BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Price discrimination in the FX market and the prediction of corporate markups

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Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

Master Thesis

Price discrimination in the FX market and the prediction of corporate markups

Examination code and name:

GRA 19702 Master Thesis

Hand in date:

01.07.2021

Campus:
BI Oslo

Study Programme:

Master of Science in Business

Major in Finance

Supervisor:

Geir Høidal Bjønnes

Acknowledgments

This master thesis ends our studies at the Master of Science program in Business with a major in Finance at BI Norwegian Business School. We wish to thank our supervisor, Geir Høidal Bjønnes, for the continuous expert guidance and support during the process. We would also like to thank Just Technologies AS for a great collaboration and for providing us with data.

Abstract

This paper explores price discrimination in the foreign exchange market and the explanation of corporate markups by studying currency trades of Scandinavian corporations. The study takes advantage of unique data, including detailed information on individual clients and the relevant dealer, enabling us to research price discrimination on a client-by-client level. We perform empirical analysis to establish a relationship between different variables and the applied markup. We find that corporate clients can achieve lower trading costs by having several counterparties, trading more frequently, trading in larger volumes, and obtaining information. Furthermore, we conclude that dealers rationally exercise price discrimination based on customer characteristics and between types of customers, where perceived market sophistication is the primary driver.

Contents

Introduction

This paper investigates price discrimination in the foreign exchange (FX) market for Scandinavian corporations. We intend to study factors causing dealers to apply different markups to different clients, where the markup is the cost of a currency trade over the interbank rate. Subsequently, we aim to use these factors to estimate the expected markup for Scandinavian corporations based on relevant characteristics. Hence, we propose the following research question:
To what extent is it possible to explain FX markups of foreign exchange transactions for Scandinavian corporations?

Foreign exchange trades in over-the-counter (OTC) markets which are characterized by a decentralized structure, meaning that clients are trading directly with dealers or intermediaries. OTC markets are less transparent and regulated compared to centralized exchanges, and information concerning trades is not made public to the market. In Forex markets, the bid-ask spread set by the dealer reflects the cost of buying or selling FX. The bid-ask spread has previously been explained by factors based on the microstructure of typical exchange markets, which includes operating costs, inventory costs, and adverse selection (Huang & Stoll, 1997). However, Bjønnes et al. (2015) propose modifying the current bid-ask spreads in OTC markets, where a price discrimination component should replace the adverse selection component. This proposal is based on the argument that price discrimination across clients is possible in OTC markets due to the lack of pre-trade anonymity.

Price discrimination is defined as dealers selling similar products with the same marginal cost at different prices (Armstrong, 2005). Since dealers have information on the identity of their counterparty before the price is set, dealers may adjust the price depending on the client. Thus, the markup expresses the additional cost above the interbank rate, which is estimated to be highly heterogeneous across clients.

This thesis aims to contribute with further research on the price discrimination component proposed by Bjønnes et al. (2015). The authors found that the estimated price discrimination component can either be negative or positive, and can range between two-thirds to six times the combined operating and inventory cost components for different client types. Their results reveal that hedge funds pay a low markup of 0.03 pips while small or medium-sized enterprises (SME) pay the highest markup of 22.74 pips, on average. Therefore, the price discrimination component is negative for large financial clients as they trade in high volumes and positive for non-financial clients as they tend to be less sophisticated. This effect shows that corporations have a considerably higher additional cost for their trades. With the data used in this study, we can study the markup of SMEs on a detailed level to see if there is a large discrepancy within the customer category, and the consequences of corporations becoming more sophisticated over time.

Furthermore, this paper will contribute to research related to transparency in the FX market. We argue that the structure of OTC markets prevents transparency as dealers are not obliged to disclose negotiated prices publicly. In addition, FX forward contracts are less transparent since forward points depend on the interest rate differential, which is exclusively accessible to the bank. This relationship makes it challenging for non-financial institutions to evaluate the spreads they receive, causing information asymmetry between the counterparties. This asymmetry enables dealers to apply larger spreads and increase their profit, thus practice price discrimination based on the counterparty's identity. The foreign exchange market is one of the most extensive asset classes globally, but unfortunately not fully understood (Bjønnes et al., 2015).

It has been established that there may be several factors that affect the pricing in a currency trade. Typically, dealers seek protection against default risk by either requiring collateral or charging higher spreads. Clients with established relationships with the dealer trade in larger quantities and thus obtain more favorable prices, causing price and trade size to be negatively correlated (Bernhardt et al., 2005). Standardized contracts should trade at a lower cost than customized contracts, as they are easier to hedge in the interdealer market (Hau et al., 2019). Also, less sophisticated clients, i.e., those with fewer counterparties, lower annual trading volume, and fewer FX contracts, receive a substantially higher spread than the more sophisticated clients (Hau et al., 2019) and clients receive different spot prices based on the information they hold (Bjønnes & Kathitziotis, 2018).

In recent times there have been several court settlements regarding FX benchmark rates, indicating the relevance of the topic. For example, in the case of Foreign Exchange (FOREX) Benchmark Rates Antitrust Litigation from 2017, the class action alleges that some of the world's most dominant financial institutions conspired to fix the prices of currencies in the foreign exchange markets from 2003 through 2013 (Wolf Popper LLP, n.d.). This behavior affected dozens of currency pairs and impacted all manner of FX instruments, where several of the world's largest banks were involved.

The lawsuit alleges that financial institutions communicated with each other to fix spot prices, manipulated FX benchmark rates, and exchanged client information to trigger stop loss and limit orders. The lawsuit cites that "The defendants conspired to fix spot prices, including in respect of USDCAD, by agreeing to artificially widen spreads quoted to clients" (Christina Davis, 2020). In 2019, the European Commission concluded that the collusive behavior affected 11 European currencies, including Scandinavian currencies (Cardoso & Tsoni, 2019). Price discrimination does not imply conspiracy; however, this shows that dealers can charge different prices to different clients.

This thesis is written in collaboration with Just Technologies AS (Just), specializing in FX analytics, enabling us to access cash flows and transaction cost analyses where both counterparties in a currency trade are identified. Just Technologies are experiencing a demand for improved transparency in the pricing of FX derivatives, and they observe that companies with highly similar cash flows receive different prices. Therefore, we would like to study price discrimination in the FX market and examine factors that can improve estimation techniques of currency trades in the future.

Non-financial corporations undertake a role in the market seeking foreign exchange to purchase goods or services. Volatility in foreign exchange markets causes exposure to transaction risk, translation risk, and economic risk; hence it affects a firm's cash flows (Hagelin, 2003). Therefore, companies use foreign exchange derivatives to minimize their exposure to exchange rate fluctuations, a critical risk management practice.

By allowing for more transparency in the field, corporations will get more insight into what they are paying for and gain leverage in negotiations. Moreover, there has been evidence of cost reduction in the bond market after implementing the TRACE reporting system (Edwards et al., 2007), indicating that transparency can reduce costs in OTC markets.

As a result of limited transparency, the markups in OTC markets have previously been challenging to study as the client's identity has been unknown. However, this study contains detailed information on each client, which creates the opportunity to account for firm-specific factors and the development of each client over time. What is unique to this paper is that the level of sophistication for the subjects change throughout the observation period. Using the Just platform will inform the clients of the markup they receive for each trade, which will provide them unique insight and increase their level of sophistication. Therefore, we can adjust for each subject's level of sophistication before and after they subscribed to the Just platform. We are not aware of any studies introducing such a dynamic component. By isolating this effect, we can estimate direct cost savings due to increased information.

Allowing corporations to benchmark their FX rates against the interbank rate will increase transparency and sophistication in the market and reduce the overall costs connected to OTC trades. However, it can be challenging to evaluate a fair price and the expected markup for corporations; therefore, we aim to provide a reference benchmark.

This paper will provide insight into the FX market as most empirical studies on this topic do not entail details for each client and the relevant dealer. Furthermore, we are not aware of any studies where the level of sophistication changes over time. With this thesis, we aim to increase the knowledge of FX markets for corporations that actively engage in FX trading and establish the importance of transparency in the pricing structure.

In section II, we review existing concepts and literature on the pricing structure of OTC instruments and supporting research on the presence of price discrimination in OTC markets. In section III, we present relevant established theories used to support our findings. In sections IV and V, we describe the data used in the study and descriptive statistics. Section VI to VII, we present the methodology and give our analysis and findings. Finally, section IX concludes our thesis and propositions to further research.

II. Related Literature

In the literature review section, we present relevant concepts such as transaction cost determination, adverse selection, strategic dealing, market microstructure, and empirical literature supporting the claim of price discrimination in OTC markets.

The idea of price discrimination came to mind after Bjønnes, Kathitziotis, and Carol (2015) revealed evidence that different players receive different spreads in the market. They showed that the FX markets are not characterized by perfect competition but rather influenced by market power and price discrimination. This relationship results from FX being traded over the counter, implying that dealers know the counterparty's identity before trade execution. The exclusive information about the counterparty gives dealers the possibility to exercise price discrimination across different clients.

Several factors are considered when transaction costs are determined in OTC markets: the market structure and design, price information and discovery, transaction and timing, volatility, and the trades disclosure regime. If a client can keep anonymity, the dealer will offer a price based on the market's characteristics and the dealer's expectation of the aggregated order flow (Kyle, 1985). If the client's identity is known, the trade can be conditioned by the client's identity. Bjønnes et al. (2015) argue that the lack of pre-trade anonymity opens the possibility of adjusting prices based on client information, market sophistication, or trading volume.

Duffie et al. (2007) predict that the structure of OTC markets opens up for price discrimination where the equilibrium properties depend on the investors' search abilities, market maker accessibility, and bargaining power. Bid-ask spreads are lower if investors can find each other more easily, indicating that corporations trading on multibank platforms receive better rates than those using a single-bank platform. The results show that dealers offer more competitive prices to sophisticated investors, who are perceived to have better external options.

Hau et al. (2019) find that transaction costs - measured by the effective spread of contractual forward rates relative to interdealer quotes - are highly heterogeneous across clients. Their analysis of EURUSD trades concludes that corporate clients at the 90th percentile of the spread distribution pay on average 52 pips over the market mid-price. In comparison, the bottom 25th percentile pays less than 2 pips. As a result, the spreads vary systematically with the level of client sophistication when controlling for contract characteristics, dealer- and time-fixed effects.

Adverse selection is considered present in markets where buyers and sellers hold different information; sellers may upwards adjust prices for informed buyers to protect themselves against the information they hold. Adverse selection implies that the price should be positively related to the information content of the trade. Since dealer-client trades are not anonymous, adverse selection theory predicts wider spreads for financial clients and larger trades. However, Osler et al. (2011) find evidence contradicting adverse selection, where client spreads are not positively related to the perceived information. They find that spreads are wider for trades that are the least likely to carry information. Furthermore, dealers hold market power because it is costly for clients to look for better quotes. The authors reveal that dealers provide better prices for informed clients that have information valuable to the dealer. While non-financial clients use currencies as a medium of exchange, their incentive to provide the dealer with useful information is limited.

According to the evidence presented by Osler et al. (2011), the price discovery in the FX market cannot follow the standard adverse selection model because dealers do not appear to adjust client spreads to protect themselves against the information content of the client's trades. The article proposes three factors that may cause this: fixed operating costs, transitory market power, and strategic dealing. The transitory market power hypothesis argues that individuals have high search costs, from which the dealer could profit. For non-financial companies, FX trading is usually one of many tasks of the administrators. Since they are not professional traders, they are seldom evaluated by execution quality and have therefore little incentive to obtain better spreads. This implication makes corporate firms the perfect target to receive wider spreads from the dealer. The strategic dealing hypothesis developed by Naik et al. (1999) argues that dealers can profit from the information of a trade if they have access to an interbank market. Therefore, they adjust their pricing to extract information from customer trades used to profit in subsequent interdealer trading. Hence, clients not perceived as informed should receive wider spreads than informed clients.

Bjønnes et al. (2015) further study the price discovery process in FX markets and finds that a price discrimination component should replace the adverse selection component in the standard model of bid-ask spreads. Price discrimination can occur in the dimensions of a client's information, the client's market sophistication, or trading volume. The paper shows that adverse selection is only relevant to hedge funds and client banks, and that strategic dealing is only applicable for dealers constructing the markup for brokers. However, the effects are minor relative to the other dimensions of price discrimination. The authors find that the following features of OTC markets; non-anonymity, and the sequential nature of competition for liquidity provision, enable OTC dealers to price discriminate across clients. Price discrimination along the dimensions of information, market sophistication, and trading volume could explain the observed inverse relation between spreads and information in OTC markets, and the three dimensions are positively correlated across client types.

Reitz et al. (2015) argue that the two-tier market structure of the FX market is assumed to create the possibility for price discrimination. The authors developed a theoretical pricing model to account for market power considerations in foreign exchange trades. They found that dealers earn lower average spreads on financial clients than non-financial clients and that asymmetric information plays a significant role in spreads received by commercial clients. Green et al. (2007) supported this, arguing that market power in quote-driven markets depends on the participants' knowledge of the current market conditions and that dealers offer the widest spreads when their market power is the greatest.

Based on the relevant literature, we argue that price discrimination in the Scandinavian foreign exchange market results from the current market structure. Therefore, we propose to study firm characteristics that may cause a dealer to quote different prices to their clients. It has been established that financial and non-financial firms receive different prices; however, the differences between non-financial clients have not been studied previously. Hence, we aim to explore other factors to help explain the composition of the price discrimination component proposed by Bjønnes et al. (2015).

III. Theory

A. Price Discrimination

Price discrimination exists when a firm sells similar products with the same marginal cost at different prices (Armstrong, 2005). Therefore, a firm's ability to offer personalized prices and price discrimination increases with the amount of information on its clients. According to Armstrong (2005), most forms of personalized pricing make a client's future prices depend on past actions. Sophisticated clients may predict the effect their efforts will have on subsequent deals and adjust their behavior accordingly. Naive clients may not adequately take this linkage into account and thus be susceptible to exploitation. Once a client has made a purchase, he typically reveals himself to be likely to purchase at the same price or higher subsequently. Moreover, Esteves (2014) has shown that clients recognized as loyal always pay a higher price than those identified as disloyal.

B. Market Power

Market power is a measure of the ability of a market participant to charge prices above the marginal cost. The market structure lays premises for how market power is distributed among the different market participants. Several factors influence market power, including market concentration, the elasticity of demand, abnormal returns, pricing power, barriers of entry, and perfect information (Pepall et al., 2014).

Market concentration is often a proxy for the intensity of competitiveness in the market. It quantifies the extent to which market shares are divided among the players in the market. A low concentration ratio indicates greater competitiveness among the market participants, while a high concentration level indicates monopoly. In a perfectly competitive market, where both buyers and sellers are price takers, it is impossible to achieve abnormal returns in the long run. However, perfectly competitive markets cannot exist due to the imperfections of real-world markets. In financial markets, imperfect competition often occurs due to incomplete information and that clients and financial assets are not perfectly homogenous. Hence, market power is gained in cases of informational asymmetries (Pepall et al., 2014).

In addition, Jacquemin (1972) argues that the modern economy creates opportunities for market participants to shape market power through a set of exogenous variables, such as mergers and product diversification. By manipulating these factors, participants can gain market power through increased barriers of entry.

In the financial sector, there is a possibility that a corporation is having a pre-existing long-term relationship with the dealer that concerns multiple divisions across the company, which might affect the power dynamics between the market participants.

Since foreign exchange is traded over the counter and the non-arbitrage relationship holds as the clients cannot trade with each other, the intermediary has an essential role in meeting the market demand. Reitz et al. (2015) argue that in FX markets, the dealer has more market power when dealing with commercial clients than financial clients due to the information the client holds.

C. Credit Hypothesis

A credit rating assesses a client's creditworthiness; it is a quantified assessment of whether a company defaults on its debt obligations (Hull, 2018). A low credit rating implies higher prices as compensation for dealers carrying counterparty risk (Hau et al., 2019). As there is no counterparty risk on SPOT transactions, the price should not include compensation for default risk.

D. Customization Hypothesis

As standardized contracts are more tradable to dealers, they should trade at a lower cost than non-standard contracts (Hau et al., 2019), implying that trades negotiated with the dealers should trade at a higher price than contracts with a fixed tenor length.

E. Volume Hypothesis

In a dealer market (OTC markets), dealers will offer more significant price improvements to regular clients, and, in turn, these clients optimally choose to submit large orders. Hence, price improvement and trade size should be negatively correlated in a dealer market (Bernhardt et al., 2005).

IV. Data

This chapter presents the data collection process and describes the characteristics and limitations of the data used in this study. In the collection process, we use one primary source of data for trades and the markup, and an independent third party for data related to company characteristics. We only use relevant data from the dataset for our analysis; thus, we clean the dataset and remove unnecessary data. In addition, all client data is anonymized and will not be disclosed publicly.

A. Primary Data

A1. Primary Data Collection

Our research uses data on corporate FX trades from 2018-2021 provided by Just Technologies (Just), specializing in transaction cost analysis for corporations. Just operates internationally; however, their main client base is in Scandinavia. Just buys data from different well-known data providers in the FX market. With several data providers, Just can benchmark even exotic cross combinations of currencies. Just purchase data on the interbank SPOT rate and the interbank forward points used to calculate the all-in rate for forward contracts. The selection of data allows Just to benchmark the rates received by clients against the interbank rate available at the appropriate time. Trades submitted to Just by their clients will include a confirmation from the dealer, which contains the applicable rate, the trade direction, and the timestamp displayed in seconds. The rates are benchmarked against the closest interbank rate that was available before the trade occurred. Since Just purchases data from several independent providers, they have comprehensive coverage of FX rates, and their algorithm is programmed to choose the most favorable interbank rate.

A2. Primary Data Description

The dataset includes a unique client ID which enables us to identify relevant characteristics for each corporation. In addition, the data will disclose the dealer of each trade, the transaction timestamp displayed in seconds, the direction of the trade, the currency pair, the all-in rate from the dealer, the all-in interbank rate, the trade type, the tenor length, and the size of the trade denominated in US dollar. The data consists of 161 clients trading with different dealers, resulting in 40 000 observations as of April 2021. Furthermore, as the data is rich in currency pairs, we include the most frequently traded pairs in our study to ensure consistency, resulting in 27 795 observations and 150 different entities (Table IB.I).

The spread calculates as the difference between the interbank rate and the rate from the dealer. As there are several different currency pairs, the spread is divided by the interbank rate to express the markup as a percentage used by the dealer above the interbank rate. In this paper, we convert the markup into basis points to ensure consistency. Thus, the markup interprets as the cost applied by the dealer over the interbank rate, measured in basis points.

A3. Primary Data Limitations

To our knowledge, this is the first study where we have access to information regarding each entity and the exact markup for each trade. As Just started in 2017 and is continuously gaining new clients, the dataset will not include an equal number of observations per entity. Therefore, we have a wide and unbalanced panel. As the panel is wide, it enables us to study several different entities; however, we should be aware of some limitations to the data as they may impact our results. One concern regarding the data is that it is not a randomly drawn sample. We acknowledge that corporations with greater cost savings potential might be more inclined to be frequent users of the Just platform, and thus be included in the study, causing a natural bias. However, as this effect would be unobservable, we have to assume that the data is a fair representation of the population. In addition, the subjects started using the platform at different times, causing an uneven distribution of the number of trades per subject which may impact the robustness of the results, increasing the number of assumptions required.

We also observe some outliers, which may result from errors made by the dealer in quoting rates or in the trade confirmations submitted to Just, yielding an abnormal markup. Especially long-term contracts face challenges regarding benchmarking due to access to forward points from the data providers.

There may also be several unobserved variables that affect the markup of corporations not included in this study. For example, such variables relate to the dealer's internal operations, variables associated with the knowledge of FX markets inside the corporations rather than firm-specific factors, or macroeconomic effects that affect the bid-ask spreads.

Finally, during March 2020, the FX market experienced a highly volatile period where several currencies appreciated or depreciated quickly. This event caused great uncertainty in the market, making it challenging to obtain the same level of preciseness in benchmarking. We argue that this period does not represent normal market conditions and therefore, the markup may not reflect a client's true risk profile. Therefore, we exclude all trades initiated in this period.

B. Secondary Data

B1. Secondary Data Collection

Based on the unique company ID, we gather firm-specific information from the independent third-party online data source "Proff" (*Proff – Nøkkeltall, Regnskap Og Roller for Norske Bedrifter*, n.d., *Proff – Nyckeltal, Resultatredovisning Och Befattningar För Svenska Företag*, n.d., *Proff – Nøgletal, Regnskaber Og Roller for Danske Virksomheder*, n.d.). Proff provides company-specific information from the Norwegian, Swedish, and Danish government records and can therefore be considered a legitimate data source. We use the most recent reported numbers (2019) for all clients to obtain consistency.

B2. Secondary Data Description

We collect client-specific information such as reported revenue, financial ratios, number of operating years, number of employees, and ownership structure based on each client's organization identification number. Revenues reported in 2019 for each client are converted to US dollars using the conversion rate of March 10, 2021.

We aim to control for counterparty risk since it may be reflected in the price of forward contracts. Most subjects included in our data are private companies (Figure IA.5); therefore, public credit ratings are limited, and ratings might differ depending on the dealer. We estimate the likelihood of bankruptcy as a proxy for counterparty risk using an altered version of Altman's Z-score (Hull, 2018, p.432). Thus, we extract each client's liquidity-, profitability- and solvency ratio from Proff **(**Table IB.VI**),** which are the most relevant ratios in this case, and assign the appropriate weights (Table IB.III).

A high score represents a low probability of bankruptcy and solid financial strength, and a low score represents a higher probability of default and weaker financial strength.

B3. Secondary Data Limitations

Proff operates as three different entities in Norway, Sweden, and Denmark and has some minor differences in the routines for data collection. Still, considering the factors we are evaluating, it will have a marginal effect on the results.

We also acknowledge that there are different accounting standards, both theoretical and practical (Fagerström & Lundh, 2009). These factors may lead to an ambiguous image of the clients' actual financial situation. However, given the parameters we are evaluating, we do not consider this to implicate our results.

Another aspect to consider is the company structure. We do not consider if the company is a part of a larger corporate group, which might lead to a wrongful interpretation of the company's actual risk profile, implicating the results when estimating firm-specific factors. However, since we use the same standards for all entities, we argue for a fair representation.

V. Descriptive Statistics

In this section, we describe the features of the data used in our analysis. The relevant data contains 27 795 observations, which we consider an acceptable sample size considering the nature of the data (Table IB.I**)**. We identify 150 different entities and 21 unique dealers (Table IB.I). Entities include all companies with a unique organization identification number, meaning that we include company subsidiaries and holding companies. Most entities report revenue of less than 50 million USD as of 2019 (Figure IA.I). We also identify the number of employees and the number of operating years for each entity. Most entities have less than 100 employees (Figure IA.2), and most entities have operated for over 20 years (Figure IA.3). There are 27 different industries included in the dataset, with an overweight of entities operating in the retail and maritime industry (Figure IA.4).

The majority of observations are forward contracts, and the average markup for the included observations is 5.61 basis points (Table IB.I). We calculate the average bps per trade of each contract based on tenor length. Table IB.II shows that spot next (SN) contracts have the lowest average markup in bps, while a 2-year contract has the highest markup in bps.

When comparing the average markup in bps based on tenor length for companies before and after they signed with Just, we observe a lower average markup after subscribing to the platform (Table IB.IV). Supporting the argument that informed clients receive smaller spreads, we test the statistical significance to establish a cause-and-effect relationship.

VI. Methodology

In this chapter, we describe and evaluate the method used to conduct our study. In this thesis, we conduct a quantitative empirical study. We test the hypotheses on the collected data using OLS to establish a cause-and-effect relationship between our dependent and independent variables. This approach is well established and allows us to test the significance of recognized economic theories.

A. Hypotheses

To consider whether it is possible to explain the expected markup applied to Scandinavian corporations in the foreign exchange market, we must first determine that different clients receive different markups. Therefore, the initial hypothesis of this paper is that different Scandinavian corporations receive different markups from the same dealer or intermediary.

The structure of OTC markets creates the possibility for dealers to exercise price discrimination due to a lack of pre-trade anonymity. To evaluate the hypothesis, we look at five different components: information, market sophistication, inventory and operating costs, firm characteristics, and contract characteristics. Information, market sophistication, and firm characteristics relate to price discrimination, inventory and operating costs are associated with the determination of bid-ask spreads, contract characteristics relate to additional market risk.

Information: We hypothesize that corporate clients are uninformed and that dealers will not profit or protect themselves from the clients’ information content. Hence, corporate clients' information content will not affect the markup.

Market sophistication: We hypothesize that sophisticated clients receive smaller markups than less sophisticated clients.

Firm characteristics: We hypothesize that dealers exercise price discrimination based on company-specific factors.

Inventory and operating costs: We hypothesize that inventory costs and operating costs increase with trade size and that small trades receive a more significant portion of the operating costs.

Contract characteristics: We hypothesize that standard contracts will be equal to lower markups and that long-term contracts result in higher markup due to uncertainty.

B. Estimating Equation

The dependent variable *Markup* is the dealer’s price on trade *t* for client *i* above the interbank rate. We intend to estimate the impact of the price discrimination component introduced by Bjønnes et al. (2015), where dealers exercise price discrimination according to client properties such as information, market sophistication, trading frequency, and trading volume. In addition, we include factors relating to the firm structure of the client and control for differences depending on the contract type.

Therefore, we propose five main areas that we predict to affect the markup received by different Scandinavian clients. Hence, the markup on transaction *t* for client *i*, $Markup_{it}$, is regressed against the vectors that capture information, market sophistication, firm characteristics, inventory risk and operating costs, and contract characteristics:

$$\begin{gathered} Markup_{it} = \delta' Information_i + \gamma' Marketsophistication_{it} \\ +\psi' Firm\ characteristics_i + \varphi' Inventory\ and\ operating\ cost_{it} \\ +\theta' Contract\ characteristics_{it} + \varepsilon_{it} \end{gathered} \tag{1}$$

C. Information

Adverse selection and strategic dealing have been central to previous literature when explaining the price structure in OTC markets. We measure the extent to which clients are informed by their average post-trade returns.

$$Information = \delta_1 Info_i \tag{2}$$

<u>*Info*:</u> As proposed by Bjønnes et al. (2015), we use daily mid-price quotes from Refinitiv and calculate the post-trade average return for each client as the following:

$$Info_i = Average_i[(MidPrice_{t+1} - MidPrice_t) D_t] \tag{3}$$

Where D_t represents the trade direction for trade *t*, taking value one when a client buys the relevant base currency and negative one when the client sells the relevant base currency. We use mid quotes instead of transaction prices since it bypasses endogenous variation in the markup since there is a possibility that the markup varies across clients. Further, we calculate the average return per client and include a zero-one dummy variable, taking the value one for positive average return and zero otherwise. Following previous research, we expect a positive coefficient under adverse selection, a negative coefficient under strategic dealing, and zero if the client is uninformed. Since most of the clients included are corporations, we expect a coefficient equal to zero. Corporations mainly use currencies as a medium of exchange; therefore, their incentive to gather information is limited.

D. Market Sophistication

To evaluate the significance of the market sophistication component, we include four subcomponents that affect the market sophistication.

$$Market\ sophistication\ component = \gamma_1 Venue_t + \gamma_2 Subscription\ Just_t + \gamma_3 NCounterparties_i + \gamma_4 Trade\ frequency_i \quad (4)$$

<u>*Venue*:</u> Clients trading on multibank platforms enjoy a higher level of sophistication and clients who rely on direct trading pay distinctly wider markups (Bjønnes et al., 2015). Thus, we include the variable *Venue* as a zero-one dummy variable, taking value one for trades occurring on a multibank platform and zero otherwise. Other studies also distinguish between trades occurring on a single-bank platform and by telephone or email. Previous research shows that the latter induces a significantly higher markup; unfortunately, our data does not allow us to study this effect.

<u>*Subscription Just*:</u> We include the variable *Subscription Just* in the model to estimate the effect of entering a contract with Just on the overall markup. After a subject enters an agreement with Just, they can benchmark their FX rates against the interbank rate, presumably increasing their level of knowledge and sophistication. The *Subscription Just* variable implies trades that occurred after a client subscribed to the Just platform and appears as a zero-one dummy variable in the model, taking the value one for trades executed after entering a contract with Just and zero for trades executed before that. We estimate that this will significantly affect the client's level of sophistication, as they now have information regarding the spread for each trade. Therefore, we expect a negative coefficient.

<u>*Number of counterparties*:</u> Clients that trade with several dealers presents as more sophisticated due to having more external options (Hau et al., 2019). The data reveals that the relevant subjects have between one and six counterparties. We estimate that having several counterparties result in a higher level of sophistication compared to fewer counterparties. Therefore, we include this variable in the regression as a zero-one dummy variable. Clients with one counterparty will take value zero, and clients with more than one counterparty take value one.

<u>*Trade frequency*:</u> Hau et al. (2021) find that clients trading more frequently appear more attractive to dealers, increasing their bargaining power and are obtaining narrower spreads. Thus, we calculate the average trade frequency weekly. The majority executes between one and three trades per week, while the highest trade frequency is 94 trades per week. We divide the subjects into two categories: low frequency corresponds to up to five trades, and high frequency is above five trades per week. The variable will appear as a zero-one dummy variable taking value one for high-frequency traders and value zero for low-frequency traders. We expect that the clients in the high-frequency category will have higher bargaining power than clients in the low-frequency category, and thus we expect a negative coefficient. However, frequent trading may not necessarily imply that a client is sophisticated in the market.

E. Firm Characteristics

We intend to study firm-specific factors that may help to differentiate between the clients and find common explanations. Therefore, we investigate whether dealers apply different markups based on five subcomponents, as these components may affect the dealer's perceived risk of the client. We include the following subcomponents for the firm characteristics component.

$$Firm\ characteristics = \psi_1 Credit_i + \psi_2 Operating\ years_i + \psi_3 Revenue_i + \psi_4 Firm\ size_i + \psi_5 Public_i + \psi_6 FinancialCompany_i \tag{5}$$

<u>*Credit*:</u> We expect the credit rating to be relevant in the pricing of forward contracts due to counterparty risk. Therefore, we expect a negative coefficient

implying that markups decrease for companies with a good credit rating. However, we acknowledge that standard industry practices might include margin accounts; however, this is impossible to account for given the available data.

Revenue: We estimate that high revenue firms typically hold more market power with the dealer. Their business relations generate more significant revenue for the dealer, and therefore, their customer relationship might be more valuable. Generally, SMEs are defined as corporations with less than 50 million Euro (Nærings- og handelsdepartementet, 2012, p. 13). Consequently, we include a zero-one dummy variable for high revenue firms, taking value one for firms with more than 50 million USD in revenue and zero otherwise. We expect a negative coefficient for this relationship.

Operating years: We estimate that a mature company is perceived as less risky than a young company due to more history on cash flows and defaults on debt. Thus, we include the variable *Operating years* where we expect a negative coefficient as perceived risk might decrease over time. However, we also open up the possibility that mature companies have long-standing relationships with the dealer, increasing the dealer's market power.

Firm size: We expect that firms with many employees to have a more extensive financial department with specialized personnel where trading could be a central task. Generally, SMEs are defined as corporations with less than 250 employees (Nærings- og handelsdepartementet, 2012, p. 13). Hence, we include a zero-one dummy variable for large firms, taking value one for firms with 250 employees or more and zero otherwise. We expect a negative coefficient in line with the transitory market power hypothesis (Osler et al., 2011).

Public: We estimate that publicly listed companies receive better terms from the dealer and trade at lower costs than private companies. The variable will appear as a zero-one dummy variable where publicly listed clients take the value one. We expect a negative coefficient since publicly listed companies might have more international trades, appear more experienced in the market, and have a larger dedicated finance division. We project that the variables *Revenue*, *Operating years*, *Firm size*, and *Public* have a combined effect on size and internationalization, which increases a client's market power with the dealer.

Financial company: We project that financial companies receive smaller markups than non-financial companies. Since financial companies are possibly more informed of the market conditions, they are consistent with their incentives (Bjønnes et al., 2015). The variable appears as a zero-dummy variable where trades by a financial company take value one and zero otherwise.

F. Inventory Risk and Operating Costs

The cost of inventory and operating expenses ought to be determined in the same manner in OTC markets as those in other markets (Bjønnes et al., 2015). Therefore, to estimate the significance of inventory and operating costs, we include the following subcomponents:

$$Inventory\ and\ operating\ cost = \phi_1 \ln(Size)_{it} + \phi_2 Large_t + \phi_3 Small_t \qquad (6)$$

Ln(size): According to Ho & Stoll (1981), the inventory risk rises with price volatility and the size of the transaction. Larger trades will move the dealer further from desired inventory and can be more challenging to net out internally. We include the variable *ln(Size)* to estimate the cost of inventory risk on the expected markup. We expect a positive coefficient since larger trades increase the inventory risk for the dealer. In addition, we expect the variable *ln(Size)* to capture some of the effects of operating expenses. Operating costs usually consist of a fixed and a variable component, and we anticipate that variable costs will rise with trade size, hence a positive coefficient. However, the fixed costs will appear as a smaller proportion of the markup in larger trades than small trades.

Large: We control for extraordinary large trades since they can be particularly challenging to net out internally for the dealer. We include a dummy variable taking the value one for trades above 5 million USD and zero otherwise. We expect that large trades will increase inventory risk and that the coefficient for the variable *Large* will be positive.

Small: We control for abnormally small trades since we expect that the fixed costs will represent a more significant proportion of the total costs. We include a dummy variable taking the value one for trades below 1 000 USD and zero otherwise. We expect the coefficient to be positive; however, we cannot control for the additional costs related to manual trades.

G. Contract Characteristics

Hau et al. (2019) suggest that contract characteristics can affect the markup charged to clients by the dealer. Therefore, we control for the following sub-variables to isolate the relevant contract characteristics:

$$Contract\ characteristics = \theta_1 Contract\ duration_{it} + \theta_2 Customized_t \qquad (7)$$

<u>*Contract duration*</u>: The credit risk hypothesis anticipates that markup increases as the contract length increases to compensate for risk and uncertainty (Hau et al., 2019). We expect a positive coefficient implying that dealers charge wider spreads for long-maturity contracts in compensation for greater market risk.
<u>*Customization*</u>: The customization hypothesis introduced by Hau et al. (2019) predicts that broken tenor contracts should trade at a higher cost as these are more difficult to hedge in the interdealer market. The variable *customization* will take value one for customized trades and zero for standard tenor contracts. Thus, we expect a positive coefficient.

In summary, we propose the following regression equation to estimate the markup on trade *t* for client *i*:

$$\begin{gathered} Markup_{it} = \delta_1 Info_i \qquad (8) \\ +\gamma_1 Venue_t + \gamma_2 Subscription\ Just_t + \gamma_3 NCounterparties_i + \gamma_4 Trade\ frequency_i \\ +\psi_1 Credit_i + \psi_2 Operating\ years_i + \psi_3 Revenue_i + \psi_4 Firm\ size_i \\ +\psi_5 Public_i + \psi_6 Financial\ company_i \\ +\phi_1 ln\ (Size)_{it} + \phi_2 Large_t + \phi_3 Small_t \\ +\theta_1 Contract\ duration_{it} + \theta_2 Customized_t + \varepsilon_{it} \end{gathered}$$

The first line captures the subjects' information content, and we expect a coefficient equal to zero, $\delta = 0$. The second line captures the market sophistication of the relevant subjects, and we expect a negative coefficient, $\gamma < 0$, for all components. The third and fourth line captures different firm characteristics which might impact their perceived risk, experience, and knowledge level. We expect a negative coefficient, $\psi < 0$, for all components. The fifth line captures the inventory risk and operating costs, and we expect a positive coefficient, $\phi > 0$, for both components. Finally, the sixth line captures control variables related to differences between contracts, and we expect a positive coefficient for both components, $\theta > 0$.

H. Method

This section will describe the method used to estimate the price discrimination component and the explanation of corporate markups.
As explained in the data description section, we have an unequal number of observations for each entity at different points in time. Thus, the data can be characterized as an unbalanced panel (Brooks, 2014, p.529). As the data is unbalanced and wide, we decide not to study the development over time or each entity's individual effects. Thus, we proceed with a simple pooled regression to estimate a single regression on the data jointly. A pooled regression implies that the dataset for the dependent variable is stacked up into a single column containing all the cross-sectional and time-series observations. Similarly, all of the observations on the explanatory variables will be stacked into a single column in the x matrix. Then this equation would be estimated using regular OLS (Brooks, 2014, p.527).

There are several advantages of using OLS on panel data that we should consider when deciding on the model. Firstly, we can address more complex structures than pure time series, or cross-sectional data would allow (Brooks, 2014, p.527). Secondly, it increases the degrees of freedom, strengthening the power of the test (Brooks, 2014, p.527). And finally, by using a pooled sample, we increase the available quantity of data and thus reduce the possibility of near multicollinearity (Brooks, 2014, p.219).

The limitation of using pooled data is that it assumes the average values of the variables and the relationships between them are constant over time and across all of the units in the sample (Brooks, 2014, p.527). We acknowledge that the choice of modeling may affect the results of this analysis. However, as OLS is a familiar framework and has been used in previous studies to estimate price discrimination, it increases the trustworthiness and dependability of our chosen methodology.

When performing an OLS regression, the underlying assumptions need to be satisfied to establish consistency, unbiasedness, and efficiency in the estimates (Brooks, 2014, p.91). Another benefit to the assumptions being satisfied is that the estimated coefficients converge towards their true value when the sample size increase (Brooks, 2014). We present the test results for the classical assumptions of the OLS in Appendix IIB.

We start by testing the assumption of normality using a Quantile-Quantile plot comparing the data against a standard line with Gaussian distribution (Figure IIB.2), and we perform a Jarque-Bera test testing for normality (Table IIB.I). The p-value of the test shows to be zero, and we reject the null hypothesis (Table IIB.I). This result concludes that the data has skewness and kurtosis that is significantly different from the normal distribution. However, since the sample size is sufficiently large, the normality assumption is excessive since the Central Limit Theorem states that the distribution of the residuals will approximate normality; thus, it is desirable to proceed with OLS (Brooks, 2014, p.210-211).

The residuals should be homoscedastic to attain unbiased estimates, implying a constant variance (Brooks, 2014, p.93). To test for heteroscedasticity, we run a simple OLS regression on the markup for each trade. We test the estimates for heteroscedasticity using White's test for heteroscedasticity. The p-value of the test is zero, and we conclude that the standard errors are heteroscedastic (Table IIB.II). We will therefore use heteroskedastic robust standard errors in our estimation.

OLS assumes no autocorrelation and refers to the degree of correlation between values across different observations within the same or across different variables (Brooks, 2014). We start by visualizing a graphical plot of the residuals to detect autocorrelation where we observe a slight tendency of a pattern (Figure IIB.4). Then we perform a Durbin-Watson test to detect autocorrelation, a test for a relationship between an error and its immediately previous value (Brooks, 2014, p.194). The null hypothesis reflects zero autocorrelation, and the alternative hypothesis states that autocorrelation is present. The Durbin Watson test shows a value of 0.49, and the null hypothesis is rejected, meaning a presence of positive autocorrelation in the residuals (Table IIB.III).

However, the positive correlation can be explained by some of the variables being inherently autocorrelated or a result of omitted variable bias, which is common when dealing with economic data series. In addition, some of the included variables are related to each other and can be a cause for positive autocorrelation. Hence, we assume that any autocorrelation observed is present in the observations for each entity but not across entities. We evaluate this assumption in the robustness test, where we cluster the standard errors. As the PanelOLS model accounts for panel data structure, autocorrelation consistent standard errors are not supported. Hence, we proceed without further action regarding autocorrelation. However, we are aware that this could cause the standard errors to be biased and increase the probability of type 1 error. It can also cause inflation of the R^2 relative to its correct value (Brooks, 2014, p.199). Therefore, to minimize the risk of biased results, we are conservative when assessing the significance of our findings. With this in mind, we argue that OLS is the most appropriate method considering our data since other methods may not fully take advantage of the richness of the data or provide as many degrees of freedom.

Finally, OLS assumes that the explanatory variables are not correlated to one another. A multicollinearity issue will result in a high R^2, while the individual variables are not significant and will cause difficulty in observing the individual contribution of each variable to the overall fit of the regression (Brooks, 2014, p.218). We calculate the Variance Inflation Factor (VIF) of the explanatory variables to quantify the presence of multicollinearity in the OLS analysis (Kennedy, 2008, p.199). The VIF-test shows a higher value for the dummy variables, which is to be expected. However, the test detects no harmful collinearity in the other variables (Table IIB.IV). As we find no evidence of perfect or near multicollinearity and have a sufficient number of observations, we conclude pooled OLS being the most appropriate model for our analysis.

We then run an OLS regression on the markup for each trade with currency pairs included in Table IB.VII, using robust standard errors. The PanelOLS function accounts for panel data structure; hence we do not propose any lags in the model. Finally, we remove the intercept from the regression equation to avoid the dummy variable trap, where we have perfect multicollinearity between the intercept and the dummy variables (Brooks, 2014, p.529).

VII. Findings

We estimate the impact of price discrimination for Scandinavian corporations using an OLS model (Equation 8) with robust standard errors. Our findings confirm our initial hypothesis since the results clearly state that different Scandinavian corporations receive different markups from the same dealer or intermediary. Furthermore, we see that dealers rationally price discriminate along different dimensions, where the perceived sophistication of the client is a significant contributor.

Our main findings are that the client profile matters to the applied markup, and we observe new contributing variables not previously studied. The results are evaluated based on the components: information, market sophistication, inventory and operating costs, firm characteristics, and contract characteristics. We observe an R^2 of 0.4985, which is consistent with previous studies in this area; however, the included variables differ to some degree. In addition, the F-statistic of our regression model is significant at all levels, which implies that the coefficients are jointly significant and that the dependent variables improve the model's fit. With this said, our findings support previous research and conclude that price discrimination exists in the FX market.

Table I

Determinants of Scandinavian Forex Customer Markups

The table reports the results from equation (8):

$$Markup_{it} = \delta_1 Info_i + \gamma_1 Venue_t + \gamma_2 Subscription\ Just_t + \gamma_3 NCounterparties_i$$
$$+\gamma_4 Trade\ frequency_i + \psi_1 Credit_i + \psi_2 Operating\ years_i\ + \psi_3 Revenue_i$$
$$+\psi_4 Firm\ size_i + \psi_5 Public_i + \psi_6 Financial\ company_i$$
$$+\phi_1 ln\ (Size)_{it} + \phi_2 Large_t + \phi_3 Small_t + \theta_1 Contract\ duration_{it} + \theta_2 Customized_t + \varepsilon_{it}$$

The dependent variable *Markup* is the dealer's price on trade t over the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Credit* is a proxy for a company’s credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial company* is a zero-one dummy variable for companies operating within the asset management industry. *Ln(Size)* is the log of trade t’s amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week (once per business day). *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client trades registered on the Just platform through the period 2018-2021, with several Scandinavian and international dealers. Robust standard errors. No constant term. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Coefficient	Standard error
Information		
Info	-4.4256***	0.4156
Market sophistication		
Venue	-3.7824***	0.5984
Subscription Just	-3.5123***	0.1252
Number of counterparties	-5.8385***	0.2989
Trade frequency	-4.3975***	0.2563
Firm specific factors		
Credit	1.6637***	0.0839
Operating years	0.1317***	0.0145
Revenue	0.1538	0.4232
Firm size	-9.3619***	0.3906
Public	-8.9049***	0.3416
Financial company	-16.7720***	1.4243
Inventory and operating costs		
ln(Size)	0.8879***	0.0260
Large	-5.7789***	0.08237
Small	1.3964***	0.1988
Contract specific factors		
Contract duration	0.0438***	0.0022
Customized	-3.0776***	0.1469
R^2	0.4985	
N. Obs.	27 795	
Entities	150	
F-statistic	1 725***	

A. Information

<u>*Information*:</u> The *Info* coefficient is negative and statistically significant, which is consistent with the strategic dealing hypothesis developed by Naik et al. (1999). Implying that dealers can profit from the clients' information content when having access to interbank rates. These results contradict the results of Bjønnes et al. (2015), which finds that strategic dealing is not significant for small and medium enterprises. However, we do not exclude the possibility that large corporations can carry information of future flows in the FX market and, therefore, receive narrower spreads from the dealer.

We hypothesize that corporate clients are uninformed and that dealers will not profit or protect themselves from the clients' information content, meaning that clients' information content will not affect the markup. The results contradict our initial hypothesis. Instead, we find evidence of dealers profiting from corporations' information content and are therefore trying to attract informed clients by offering them a lower markup. However, the variable *Info* has relatively wide confidence levels (Table IB.XII), indicating less precise population estimates. This implication is not surprising since it is reasonable to assume a high spread across different clients' information content.

On the other hand, a non-positive coefficient supports the argument that adverse selection is not relevant in determining bid-ask spreads. Thus, the analysis supports the proposed altering of the current model where a price discrimination component should replace the adverse selection component. Further, we acknowledge that using daily prices might yield a less accurate result than using minute intervals. Thus, we should emphasize the implications of the coefficient rather than the coefficient's value itself.

B. Market Sophistication

<u>*Venue*:</u> The coefficient *Venue* is negative and statistically significant, supporting the findings of Bjønnes et al. (2015). Trading on a multibank platform (MBP) reduces the markup compared to trading directly with a dealer. However, as there is only one firm included in this study that operates on an MBP, we do not have sufficient evidence to state that the variable is significant. Therefore, we cannot

make any assumptions about the general population based on the included observations.

<u>*Subscription Just*</u>: The coefficient for the variable *Subscription Just* is significant and suggests that using the Just platform lowers the client's markup. This result is supported by Reitz et al. (2015), who find that based on the information the client holds, the dealer has more market power dealing with commercial clients compared to financial clients; therefore, the client achieves better prices carrying information. Osler et al. (2011) propose evidence for transitory market power; dealers can take advantage of the costs for companies to search for better quotes. As Just quantifies the markup over the interbank rate, potential areas for cost savings are disclosed, and clients do not need to search for information. This information might encourage the client to take advantage of the cost-saving potential and look for better quotes. The result is consistent with our hypothesis, and we find it feasible that sophisticated clients receive smaller markups than less sophisticated clients.

<u>*Number of counterparties*</u>: Our findings show that the variable *Number of counterparties* is significant, implying that having more than one counterparty reduces the expected markup by 5.8385 bps. The result is consistent with the theory of market power (Pepall et al., 2014); when a client has more than one counterparty, the bargaining power of the client increases while the dealer's market power weakens. Our findings are also consistent with Hau et al. (2019), who finds that clients who are trading with more than one dealer are considered more sophisticated. However, we do not estimate the marginal effect on the markup from additional counterparties. We consider this result as substantial as it has the most significant impact on the markup. Thus, we conclude that having external options reduces the dealer's market power and has the greatest enhancement in the market sophistication of the firm.

<u>*Trade frequency*</u>: Our analysis shows that clients trading more frequently receive a substantial discount on the markup. Clients who trade five times a week or more obtain a reduction in the markup of 4.3975 bps. The results align with Hau et al. (2021), which shows that clients trading frequently receive lower markups. As the coefficient is statistically significant and has an enormous impact on the markup, we consider this a substantial contribution to a firm's market sophistication. We

find it plausible that clients trading more frequently obtain better terms (Bernhardt et al., 2005) and that trading frequently also increases the client's bargaining power. In addition, if trading is a day-to-day task, the client has an incentive to assess the performance of their trades.

Summary: In our analysis, we observe that dealers rationally price discriminate based on the market sophistication of the client. Firms with more than one counterparty and that trade frequently benefit from the most significant reduction on the markup. This result shows that increased sophistication greatly reduces the market power of the dealer. We also find that the increased sophistication from quantifying the additional price benefits the clients as it significantly reduces their markup. In addition, confidence intervals of these variables support the conclusion (Table IB.XII)**.** Finally, our analysis supports the argument that clients get better spreads when trading on an MBP; however, our sample is not large enough to conclude.

C. Firm Characteristics

Credit: Our findings are statistically significant and imply that clients with sound financial health receive higher markups, contradicting our hypothesis and is inconsistent with economic theory. This effect could result from omitted variable bias or that the variable does not fully capture the client's bankruptcy risk. Since the dealers' internal practices for risk assessment of the clients is unknown, there is a possibility that the dealer does not account for bankruptcy risk in the pricing structure by only requiring collateral. Since most analyzed data consists of forward contracts (Table IB.I), the forward trades will significantly impact the overall results. We do not find it plausible that the variable is economically significant as we suspect that the variable does not capture how the dealers evaluate or treat counterparty risk. Due to the nature of spot trades, we do not expect the variable *Credit* to be significant on spot trades regardless.

Operating years: Based on our analysis, we find that a one-year increase in operating years results in a 0.1317 bps increase in the expected markup. A positive and statistically significant coefficient contradicts our initial expectations. However, considering the time aspect, one can argue that a pre-existing long-term relationship between a dealer and a client may affect the power dynamics between the two parties. We are arguing that the dealer can charge higher prices because of established client relations.

Revenue: The coefficient for the variable *Revenue* is not statistically significant. Therefore, we cannot establish a cause-and-effect relationship between the client's annual revenue and the expected markup. We estimate that companies with large revenue streams hold more market power than companies with smaller revenue streams. However, we only include the clients' revenue from 2019, which only gives a snapshot of the clients' financial situation, which can explain the result.

Firm size: As projected, firm size significantly impacts the markup clients receive and reduces the markup by 9.3619 basis points. It is expected for a company with many employees to have more sophisticated routines due to higher regulatory pressure and dedicated personnel. There is also a possibility that larger firms have more international exposure, incentivizing acquiring knowledge about trading in FX. Hence, we argue that firm size has a significant reduction in the markup.

Public: Our analysis shows that publicly listed companies receive lower markups equal to 8.9049 bps than private companies. We expect this could result from their position in the market, its size, and the perception of being knowledgeable. In addition, we estimate contributing factors to being a publicly listed company such as reporting standards, shareholder obligations, company structure, financial departments, and available resources.

Financial company: Our analysis supports the findings by Bjønnes et al. (2015) where financial companies on average pay less in the FX market than SMEs. Thus, financial companies receive a markup that is 16.7720 bps lower than the non-financial companies included in this study. Thus, showing that dealers rationally price discriminate based on the client and their financial experience.

Summary: We hypothesize that dealers' price discriminates based on company-specific factors. Our findings support our hypothesis, and we observe that price discrimination based on company-specific factors is present due to non-zero coefficients. All included variables are statistically significant at a 1% significance level, except the variable *Revenue,* which is not statistically significant. All variables have relatively low standard errors, except for the variable *Financial company,* which has the largest standard error of 1.4243 due to few clients represented in the category. We observe that being a financial company has the most significant impact on the markup. In addition, we observe that being a public company and a large firm have a relatively immense effect on the markup and reduce the markup received by 8.9049 bps and 9.3619 bps, respectively. However, we suspect there is a chance the variables impact each other, affecting the precision of the variables. We find that the variables *Credit* and *Operating years* are not in line with our initial expectations and positively affect the expected markup clients receive. We do not see it reasonable that the *Credit* variable is economically significant. We believe that the variable cannot capture the client's bankruptcy risk or correlates with an unobservable variable. To conclude, we find evidence that dealers also price discriminates based on client-specific factors. The most critical factors that negatively impact markup are financial experience and how knowledgeable the client is perceived.

D. Inventory Risk and Operating Costs

Ln(Size): Our analysis shows that the markup is expected to increase as the trade size increases. We find this consistent with inventory costs increasing with trade size. The variable measures the natural logarithm of the trade size, meaning the increase in costs will lessen with trade size. We propose this as an effect of inventory costs rising with trade size while the total costs represent a smaller proportion as trade size increases.

Large: Our analysis shows that the markup is expected to decrease for large trades above 5 million USD. This result contradicts the results by Bjønnes et al. (2015), which predicts that large trades are more difficult to net internally and thus become more expensive. As our analysis results in a negative coefficient, we find it likely that this variable could be influenced by the volume discount hypothesis by Bernhardt et al. (2005). However, we are not able to estimate these effects individually, given the available data. In addition, the variable has a more significant impact than expected, which is why we allow for the possibility that the variable also measures something unexplained by the regression equation, thus inflating the coefficient.

Small: The coefficient is positive and statistically significant for trades smaller or equal to 1 000 USD. Small trades result in a 1.3964 bps increase in the client's expected markup, aligning with our expectations. Smaller trades should result in a wider spread since the proportion of fixed costs is expected to be higher than that of larger trades.

Summary: Our analysis supports the hypothesis that the inventory and operating costs increase in trade size. All results are significant at the 1% level. The confidence interval for *ln(size)* is narrow, and a low standard error supports our conclusion (Table IB.XII). However, the variable *Large* displays wide confidence intervals, which indicate weakness in the variable (Table IB.XII). We are therefore not able to conclude that large trades in themselves imply a discount on the markup. However, we find evidence that small trades result in a higher markup than larger trades.

E. Contract Characteristics

<u>*Contract duration*</u>: In our analysis, we use contract duration as a control variable. Our analysis shows that when the duration of a trade increases by one business day, the expected markup increases by 0.0438 bps. This variable should then capture the difference between short-term and long-term trades. A positive coefficient implies that dealers include a premium for uncertainty for forward contracts with longer maturity. These results are consistent with the findings of Hau et al. (2019), which argues that dealers charge higher spreads for long-maturity contracts in compensation for greater market risk. However, the applied premium may differ between dealers as a result of a lack of transparency. Hence, the dealer may exercise price discrimination in this area as well.

<u>*Customized*</u>: Our analysis predicts that customized contracts receive a discount of 3.0776 bps, and the variable is significant at all levels. This result contradicts previous research by Hau et al. (2019) and the hypothesis that standardized contracts trade at a lower cost. However, it is plausible that the variable captures an effect unexplained by the regression equation or that these clients are more familiarized with the FX market and have better leverage with the dealer. Therefore, we cannot state that the variable is economically significant even though it is statistically significant, as the results contradict both theory and past research.

Summary: In conclusion, our analysis supports previous findings by Hau et al. (2019), where the price increases as the tenor length increases, while it contradicts the hypothesis that standardized contracts trade at a lower cost. We observe narrow confidence intervals (Table IB.XII) for the variable *Contract duration* and low standard errors. Thus, we are confident when we conclude that dealers charge an extra cost for increased market risk, not reflected by the interest rate differential and time value of money. We argue that dealers take advantage of the increased market risk for long-term contracts by including a significant premium on the implied price of the forward rates. Hence, long-term contracts may impose a substantial cost to customers as we estimate that a contract of 252 business days points to an additional charge of 11.44 bps.

VIII. Robustness Tests

As a supplement to the empirical analysis, we examine the robustness of our results by including new control variables, subsampling, and clustering the standard errors. In the first robustness test, we include new control variables for each currency pair. The first test assesses the robustness of the estimated coefficients while allowing for variation in the currency pairs. In the second robustness test, we subsample the data into only including trades for NOKEUR. This test aims to measure the robustness of our variables where they are less impacted by currency pairs. In the final robustness test, we cluster the standard errors by entity. With this robustness test, we aim to account for situations where the observations within each entity are not independent and identically distributed (i.i.d.).

A. Controlling for Currency Pairs

We include a zero-one dummy variable for each currency pair in this test, using EURUSD as the reference currency pair. As a result, we observe a significant difference in the estimated bps between each pair (Table IB.VIII). We observe a greater markup for clients that trade between Scandinavian pairs than for trades that involve EUR or USD which is to be expected due to liquidity in the market. All the coefficients are significant, except for the variable *Venue*. Most importantly, we observe that the coefficient signs remain which supports our findings (Table IB.VIII).

B. Subsampling

In this test, we only include observations involving the pair NOKEUR, isolating the impact of our estimated variables without accounting for different currency pairs. This dataset contains about 5 500 observations for 150 entities. The estimated regression significantly increases R^2, implying higher explanatory power of the variables (Table IB.IX). The variable *Info* is no longer significant while the variable *Revenue* continues not to be significant. As the variable *Info* is not significant it is also consistent with the expectations that corporate firms are treated as uninformed, meaning that dealers do not trade on the information they hold. Finally, there is a change in the signs for the variables *Firm size* and *Customized* (Table IB.IX). The result for *Customized* is now in line with the results of Hau et al. (2021) and our expectations.

C. Clustered Standard Errors

In panel data, each cluster may typically represent one entity. Therefore, clustering by entity allows for heteroscedasticity and autocorrelation within each entity, while treating the errors as uncorrelated across entities. Thus, in the final test, we cluster the standard errors by entity to account for unexplained variation in the dependent variable that is correlated across time and cluster by time to control for correlation between entities in a time period. As a result, we find that clustering by entity reduces the t-statistics (Table IB.X), which shows that there are some unexplained variations that are correlated across time. However, clustering by time has no additional contribution to the t-statistics after correlation within each entity has been controlled for (Table IB.X), which implies independence across entities. Thus, the result supports our assumption that autocorrelation is only present within the observations for each unit.

When we account for the autocorrelation within each entity, we do not have to be as conservative in the significance levels. Therefore, most variables are still significant at the 10% significance level except for *Venue*, *Trade frequency*, *Operating years*, *Revenue*, and *Small* (Table IB.XI). We consider this a result of either not enough observations for each variable or a lack of previous research supporting the relevance of the variable, thus causing ambiguous results in the initial analysis. The variable *Info* is also no longer significant, and we can therefore not accurately state that strategic dealing is relevant for corporations. This result supports previous research (Bjønnes et al., 2015) and implies that dealers do not expect to profit from interdealer trading based on the information corporate clients carry. Further, we are comfortable when stating that adverse selection is not relevant in this case, supporting previous research. When accounting for autocorrelation, information appears irrelevant when explaining the markup for corporations. The finding is consistent with corporations limited incentive to gather information as trading is not their primary source of value creation and that they rarely engage speculative trading (Osler, 2006). For the remaining variables, we are comfortable in our analysis and interpretation.

IX. Conclusion

In this paper, we provide an empirical analysis of price discrimination in the FX market. We investigate different factors behind the spread faced by Scandinavian corporations to determine to what extent one can explain the expected markup in the foreign exchange market.

The data used in this paper allows us to study the actual FX markup at a more specific level than previous studies on the topic. To our knowledge, this is the first study to examine the existence of price discrimination between entities and not just between categories of customers. Thus, the data confirms already established relationships in addition to validating new hypotheses.

This paper supports the findings of that the structural differences between auction-based markets and decentralized OTC markets allow the dealer to price discriminate based on lack of pre-trade anonymity. Implying that the adverse selection component should be replaced by a price discrimination component when determining the spread set by the dealer. In addition, the structural difference also affects the client's ability to compare quotes. Clients who trade in auction-based markets can compare quotes directly, while clients trading in OTC markets are forced to search for competitive quotes across dealers, representing an additional cost. This paper also supports the findings of Reitz et al. (2015), that the structure of OTC markets allows for different market power dynamics between the client and the dealer because of information asymmetry. Thus, we find that dealers will quote narrower spreads to more sophisticated clients consistent with Duffie et al. (2007) and Green et al. (2007) and clients with higher trading volume (Bernhardt et al., 2005).

Hau et al. (2019) conclude that clients with a high credit score obtain better rates and that customized contracts should trade at a higher cost than standard contracts. Our results contradict these hypotheses as a high credit score implies a more significant markup and customized contracts trade at a discount. However, we suspect that an unobservable factor influences these variables or that the variable *Credit* does not fully capture the client's bankruptcy risk.

This study provides new results, breaking the unknown, by examining the presence of price discrimination based on the customer rather than by type of customer and observing the effect of an increased level of sophistication over time. The data allows us to study new effects and conclude that price discrimination also exists at this level. Our proposed model captures the expected markup through five main components with an explanatory power of 49%; thus, we estimate unobservable contributing factors not included in this model. We propose this to be related to the dealer's ability to estimate each client's willingness to pay and the dealer's ability to make a profit.

We conclude that the markup is explainable. Having several counterparties, trading more frequently, trading in larger volumes, and quantifying the markup using the Just platform contributes to a lower trade cost. In addition, we state that large firms and publicly listed firms obtain a discount compared to smaller private firms. However, we also see that having long-term bank relations and trading in long-term contracts impose a significant additional cost.

The main implications of this study are increased awareness of the pricing in FX markets and thus enhanced transparency. Clients may use the information to evaluate their appropriate spread and alter their expectations with new information going forward. Therefore, an implication of this study is that it will reduce the dealer's market power and thus his ability to make a profit. Another implication of increased awareness in FX markets is that both clients and dealers can make more informed decisions, making it harder for dealers to mislead the clients regarding price, leading to a competitive and transparent marketplace.

Propositions to Future Research

For future research, we recommend implementing a more balanced dataset to fully take advantage of the benefits of using panel data. With a more extended dataset, it opens the possibility to study the effects across time. We also recommend using a randomly collected sample. A random sample will eliminate any possible bias where firms with higher markups are more prone to being included in the study. We also recommend testing if the results apply to other geographical areas with different economies to determine if the results are generalizable.

We suggest incorporating qualitative and quantitative data, contributing to an increased understanding of drivers behind market sophistication. Finally, we would recommend studying the marginal effect of additional counterparties. Qualitative data could allow for a better understanding of the impact on a dealer's market power and enhanced market sophistication.

References

Armstrong, M. (2005). Recent Developments in the Economics of Price Discrimination. *Advances in Economics and Econometrics: Theory and Applications: Ninth World Congress*, *2*. https://doi.org/10.1017/CBO9781139052276.006

Bernhardt, D., Dvoracek, V., Hughson, E., & Werner, I. M. (2005). Why Do Larger Orders Receive Discounts on the London Stock Exchange? *The Review of Financial Studies*, *18*(4), 1343–1368.

Bjønnes, G. H., & Kathitziotis, N. (2018). Hva koster det å kjøpe og selge valuta? *Praktisk økonomi & finans*, *34*(03), 239–254. https://doi.org/10.18261/issn.1504-2871-2018-03-07

Bjønnes, G., Kathitziotis, N., & Osler, C. (2015). *Price Discrimination and the Cost of Liquidity in OTC Markets*. 43.

Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd Edition). Cambridge University Press.

Cardoso, R., & Tsoni, M. (2019, May 16). *Antitrust: Commission fines five banks €1.07 billion* [Text]. European Commission - European Commission. https://ec.europa.eu/commission/presscorner/detail/en/IP_19_2568

Christina Davis. (2020, June 1). *Price-Fixing Conspiracy Class Action Lawsuit Certified Against Dozens of Banks*. Top Class Actions Canada. https://ca.topclassactions.com/lawsuit-settlements/banking-news/price-fixing-conspiracy-class-action-lawsuit-certified-against-dozens-of-banks/

Duffie, D., Gârleanu, N., & Pedersen, L. H. (2007). Valuation in Over-the-Counter Markets. *The Review of Financial Studies*, *20*(6), 1865–1900. JSTOR.

Edwards, A. K., Harris, L. E., & Piwowar, M. S. (2007). Corporate Bond Market Transaction Costs and Transparency. *The Journal of Finance*, *62*(3), 1421–1451. JSTOR.

Esteves, R.-B. (2014). Price Discrimination with Private and Imperfect Information. *The Scandinavian Journal of Economics*, *116*(3), 766–796.

Fagerström, A., & Lundh, S. (2009). Accounting development in the Nordic countries: A comparative study. *J. for Global Business Advancement*, *2*. https://doi.org/10.1504/JGBA.2009.023091

FX Foward Market—FX Forward Points. (n.d.). Genbaforex. Retrieved February 25, 2021, from https://www.genbaforex.com/forward-points

Green, R. C., Hollifield, B., & Schürhoff, N. (2007). Financial Intermediation and the Costs of Trading in an Opaque Market. *The Review of Financial Studies*, *20*(2), 275–314. https://doi.org/10.1093/rfs/hhl012

Hagelin, N. (2003). Why firms hedge with currency derivatives: An examination of transaction and translation exposure. *Applied Financial Economics*, *13*(1), 55–69. https://doi.org/10.1080/09603100110094501

Hau, H., Hoffmann, P., Langfield, S., & Timmer, Y. (2019). Discriminatory Pricing of Over-the-Counter Derivatives. *INTERNATIONAL MONETARY FUND*, *2019/100*, 45. http://dx.doi.org/10.5089/9781498303774.001

Hau, H., Hoffmann, P., Langfield, S., & Timmer, Y. (2021). Discriminatory Pricing of Over-the-Counter Derivatives. *Management Science*, mnsc.2020.3787. https://doi.org/10.1287/mnsc.2020.3787

Ho, T., & Stoll, H. R. (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, *9*(1), 47–73. https://doi.org/10.1016/0304-405X(81)90020-9

Huang, R. D., & Stoll, H. R. (1997). The Components of the Bid-Ask Spread: A General Approach. *The Review of Financial Studies*, *10*(4). http://www.business.unr.edu/faculty/liuc/files/RUC/topic_bidask/Huang_Stoll_1997.pdf

Hull, J. C. (2018). *Risk Management and Financial Institutions* (5th edition). John Wiley & Sons, Inc.

Jacquemin, A. P. (1972). Market Structure and the Firm's Market Power. *The Journal of Industrial Economics*, *20*(2), 122–134. https://doi.org/10.2307/2098240

Kennedy, P. (2008). *A guide to econometrics* (6th ed.). Blackwell Publishing.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, *53*(6), 1315–1335. https://doi.org/10.2307/1913210

Nærings- og handelsdepartementet. (2012). *Små bedrifter – store verdier*. 107.

Naik, N. Y., Neuberger, A., & Viswanathan, S. (1999). Trade Disclosure Regulation in Markets with Negotiated Trades. *The Review of Financial Studies*, *12*(4), 873–900. https://doi.org/10.1093/rfs/12.4.873

Osler, C. L. (2006). Macro lessons from microstructure. *International Journal of Finance & Economics*, *11*(1), 55–80. https://doi.org/10.1002/ijfe.288

Osler, C. L., Mende, A., & Menkhoff, L. (2011). Price discovery in currency markets. *Journal of International Money and Finance*, *30*(8), 1696–1718. https://doi.org/10.1016/j.jimonfin.2011.08.004

Pepall, L., Richards, D., & Norman, G. (2014). *Industrial Organization—Contemporary Theory and Empirical Applications* (5 th edition). Wiley.

Proff® – Nøkkeltall, Regnskap og Roller for norske bedrifter. (n.d.). Retrieved May 16, 2021, from https://proff.no/

Proff^{TM} – Nøgletal, Regnskaber og Roller for danske virksomheder. (n.d.). Retrieved May 16, 2021, from https://proff.dk/

Proff^{TM} – Nyckeltal, Resultatredovisning och Befattningar för svenska företag. (n.d.). Retrieved May 16, 2021, from https://proff.se/

Reitz, S., Schmidt, M. A., & Taylor, M. P. (2015). Financial intermediation and the role of price discrimination in the foreign exchange market. *The European Journal of Finance*, *21*(8), 629–645. https://doi.org/10.1080/1351847X.2013.830139

Sueppel. (2016, April 14). *Understanding bid-offer spreads in OTC markets | Systemic Risk and Systematic Value*. https://www.sr-sv.com/understanding-bid-offer-spreads-in-otc-markets/

Wolf Popper LLP. (n.d.). *Foreign Exchange (FOREX) Benchmark Rates Antitrust Litigation | Case*. Wolf Popper LLP. Retrieved October 29, 2020, from https://www.wolfpopper.com/case.cfm?ID=1149

I. Appendix A

IA. Figures

Figure IA.1

Distribution of Revenues Denoted in USD

The figure illustrates the total revenue in 2019 for each entity included in the study. The majority of entities report revenue that exceeds 100 000 000 USD in 2019.

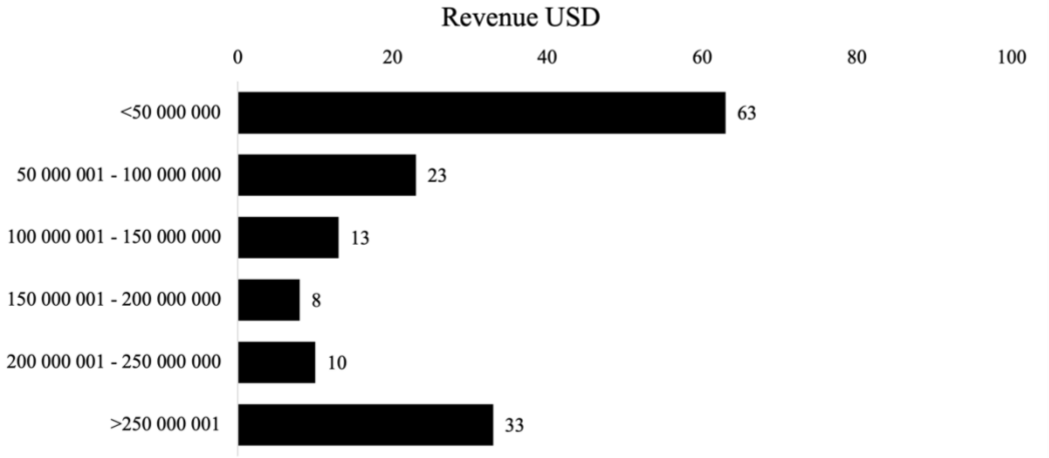


Figure IA.2

Distribution of the Number of Employees per Entity

The figure shows the distribution of the number of employees per analyzed entity as of 31.12.19. Most entities report less than 100 employees.

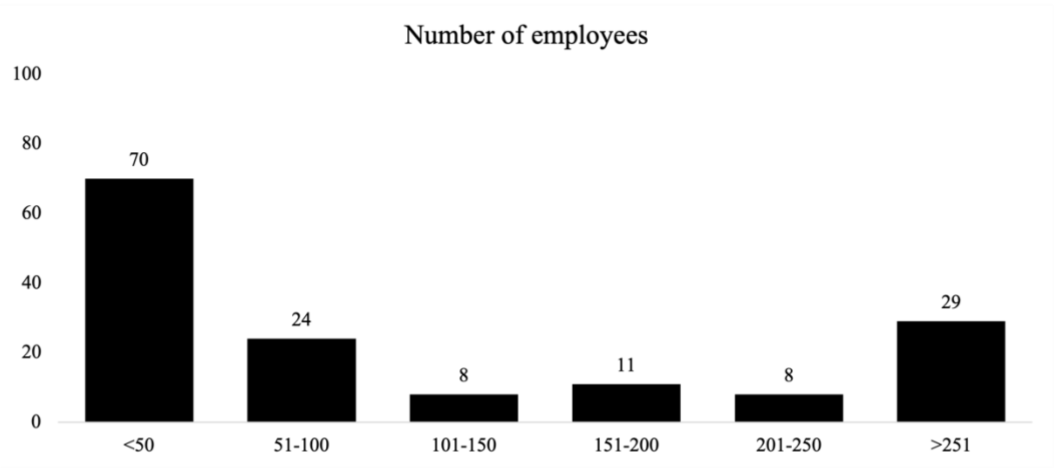


Figure IA.3

Distribution of Operating Years per Entity

The figure shows the distribution of operating years of the included entities per 31.12.19. The majority of companies have been operating for over 15 years.

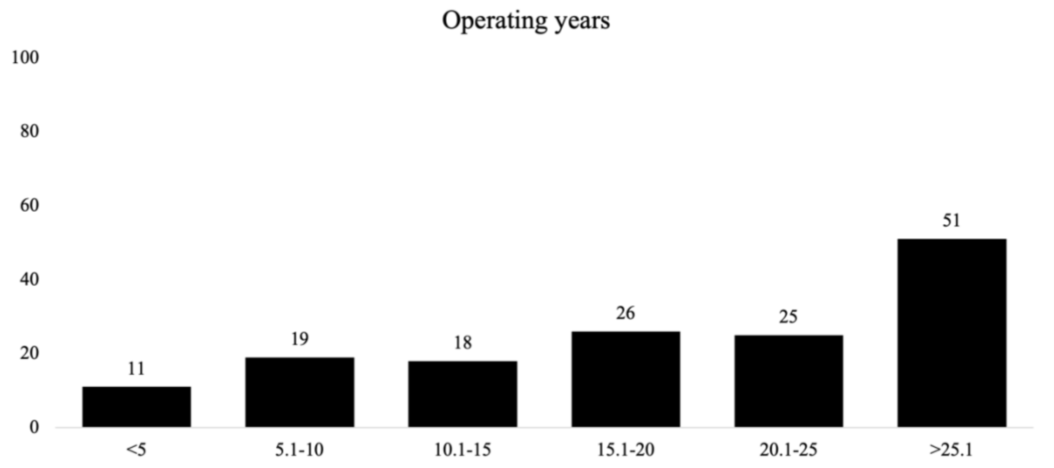


Figure IA.4

Distribution of Entities per Industry

The figure shows the total number of entities analyzed categorized by industry.

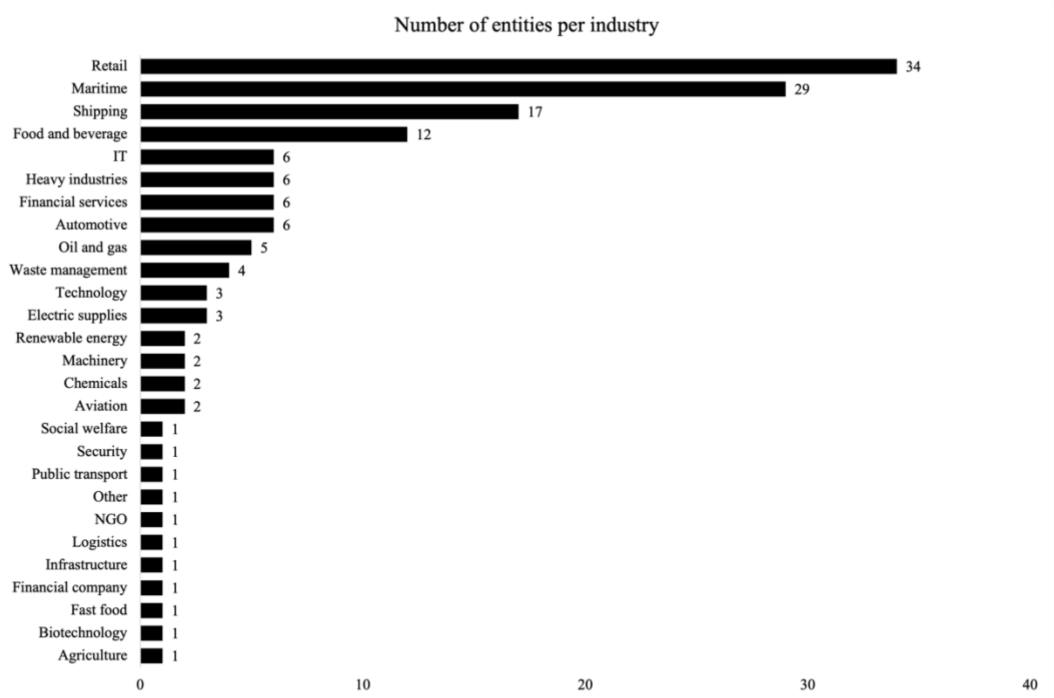
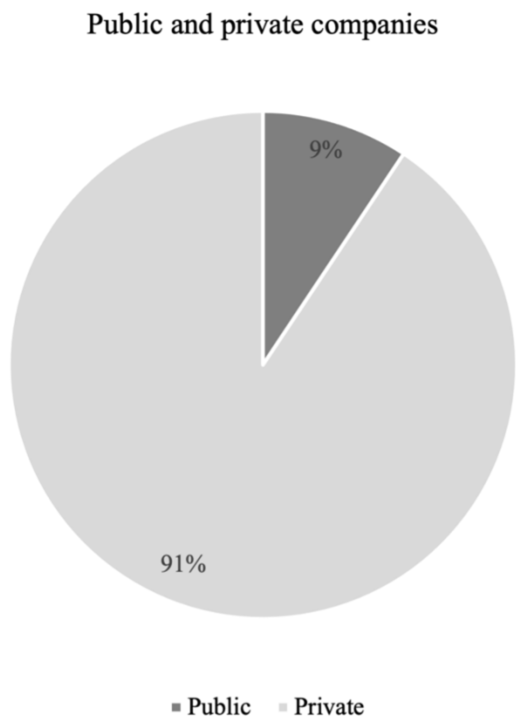


Figure IA.5

Percentage of Public and Private Corporations

The figure shows the total number of companies analyzed categorized by industry.



IB. Tables

Table IB.I

Descriptive Statistic of the Data Sample

A general overview of the basic features of the dataset.

	Total
Clients	150
Average bps	5.61
Minimum bps	-34.74
Maximum bps	95.22
Median bps	3.84
Unique dealers	21
Observations	27 795
SPOT trades	1 965
Forward trades	25 830

Table IB.II

Average Markup and Trading Amount (USD) by Tenor Length

An overview of the average markup bps based on the traded contracts tenor length before and after the client subscribed to the Just platform.

Tenor Length	Average bps *Before*	Average bps *After*
SPOT	9.77	5.17
TOD	16.25	9.76
TOM	12.76	5.39
SN	3.13	2.86
1-3 WEEKS	4.89	2.17
1-2 MONTHS	6.47	1.39
3-4 MONTHS	5.27	2.92
5-6 MONTHS	9.80	7.265
7-8 MONTHS	11.93	11.24
9-10 MONTHS	10.66	5.76
11-12 MONTHS	11.65	
2 YEAR	55.98	

Table IB.III

Overview of Formulas used to Determine Bankruptcy Risk

The table presents the weights applied to each accounting ratio inspired by Altman's Z-score. We calculate each entity's score to estimate the counterparty risk included in the pricing of forward contracts.

Ratio	Equation
Altman Z-score	$Z_{score} = \frac{1.2 * Liquidity + 3.3 * Profitability + 0.6 * Solvency}{3}$

Table IB.VI

Classification of Accounting Ratios

The table presents how the liquidity-, profitability- and solidity ratios are classified, 1 is considered a weak score, and 5 implies a high score.

Evaluation	Score	Liquidity ratio	Profitability (%)	Solidity (%)
Not satisfactory	1	<0.50	<1.00	<3.00
Weak	2	0.50-0.99	1.00-5.90	3.00-9.00
Satisfactory	3	1.00-1.49	6.00-9.90	10.00-17.00
Good	4	1.50-2.00	10.00-15.00	18.00-40.00
Very good	5	>2.00	>15.00	>40.00

Table IB.VII

Number of Observations per Currency Pairs

The table illustrates the currency pairs included in equation 8, representing the most frequent and liquid currency pairs. The sample contains 27 775 unique observations.

Currency pairs	Observations
EURUSD	423
NOKUSD	6 633
NOKEUR	5 478
NOKSEK	1 556
NOKDKK	556
SEKUSD	3 058
SEKEUR	9 048
SEKDKK	459
DKKUSD	585
Number of observations	27 795
Number of entities	150

Table IB.VIII

Robustness Test: Controlling for Differences Between Currency Pairs

Table reports extensions and robustness tests for equation (8). Below, the results are controlled for differences between currency pairs where we include a dummy variable for the different combinations. The variable for EURUSD trades is dropped and thus the reference. The dependent variable *Markup* is the dealers' price on trade *t* above the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Ln(Size)* is the log of trade t's amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week. *Credit* is a proxy for a company's credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial*

company is a zero-one dummy variable for companies operating within the asset management industry. *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client trades registered on the Just platform through 2018-2021, with several Scandinavian and international dealers. Robust standard errors. No constant term. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Coefficient	Standard error
Information		
Info	-5.0063***	0.4356
Market sophistication		
Venue	-0.3824	1.0281
Subscription Just	-3.2822***	0.1292
Number of counterparties	-6.1453***	0.3409
Trade frequency	-4.0015***	0.2793
Firm specific factors		
Credit	1.1807***	0.1070
Operating years	0.1155***	0.0139
Revenue	-1.3875***	0.4282
Firm size	-7.6830***	0.4253
Public	-7.6284***	0.3500
Financial company	-18.777***	0.9141
Inventory and operating costs		
ln(Size)	0.6719***	0.0302
Large	-5.2828***	0.7547
Small	1.0829***	0.1966
Contract specific factors		
Contract duration	0.0436***	0.0021
Customized	-2.3573***	0.1540
Currency pairs		
NOKEUR	5.7944***	0.5490
SEKEUR	2.3814***	0.6201
NOKUSD	7.1422***	0.5123
SEKUSD	3.9875***	0.6713
DKKUSD	9.0611***	0.6685
NOKSEK	11.643***	0.6121
NOKDKK	11.822***	0.7092
DKKSEK	5.5907***	0.7683
R^2	0.5255	
N. Obs.	27 795	
Entities	150	
F-statistic	1 281***	

Table IB.IX

Robustness Test: Subsampling by Currency Pairs

Table reports robustness test for equation (8). Below, the data is subsampled into NOKEUR trades. The dependent variable *Markup* is the dealer's price on trade *t* in above the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Ln(Size)* is the log of trade t's amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week. *Credit* is a proxy for a company's credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial company* is a zero-one dummy variable for companies operating within the asset management industry. *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client NOKEUR trades registered on the Just platform through 2018-2021, with several Scandinavian and international dealers. Robust standard errors. No constant term. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Coefficient	Standard error
Information		
Info	0.4947	0.6985
Market sophistication		
Venue	-10.011***	1.0458
Subscription Just	-0.6192***	0.2256
Number of counterparties	-5.2877***	0.5948
Trade frequency	-5.1920***	0.5884
Firm specific factors		
Credit	0.5727***	0.1324
Operating years	0.2991***	0.0302
Revenue	-0.3307	0.5666
Firm size	2.2903***	0.8109
Public	-7.6514***	0.5750
Financial company	-10.357***	0.6969
Inventory and operating costs		
ln(Size)	0.4658***	0.0565
Large	-4.9197***	1.0112
Small	5.0162***	0.8610
Contract specific factors		
Contract duration	0.0232***	0.0017
Customized	0.7390***	0.2375
R^2	0.6702	
N. Obs.	5 478	
Entities	150	
F-statistic	693***	

Table IB.X

Robustness Test: Clustered Standard Errors

Table reports the t-statistics for robustness tests for equation (8). Below, the standard errors are clustered by entity, and by time and entity combined.
The dependent variable *Markup* is the dealers' price on trade *t* above the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Ln(Size)* is the log of trade t's amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week. *Credit* is a proxy for a company's credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial company* is a zero-one dummy variable for companies operating within the asset management industry. *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client trades registered on the Just platform through 2018-2021, with several Scandinavian and international dealers.

Variable	T-statistic robust standard errors	T-statistic entity clustered standard errors	T-statistic time-entity clustered standard errors
Information			
Info	-10.6477	-1.2799	-1.2799
Market sophistication			
Venue	-6.3212	-0.9517	-0.9517
Subscription Just	-28.0626	-2.4057	-2.4057
Number of counterparties	-19.5345	-1.7622	-1.7622
Trade frequency	-17.1588	-1.5047	-1.5046
Firm specific factors			
Credit	19.8343	2.4349	2.4349
Operating years	9.0953	0.8609	0.8609
Revenue	0.3634	0.0328	0.03278
Firm size	-23.9697	-2.3592	-2.3591
Public	-26.0694	-2.2938	-2.2938
Financial company	-11.7759	-3.9631	-3.9629
Inventory and operating costs			
ln(Size)	34.1971	2.8569	2.8568
Large	-7.0158	-2.4947	-2.4947
Small	7.0235	1.2849	1.2848
Contract specific factors			
Contract duration	20.3594	2.7643	2.7643
Customized	-20.9458	-1.8812	-1.8812

Table IB.XI

Robustness Test: Entity Clustered Standard Errors

The table reports a robustness test for equation (8). Below, reports entity clustered standard errors. The dependent variable *Markup* is the dealers' price on trade *t* above the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Ln(Size)* is the log of trade t's amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week. *Credit* is a proxy for a company's credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial company* is a zero-one dummy variable for companies operating within the asset management industry. *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client trades registered on the Just platform through 2018-2021, with several Scandinavian and international dealers. Entity clustered standard errors. No constant term. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Coefficient	Standard error
Information		
Info	-4.4256	3.4577
Market sophistication		
Venue	-3.7824	3.9742
Subscription Just	-3.5123**	1.4599
Number of counterparties	-5.8385*	3.3132
Trade frequency	-4.3975	2.9226
Firm specific factors		
Credit	1.6637**	0.6833
Operating years	0.1317	0.1530
Revenue	0.1538	4.6898
Firm size	-9.3619**	3.9683
Public	-8.9049**	3.8822
Financial company	-16.7719***	4.2321
Inventory and operating costs		
ln(Size)	0.8879***	0.3108
Large	-5.7789**	2.3164
Small	1.3964	1.0868
Contract specific factors		
Contract duration	0.0438***	0.0158
Customized	-3.0776*	1.6360

Table IB.XII

Detailed Version of Determinants of Scandinavian Forex Customer Markups

The table reports the results from equation (8):
The dependent variable *Markup* is the dealer's price on trade *t* above the interbank rate for client *i*. *Info* measures the extent to which clients are informed by their post-trade returns. *Venue* is trades that occurred on a Multibank platform. *Subscription Just* is trades that occurred after a client started using the Just platform. *Number of counterparties* is a zero-one dummy variable for clients with more than one counterparty. *Ln(Size)* is the log of trade t's amount measured in USD. *Large* is a zero-one variable for trades larger than five million USD. *Small* is a zero-one variable for trades smaller than 1 000 USD. *Trade frequency* is a zero-one dummy variable for clients that trade more than five times per week. *Credit* is a proxy for a company's credit rating. *Operating years* show how long a company has been in business. *Revenue* is a zero-one dummy variable for firms with more than 50 million USD in revenue. *Firm size* is a zero-one dummy variable for companies with more than 250 employees. *Public* is a zero-one dummy variable for publicly listed companies. *Financial company* is a zero-one dummy variable for companies operating within the asset management industry. *Contract duration* is the length of a contract in business days. *Customized* is a zero-one dummy variable for trades with a broken tenor.
Data include Scandinavian client trades registered on the Just platform through 2018-2021, with several Scandinavian and international dealers. Robust standard errors. No constant term. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The table shows the 95% confidence intervals (CI) for each coefficient.

Variable	Coefficient	Standard error	Lower CI	Upper CI
Information				
Info	-4.4256***	0.4156	-5.2402	-3.6109
Market sophistication				
Venue	-3.7824***	0.5984	-4.9552	-2.6096
Subscription Just	-3.5123***	0.1252	-3.7576	-3.2670
Number of counterparties	-5.8385***	0.2989	-6.4243	-5.2527
Trade frequency	-4.3975***	0.2563	-4.8998	-3.8951
Firm specific factors				
Credit	1.6637***	0.0839	1.4993	1.8281
Operating years	0.1317***	0.0145	0.1033	0.1601
Revenue	0.1538	0.4232	-0.6757	0.9833
Firm size	-9.3619***	0.3906	-10.127	-8.5964
Public	-8.9049***	0.3416	-9.5744	-8.2354
Financial company	-16.7720***	1.4243	-19.564	-13.980
Inventory and operating costs				
ln(Size)	0.8879***	0.0260	0.8370	0.9388
Large	-5.7789***	0.08237	-7.3934	-4.1644
Small	1.3964***	0.1988	1.0067	1.7861
Contract specific factors				
Contract duration	0.0438***	0.0022	0.0396	0.0480
Customized	-3.0776***	0.1469	-3.3656	-2.7896
R^2	0.4985			
N. Obs.	27 795			
Entities	150			
F-statistic	1 725***			

II. Appendix B

IIA. Definition of Terms

Price discrimination: Occurs when firms can sell similar products with the same marginal cost at different prices. Thus, clients may receive different prices depending on their marginal willingness to pay or their characteristics.
Market power: A measure of the ability of a market participant to charge prices exceeding marginal cost. The structure of the market lays premises for how market power is distributed among the different market participants.
Interdealer market: A global trading market that is only accessible to financial institutions. The interdealer market is also an OTC market, but financial institutions can execute trades through their trading terminals.
Market sophistication: Can be described by the level of awareness of one's marketplace, including knowledge of the market, access to market makers and investors.
Adverse selection: Describes a negative result that occurs when buyers and sellers have access to different information. Sellers may set higher prices for informed buyers to protect themselves against the information content they hold.
Forward contract: A standardized or customized contract between two counterparties to buy or sell an asset at an agreed price on a future date. The price of the contract is determined by the current spot rate and forward points that are a component of the interest rate differential between the two currency pairs (*FX Foward Market - FX Forward Points*, n.d.). As the contract settles on a future date, the contract is subject to default risk, which the dealer may incorporate in the price.
SPOT trade: A trade that settles within two banking days after the transaction, so it does not consider the time value of the payment, and hence there is no default risk involved.
Volume hypothesis: Findings by Bernhardt et al. (2005) show that in OTC markets (a dealer market), dealers will offer greater price improvements to regular clients, and, in turn, these clients optimally choose to submit large orders. Hence, price improvement and trade size should be negatively correlated in a dealer market.

Credit risk hypothesis: Dealers may incorporate a premium or require collateral to protect themselves against default risk. Credit risk only applies to forward contracts.

Customization hypothesis: Standardized contracts should trade at a lower cost than non-standardized contracts.

Bid-ask spreads in OTC markets: The bid-ask spread reflects the price of liquidity, which is assumed to be determined by adverse selection, inventory costs, and operating costs.

Inventory costs: The market maker's costs of holding securities of derivatives on his/her balance sheet, which includes capital cost and a premium for the risk carried. (Sueppel, 2016)

Operating costs: The cost for executing a transaction that is both fixed and variable.

IIB. Standard Robustness Tests

Table IIB.I

Jarque-Bera Test for Normality

The table presents the results of the Jarque-Bera test for normality. The null hypothesis states that the sample dataset skewness and kurtosis match a normal distribution. The p-value of the Jarque-Bera test is zero. Therefore, we reject the null hypothesis and conclude that the dataset has skewness and kurtosis that do not match the normal distribution.

Metric	Value
Jarque-Bera statistics	251 165.10
Jarque-Bera p-value	0.00

Figure IIB.1

Distribution of Observations in the Sample

The figure shows the distribution of the dataset. As shown, the distribution of the dataset does not fit the normal distribution.

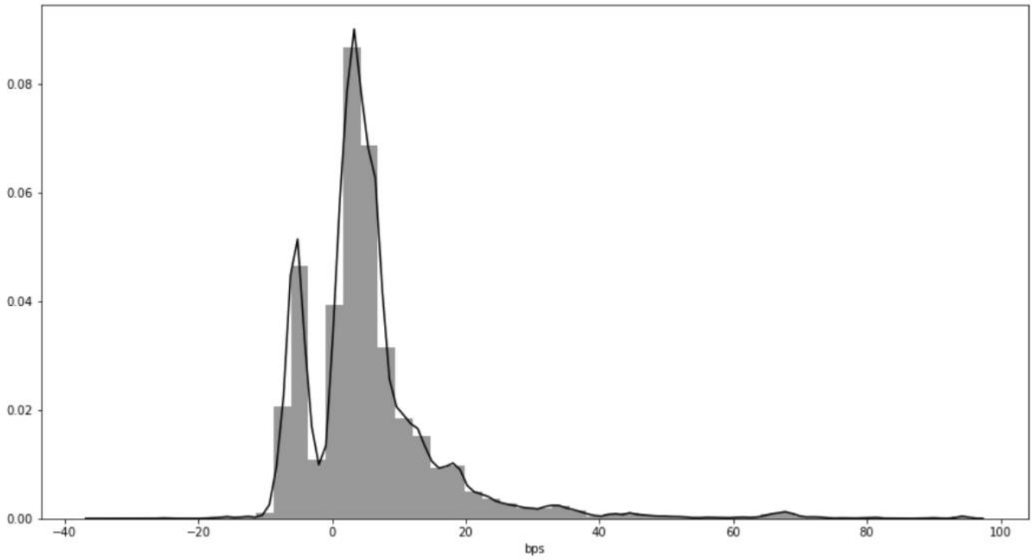
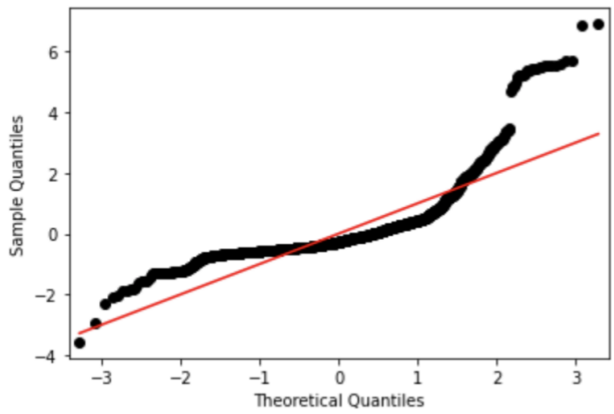


Figure IIB.2

Quantile-Quantile Plots for SPOT Trades and Forward Contracts

The figure shows the theoretical Quantile-Quantile plot. As can be observed, there is evidence of large outliers in the dataset. Plot A illustrates the distribution of spot trades, and plot B illustrates the distribution of forward contracts.

Plot A



Plot B

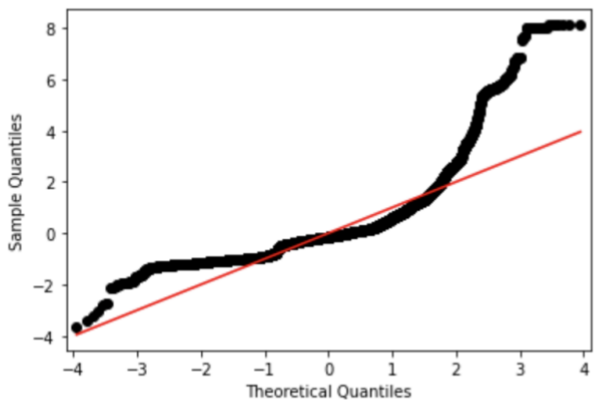


Figure IIB.3

Fitted vs. Non-Fitted Residuals

The scatter plot illustrates the model's residuals on the y-axis and the fitted residuals on the x-axis. As shown, we observe some extreme outliers and tendencies of unequal variance in the standard errors.

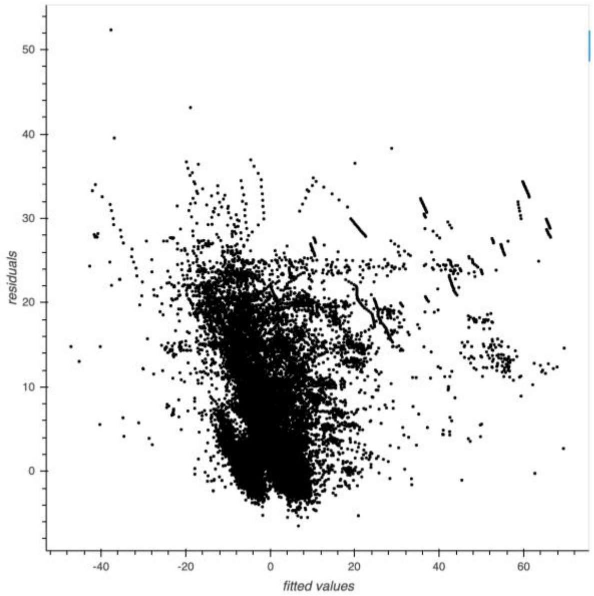


Table IIB.II

White’s Test for Heteroskedasticity

The table presents the results of White’s test for heteroskedasticity, which tests for the variance in the standard errors. We obtain a p-value of zero on both the Lagrange multiplier and F-statistics, implying that the standard errors in the model are heteroskedastic. Therefore, we apply heteroskedastic robust standard errors in our model.

Metric	Value
Lagrange multiplier	12 051.48
Lagrange multiplier p-value	0.00
F-Statistics	181.08
F-statistics p-value	0.00

Figure IIB.4

Residual Plot

The figure illustrates a residual plot of the model. The y-axis shows the residuals, and the x-axis shows the expected markup in bps. As illustrated, the residuals show a tendency of a pattern.

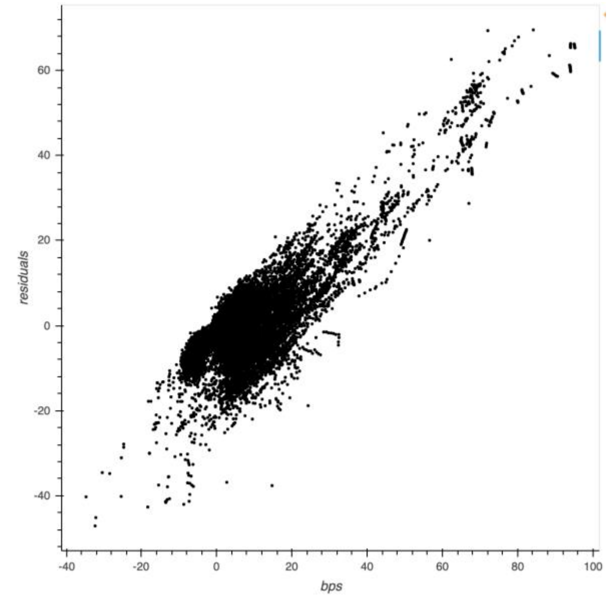


Table IIB.III

Durbin Watson Test for Autocorrelation

The table presents the results of the Durbin Watson test performed to measure autocorrelation in the OLS model. A value of 2.0 indicates no autocorrelation, a value between zero and 2.0 indicates a positive correlation, and a value between 2.0 and 4.0 indicates a negative correlation. We conclude that the test shows that there is positive autocorrelation in the data sample.

Metric	Value
Durbin Watson	0.49

Table IIB.IV

Variance Inflation Factor for Multicollinearity

The table presents the variance inflation factor (VIF) test performed to measure the multicollinearity of the explanatory variables included in the model. A VIF of one indicates no correlation between the variables, a VIF below 10 implies no harmful collinearity (Kennedy, 2008, p.199).

Variable	VIF Factor
Info	5.30
Venue	1.00
Subscription Just	1.20
Number of counterparties	3.60
Trade frequency (low)	23.80
Trade frequency (high)	121.40
Credit	5.00
Operating years	1.70
Revenue	1.90
Firm size	4.50
Public	4.50
Financial company	1.00
ln(size)	2.30
Large	1.00
Small	1.70
Contract duration	1.30
Customized	1.50