organizations. Our findings suggest that in such cases, the trust resulting from professional ties could potentially provide value for both sides of a deal.

We also explored potential mechanisms whereby professional ties affect B2B prices. While we found evidence of supply reliability, we note that the demand in the market that we study is somewhat inelastic, considering the crucial role of cash in banking operations. Such inelastic demand makes the role of reliable supply more pronounced, providing room for a supply reliability mechanism. In markets where the demand is elastic, however, mechanisms like information premium or internal signaling could play a significant role in defining the role of professional ties on price. Future research might explore the potential for such mechanisms in more price elastic contexts.

Our findings have important implications for academics, policymakers, and practitioners. From an academic perspective, our findings have revealed the role of individuals in B2B relationships and transactions. We showed economically significant effects of professional ties on pricing in a setting with virtually risk-free transactions and extremely homogeneous commodities. Ultimately, we argue professional ties can play a more significant role in markets wherein transactions are not risk-free; thus, individuals must build trust. Similarly, in transactions where the commodity of exchange is less homogeneous, individual relationships can potentially affect the evaluation of the commodity of exchange, influencing the price even more. Future research can try to tackle challenges in measuring the role of individuals in such contexts. Our findings also highlight a less-studied mechanism through which social ties can provide value for both buyers and sellers in B2B markets. Most of the literature on social ties in marketing has focused on how social ties can provide value in B2C settings by facilitating the transfer of information. In contrast, our work shows that social ties can provide value for B2B buyers by increasing their supplier's reliability; the supplier, in turn, can extract part of that value by charging the buyer a "reliability premium."

Our findings have implications for policymakers as well. While the significance of someone's career history is considered when a person leaves a company to work for a competitor, our work suggests that the significance of professional ties goes beyond non-compete clauses to include buyer-seller relationships. For example, in the context of financial markets, professional ties might influence financial advisers with fiduciary duties. Many public servants continue their careers in the private sector in various advisory capacities, either as lobbyists or on the board of directors of different companies. Similarly, individuals with work experience for private companies can take public offices that regulate or oversee their previous employers. Our results demonstrate the importance of exploring the influence of connections on decision-making.[30]

Finally, our work also has important implications for practitioners given that many pricing decisions in B2B contexts are made by individuals with multiple professional ties. For example, given the significant role of pricing in profitability, managers might want to consider the professional ties of their team members (i.e., whether a current employee is a former employee of a client) when crafting their sales teams (Bruno et al. 2012, Khatami et al. 2016, Marin and de Maya 2013). Similarly, managers should be aware of professional ties when making recruiting decisions because, as our research reveals, new employees bring

[30] There are cases where professional ties have been considered in appointment of public officials. For example, prior work experience with "Big Tech" was cited as one reason for public backlash against appointment of a European Commission's chief competition economist (see *Financial Times* article 1 and *Financial Times* article 2, accessed August 2023).

assets beyond their experience and expertise that can affect their contributions to a firm's profitability.

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Appendix A: B2B Relationships Literature

Researchers have explored various aspects of business relationships, including the effect of business relationships on different transaction and market outcomes (Geylani et al. 2007, Wang et al. 2010, Palmatier et al. 2006, Jap 1999, Sa Vinhas and Heide 2015, Shachat and Wei 2012, Vickery et al. 2004, Vosgerau et al. 2008), evolution and dynamics of business relationships (Bohlmann et al. 2006, Dwyer et al. 1987, Fang et al. 2016, Keep et al. 1998, Jap and Anderson 2007, Narayandas and Rangan 2004, Vinhas and Anderson 2005), trust and opportunism in business relationships (Beer et al. 2018, Doney and Cannon 1997, Ganesan 1994, Hallen et al. 1991, Morgan and Hunt 1994, Smith and Barclay 1997, Zhang et al. 2014), and classification and taxonomy of business relationships (Anderson and Weitz 1989, Bensaou and Venkatraman 1995, Cannon and Perreault Jr 1999, Dwyer and Welsh 1985, Gundlach and Cadotte 1994, Rust and Chung 2006), among other topics.

We present a systematic analysis of the literature on B2B relationships in this appendix. We first prepared a list of pertinent keywords starting with "business-to-business relationships" then added to the list iteratively. Our final list of keywords included: ("Inter organizational" OR "Interorganizational" OR "BTB" OR "B-to-B" OR "Business-to-Business" OR "buyer-seller") AND ("Relationship" OR "Relation" OR "Exchange" OR "Network") OR ("B2B" OR "BTB" OR "Industrial") AND ("CRM" OR "Customer Relationship Management") OR ("Business marketing" OR "Supplier" OR Supplier-Buyer") AND ("relationship"). Here, "AND" and "OR" represent the corresponding logical operators.

Second, using the "Publish or Perish" software, we searched the following journals for papers including any of the keywords:

- Marketing Science, ISSN: 0732-2399 (print), 1526-548X (web)
- Journal of Marketing Research, ISSN: 0022-2437 (print), 1547-7193 (web)
- Journal of Consumer Research, ISSN: 0093-5301 (print), 1537-5277 (web)
- Management Science, ISSN: 0025-1909 (print), 1526-5501 (web)
- Quantitative Marketing and Economics, ISSN: 1570-7156 (print), 1573-711X (web)
- Journal of Marketing, ISSN: 0022-2429 (print), 1547-7185 (web)

We selected the relevant papers based on their abstracts. Table A1 shows the result of our initial search and selection. We then performed a more thorough inspection of the relevant papers and categorized them in terms of the methodology used, the data properties (for empirical papers), and the topic. Tables A2, A3, and A4 present the results of our categorization. Note that in tables A2 and A4, a paper might be counted more than once if it uses more than one methodology or covers more than one topic.

Most papers in this literature have focused on the evolution of B2B relationships over time (i.e., relationship dynamics), the effect of various aspects of relationships on different outcomes (e.g., price), and taxonomies of B2B relationships. Interestingly, Table A2 shows that only 19% of the papers use transactional data to study B2B relationships. Although two firms comprise any relationship, Table A3 shows that only 28% of papers that study B2B relationships empirically use data on both sides of the relationship. The table also shows that only about a quarter of empirical papers studying B2B relationships use longitudinal data, even though by definition a relationship is formed over time.

Table A1 Search Results for Papers about B2B Relationships

Journal	# Search Results	# Selected Papers
Marketing Science	26	10
Journal of Marketing Research	157	58
Journal of Consumer Research	34	7
Management Science	147	79
Quantitative Marketing and Economics	3	2
Journal of Marketing	342	234
Total	709	390

This table presents our search results from a sample of top marketing journals. We searched each journal for papers containing at least one of the keywords in our list (explained in the text of the appendix). We then filtered the resulting papers by reading the abstract of each to ensure the paper is relevant to the topic of B2B relationships. The second column of the table shows the number of papers we found in our initial search, and the last column presents the number of relevant papers.

Table A2 Categorization of Papers that Focus on B2B Relationships by Methodology

	Methodology					
	Survey/Interview	Conceptual Mdl.	Analytical Mdl.	Lab Exp.	Transactional Data	Other
Marketing Science	6	3	2	1	1	0
Journal of Marketing Research	29	9	8	10	16	0
Journal of Consumer Research	2	2	0	3	0	0
Management Science	4	6	45	6	22	3
Quantitative Marketing and Economics	0	0	2	0	0	0
Journal of Marketing	118	104	9	18	35	40
Total	159	124	66	38	74	43
Share	41%	32%	17%	10%	19%	11%

This table shows the result of categorizing the papers in our search based on their methodology. We categorize papers into six main groups: 1) survey-based papers that use questionnaires or interviews to collect data from various informants in B2B companies about business relationships or other aspects of their business; 2) papers that use conceptual models to study business relationships; 3) papers that use utility based or game theory models to study various aspects of business relationships; 4) papers that use lab experiments, usually by asking participants to imagine themselves in the role of different decision makers in organizations to study business relationships; 5) empirical papers that use transactional data; 6) papers that do not quite fit in any of the previous categories. Some papers might be included in more than one category depending on their methods.

Table A3 Breakdown of Empirical Papers about B2B Relationships by Type of Data

	Data Properties				
	Only on Seller	Only on Buyer	Both	Cross Sectional	Longitudinal
Marketing Science	1	3	0	3	1
Journal of Marketing Research	15	20	19	32	22
Journal of Consumer Research	0	2	3	4	1
Management Science	11	7	8	16	10
Journal of Marketing	58	52	35	120	25
Total	85	84	65	175	59
Share	36%	36%	28%	75%	25%

Focusing on papers that use empirical methods, this table presents a breakdown of the papers on B2B relationships based on the properties of the data from two perspectives. The left panel breaks down the papers based on what is observed (i.e., information about only the seller, only the buyer, or both). The right panel reflects whether the data used in the paper is cross sectional (i.e., provides only one snapshot) or longitudinal (i.e., multiple snapshots over time).

Table A4 Breakdown of Papers about B2B Relationships by Topic

	Topic						
	Taxonomy of B2B Rel.	Evolution of Rel.	Rel. $\rightarrow$ Outcome	Trust & Rel.	Rel. Dynamics	Per. Rel.	Other
Marketing Science	2	1	6	1	0	0	0
Journal of Marketing Research	8	2	26	0	21	4	1
Journal of Consumer Research	1	0	1	1	2	0	2
Management Science	12	5	24	8	26	2	4
Quantitative Marketing and Economics	0	0	1	0	0	0	1
Journal of Marketing	45	11	75	11	90	5	2
Total	68	19	133	21	139	11	10
Share	17%	5%	34%	5%	36%	3%	3%

This table categorizes by topic the papers focused on B2B relationships in our sample of journals. It establishes six categories: 1) papers that focus on taxonomy of B2B relationships, trying to classify various B2B relationships into multiple categories; 2) papers that study the evolution of B2B relationships and their various stages from formation to termination; 3) papers concerned with the effect of various aspects of B2B relationships on various outcomes (e.g., price); 4) papers that consider the role of trust in B2B relationships, both the effect of the relationship on trust and the way trust can affect the relationship; 5) papers that focus on relationship dynamics and how various aspects of relationships affect each other and change over time. This category is broader than then second category (i.e., evolution of relationships). We could have included the second category under this title, but decided to separate it as the largest well-defined category under relationship dynamics; 6) papers that consider the role of individuals in B2B relationships; 7) papers that do not fit well in any other category. Note that a paper might belong to more than one category or topic. For example, many papers that consider the role of personal relationships focus on the effect of B2B relationships on outcomes while also addressing individuals in B2B relationships.

Appendix B: B2B Pricing Literature

A sizable number of papers in the B2B pricing literature have focused on design and other aspects of auctions, for example: Chaturvedi et al. 2019, Chen 2007, Chen et al. 2009, Engelbrecht-Wiggans and Katok 2006, Fugger et al. 2019, Jap 2003, 2007, Jap and Haruvy 2008, Shachat and Wei 2012, Amaldoss and Jain 2008. There are also numerous papers on the role of bargaining (Anderson and Weitz 1989, Buchan et al. 2004, Corfman and Lehmann 1993, Dahlstrom and Nygaard 1999, Nygaard and Dahlstrom 2002, Saboo et al. 2017, Schurr and Ozanne 1985), capacity constraints (Anand and Aron 2003, Elmaghraby and Keskinocak 2003, Li et al. 2012b,a, Scheffler et al. 2016, Shen et al. 2014, Wu and Kleindorfer 2005), contract structure (Anderson and Dekker 2005, Ghosh and John 2005, Ghosh et al. 2006, Mojir and Sudhir 2019, Seshadri 1995, Susarla et al. 2020, Wu and Kleindorfer 2005), sales reps and sales organization (Lim and Ham 2014, Simester and Zhang 2014), and switching costs (Cosguner et al. 2018) on price.

Here, we follow the procedure laid out in Appendix A to present a systematic analysis of the literature on B2B pricing. We started with "b2b pricing" and formed a complete list of key words and phrases for the B2B pricing literature iteratively. The final set of key words and phrases that we used for our analysis are as follows: (("business" OR "b2b" OR "business-to-business" OR "industrial" OR "supplier" OR "distributor" OR "channel") AND ("pricing" OR "auction" OR "exchange" OR "relationship")) OR ("b2b" OR "business-to-business") AND ("value pricing" OR "value-based pricing") OR "procurement" OR "supplier development". Here, "AND" and "OR" represent the corresponding logical operators.

The results of our analysis are presented in the next four tables. Table B1 presents the results of our search and initial filtering. Table B2 shows that a fairly small percentage of papers in this literature (11%) use transactional data; most papers use either analytical models or survey data to study B2B pricing questions. Table B3 reveals that among the papers using empirical methods (mostly transactional data or survey data), most use cross-sectional data (73%) while only 50% have data on both buyers and sellers. Finally, in terms of topics, Table B4 shows that many papers in this literature focus on such buyer or seller strategies as sole-sourcing decision, price discount decisions (44%), role of firm-level trust (24%), and auctions (21%). Few papers (3%) consider the role of personal connections in B2B pricing.

Table B1 Search Results for Papers about B2B Pricing

Journal	# Search Results	# Selected Papers
Marketing Science	120	23
Journal of Marketing Research	89	9
Management Science	390	76
Quantitative Marketing and Economics	17	4
Journal of Marketing	198	21
Total	814	133

This table presents the search results focused on a sample of top marketing journals for papers on B2B pricing. We searched each journal for papers containing at least one of the keywords mentioned in Appendix B. We do not include any papers from Journal of Consumer Research (compared to our analysis in Appendix A) because none met our criteria, i.e., directly addressing the topic of B2B pricing. We filtered the resulting papers by reading the abstract of each paper to make sure the search is relevant to the topic of B2B pricing. The second column of the table shows the number of papers we found in our initial search, and the last column presents the number of relevant papers.

Table B2 Categorization of Papers that Focus on B2B Pricing by Methodology

	Methodology					
	Survey/Int.	Conceptual Mo.	Analytical Mdl.	Lab Exp.	Transactional Data	Other
Marketing Science	1	0	14	2	6	0
Journal of Marketing Research	5	0	1	0	3	0
Management Science	2	0	55	10	4	1
Quantitative Marketing and Economics	0	0	4	0	0	0
Journal of Marketing	16	1	0	2	2	0
Total	24	1	74	14	15	1
Share	18%	1%	56%	11%	11%	1%

This table shows the results of categorizing papers in our search based on each paper's methodology. We categorize papers into seven groups: 1) papers that collect data from various informants in B2B companies using questionnaires or interviews; 2) papers that use conceptual models, most often between two or more constructs to explore B2B pricing; 3) papers that use utility-based or game theory models; 4) papers that use lab experiments usually asking participants to imagine themselves in the role of different decision makers in organizations; 5) empirical papers that use transactional data; 6) papers that do not quite fit in any of the previous categories. Some papers might be included in more than one category depending on their methods.

Table B3 Breakdown of Empirical Papers Focused on B2B Pricing by Type of Data

	Data Properties				
Journal	Buyer Only	Seller Only	Both	Cross-sectional	Longitudinal
Marketing Science	1	3	3	2	5
Journal of Marketing Research	0	1	7	7	1
Management Science	3	2	2	6	1
Quantitative Marketing and Economics	0	0	0	0	0
Journal of Marketing	6	4	8	14	4
Total	10	10	20	29	11
Share	25%	25%	50%	73%	27%

Focusing on papers that use empirical methods, this table presents a breakdown of papers in the B2B pricing literature based on properties of the data from two perspectives. The left panel breaks down the papers based on what is observed (i.e., information about only the seller, only the buyer, or both). The right panel reflects whether the data used in the paper is cross-sectional (i.e., provides only one snapshot) or longitudinal (i.e., multiple snapshots over time).

Table B4 Breakdown of Papers about B2B Pricing by Topic

	Topics					
Journal	Emp. Out.	Auctions.	Buyer-Seller Str./Structure	Role of Trust/Rel.	Role of Per. Rel.	Other
Marketing Science	2	2	13	3	0	6
Journal of Marketing Research	3	2	2	4	1	2
Management Science	0	18	41	6	0	13
Quantitative Marketing and Economics	0	2	2	0	0	0
Journal of Marketing	2	4	1	19	3	1
Total	7	28	59	32	4	22
Share	5%	21%	44%	24%	3%	17%

This table categorizes by topic the papers focused on B2B pricing in our sample of journals. It establishes six categories: 1) papers that focus on the effect of pricing on an empirical outcome (e.g., the effect of pricing on revenue or length of a business relationship); 2) papers that study auctions and auction pricing; 3) papers that are concerned with buyers and sellers' strategies and structures in B2B contexts (e.g., the decision to sole-source and how that affects pricing or pricing strategies on quantity-based discounts) including papers that study the role of bargaining, capacity constraints, and contract structure; 4) papers that consider the role of firm-level trust and relationships in pricing; 5) papers that focus on the role of personal relationships in B2B pricing; 6) papers that do not fit well in any other category.

Appendix C: The Effect of Professional Ties on Sellers' Profit

In this section, we explain how we estimate the effect of incremental price increases caused by professional ties on sellers' profitability. We use the following formula to calculate the incremental revenue from a professional tie for a seller:

$$\begin{aligned}
\text{Incremental profit from a professional tie} &= \frac{\text{Increased profit from a professional tie}}{\text{Total transaction volume} \times \text{Profit margin}} \\
&= \frac{\begin{pmatrix} \Delta \text{ price due to professional tie } \times \\ \text{average daily transaction volume (conditional on trading) } \times \\ \text{average number of trading days for professionally tied buyer-sellers} \end{pmatrix}}{\begin{pmatrix} \text{average daily transaction of a seller per buyer } \times \\ \text{average daily number of buyers per seller } \times \\ \text{number of trading days per year} \end{pmatrix} \times \text{Profit margin}} \\
&= \frac{(0.0025/365/100) \times \$1B \times 126}{(\$1B \times 10 \times 252) \times 0.0815\%} \\
&= 15 \text{ basis points}
\end{aligned}$$

As explained in the paper, sellers in this market have the opportunity to lend their cash in the Overnight Reverse Repo Facility (ON RRP). The ON RRP rate is set by the Federal Reserve and represents the outside option or the opportunity cost of participating in the repo market for the sellers. Therefore, we can assume the difference between the repo price and ON RRP rate (i.e., the ON RRP-adjusted rate) estimates the seller's profit margin. The average ON RRP-adjusted rate for seller in this market for the duration of our study is 0.0815%. Using the above formulas, we estimate the incremental revenue from a professionally-tied IDM for an average seller at **15 basis points**.

Appendix D: Additional Summary Statistics & Results

In this section we present the results of some additional analyses mentioned in the paper.

Table D1 Effect of professional ties on Non-Adjusted Prices

	(1) Price
Professional Tie	0.0025***
	(2.75)
Buyer Rolling Share of Business	0.0065
	(1.27)
Seller Rolling Share of Business	0.0053
	(1.12)
Recency	-0.0000*
	(-1.74)
Volume	-0.0010
	(-0.45)
Frequency	0.0001
	(0.83)
Buyer & Seller Controls	Yes
Buyer × Seller FE	Yes
Time FE	Yes
Observations	212,028
Adjusted R^2	0.9996

This table displays the effect of professional ties on non-adjusted repo prices. *Price* is the rate charged between the buyer and seller, not adjusted for IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, and Volume are defined in Section 3.3. Other buyer controls include market share, total assets, and STFD. Other seller controls include total assets under management, total Treasury repo position, and Treasury security position. These control variables are also defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019. t statistics are shown in parentheses. Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data.

Table D2 Effect of Professional ties on Prices

	(1) Price
Professional Tie	0.0025***
	(2.75)
Buyer Rolling Share of Business	0.0065
	(1.27)
Seller Rolling Share of Bus.	0.0053
	(1.12)
Frequency	0.0001
	(0.83)
Recency	-0.0000*
	(-1.74)
Volume	-0.0010
	(-0.45)
Buyer Market Share	0.0243
	(1.34)
Buyer STFD	-0.0008**
	(-2.27)
Buyer Total Assets	0.0000
	(0.06)
Seller AUM	0.0010
	(1.14)
Seller Tsy. Pos.	0.0001
	(0.27)
Seller Tsy. Repo Pos.	0.0001
	(0.19)
Buyer × Seller FE	Yes
Time FE	Yes
Observations	212,028
Adjusted R^2	0.9721

This table displays the effect of professional ties on repo prices with all control variables shown. *Price* is the rate charged minus IORB. *Professional Tie* equals 1 if the IDM at the seller j used to work for buyer i and signed the Form N-MFP on day t. Buyer Rolling Share of Business, Seller Rolling Share of Business, Frequency, Recency, Volume, Buyer Market Share, Buyer STFD, Buyer Total Assets, Seller AUM, Seller Treasury Position, and Seller Treasury Repo Position are defined in Section 3.3. We include buyer, seller, buyer-seller pair, and daily time fixed effects. Standard errors are clustered at the buyer-seller pair level. Data are overnight Treasury tri-party repo transactions between August 22, 2014, and September 13, 2019.

Statistical significance: *** p $\leq$ .01, ** p $\leq$ .05, * p $\leq$ .10. Source: Bank of New York Mellon tri-party data, LinkedIn, Capital IQ, Bloomberg.

Table D3 Summary Statistics about the Evergreen Market

Variable	N	Mean	Median	Std. Dev.
Price (in %)	175,520	1.11	1.02	0.89
Amount (in millions)	175,520	1,137	500	1,939
Rolling Length (in months)	175,520	1.4	0.2	3
Total (Implemented) Length (in months)	175,520	23.6	20.5	17.1

This table provides summary statistics about the trades in the evergreen market. *Rolling Length* is the number of months until the maturity of the evergreen trade. *Total Length* is the number of months of the entire trade. Source: Bank of New York Mellon tri-party data.

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