The Effect of Interdealer Spread Trading on Market Quality

Master Thesis

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Abstract

This thesis analyses the impact of interdealer spread trading strategies on market quality, in a multi-asset market beset by supply and demand shocks from end users. This research hypothesizes that spread trading, common in fixed income interdealer markets, improves the efficacy of risk sharing between dealers and should result in reduced asset volatility, improved price discovery and greater market liquidity. The chosen methodology follows a simulation set-up that mimics a pure OTC fixed income market microstructure. This market is characterized by having a RFQ-based dealership market combined with an interdealer market which is price-setting. End users demand and supply are stochastically simulated, in a way that dealer inventories can become strained. Main findings suggest that dealers bear a lower inventory risk when spread trading strategies are introduced to the interdealer market. This lower inventory risk is then translated into a better market quality due to lower asset volatility and greater market liquidity.

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Chapter 1

Introduction

Previous research have shown that market microstructure is a key determinant of market quality when measured by price discovery, liquidity, and volatility (Biais et al., 2005), (Madhavan, 2000), (Manaster & Mann, 1996), (Pagano & Röell, 1996). Moreover, it has been extensively studied that, basket-like instruments such as ETFs and Index Futures influence the underlying assets' market quality (Bhattacharya & O'Hara, 2018), (Box et al., 2018), (Ivanova et al., 2013). This points to the importance of how instruments are traded in electronic markets. In contrast, the fixed income markets (being primarily OTC) instruments are often traded as packages. e.g., instead of a dealer subsequently buying A and selling B, it tries to find a dealer to sell him (A-B) as one package. Market participants define such package as a 'spread'. Indeed, two of the major interdealer brokers (ICAP and BGC Partners) claim that spread trading accounts for about 50% to 65% of the interdealer trading activity[1]. Furthermore, BGC partners asserts that in the euro swaps market, the increased volatility during the last year has led to a peak in spread trading activity. The relevance of spread trading begs the question, what is the impact of this behavior on the fixed income market quality. Because the development of a market microstructure is a path-dependent process, it can reach a sub-optimal status and therefore its design is a relevant issue for regulators and

[1] This information was obtained from interviews with senior brokers from ICAP and BGC Partners in the context of this thesis development

market participants.

Actual fixed income markets have a dealership microstructure, whereby end users engage with dealers via Request-for-Quote and dealers engage with each other in a parallel interdealer market as in Vogler (1997). In practice, dealers enter the interdealer market to hedge their inventory risk measured as the variance of their portfolio. Previous literature assumes that dealers can be treated as mean-variance agents (Viswanathan & Wang, 2002). This thesis utilize this assumption, as it allows to model both dealers' price setting behavior and risk sharing behavior, conditional on their existing portfolio variance. As a consequence of the mean-variance assumption, dealers trade with each other to manage their inventory risk as in an actual interdealer market, this is known as risk sharing.

To address the extent to which the use of spread trading has an effect on the market quality, one should be able to compare it to a market in which spreads are not tradeable. Additionally, since spread trading is utility enhancing for the dealers, it would be difficult to find identical markets with dissimilar spread trading behavior. Therefore, an empirical approach seems unfeasible. For these reasons, this work opts for a simulation framework. As a simulation allows to compare two identical markets with different tradeable strategies. More specifically, we simulate a market without spread trading as the base case scenario and compare its market quality to that of a market in which spread trading is allowed. This answers the main research question. Afterwards, we analyze how the spread trading effect on market quality interacts with different market conditions. Some of these conditions are: dealers' risk aversion, degree of interdealer competition, inter-asset correlations, heterogeneity of dealers behavior, trading costs and supply and demand shocks.

Results in this thesis suggest that the use of spread trading strategies, within the interdealer market, enhances the overall market quality. This is a consequence of a better risk sharing capacity[2] that leads to lower market

[2]In this thesis, risk sharing capacity refers to the extent to which risk can be transferred

risk exposure for dealers. The risk sharing improvement is a direct consequence of a larger number of tradeable hedging strategies resulting from the incorporation of spreads in addition to single asset trades. The transmission mechanism works as follows, spread strategies enable a larger set of risk reducing strategies[3] leading to a lower inventory risk for dealers. Because dealers bear lower inventory risk and prices are linked to inventory risk, they quote tighter bid ask spreads to clients. This risk-to-quoting dynamic is the transmission mechanism through which the overall market quality is improved. More specifically, the improvement takes place in features such as market liquidity, dealers inventory risk, dealers capital consumption, and price volatility.

This work is organized as follows, the first chapter is the introduction. In the second chapter, a literature review is conducted with the aim to present how does this work differs and resemble previous works in the field of market microstructure. The third chapter, gives a thorough definition of the simulated market accompanied by a detailed example of the main stages of the simulation. In addition, in the third chapter the metrics used to measure the simulated market performance are defined. In the fourth chapter the main results and robustness tests are presented. The fifth chapter gives a brief discussion and the sixth chapter presents the conclusions about the results, methodology, and possible future research paths.

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or offset between dealers' inventories

[3]Risk reducing strategies trades refer to any trade a dealer can execute so its inventory risk is diminished

Chapter 2

Literature Review

The study of market microstructure often involves the understanding of the dynamics between price discovery and market organization. This chapter briefly describes some of the most relevant models developed to study these dynamics. The aim of this review is to describe the existing link between previous works and the methodology presented in this this thesis. This section encompasses the following market micro structure theoretical approaches: structural transaction cost model, inventory costs and warehousing capacity, asymmetric information and strategic behavior, and market design.

2.1 Transaction Costs

The first set of models that study the market microstructure under the competitive approach is the *transaction cost* line of research. One of the most relevant models is the structural model designed by Roll (1984). This model assumes that dealers are risk neutral agents and face identical transaction costs while clients do not react to prices. Additionally, buy and sell orders are equally likely and the arrival of a sell order is independent from the arrival of a buy order. Under this model the only driver of dealers' utility is the margin charged to clients, hence, competition between dealers arises from the desire to capture client orders. This thesis differs from Roll's structural model as dealers are assumed to be risk averse agents. This reflects actual dealers behavior and more recent theoretical approaches like the *inventory constraints* approach reviewed next. In addition, clients order arrivals are not assumed to be equally likely.

2.2 Inventory Constraints

This literature incorporates the fact that dealers are constrained by their warehousing capacity, understood as the market risk exposure they are allowed or willing to bear. Following recent literature developments (Etula, 2013), this thesis incorporates inventory constraints by assuming that dealers are mean-variance risk averse agents. This assumption ensures that each dealer's inventory risk becomes the main determinant of the bid-ask spread quoted to clients. Hence, dealers will modify their quoted prices in order to reflect the inventory risk of new trades. In contrast, authors as Amihud and Mendelson (1980) assume that dealers are risk-neutral agents. Under this assumption, inventory constraints arise as a consequence of limits imposed to inventory risk, resembling common regulatory and internal constraints. Here the relationship between prices and risk arises as dealers adjust their inventories to comply with imposed limits. On the empirical side, authors as Ho and Macris (1984) use trading book information to show that the inventory risk plays a relevant role in bid-ask quoted by dealers. These findings support the assumption of risk averse dealers as modeled in this research.

In line with the inventory constraints literature, Biais et al. (2005), analyze how some authors as Reiss and Werner (1998) and Hansch et al. (1998) have worked on the empirical side of inventory constraints. They find that in some exchanges as the London Stock Exchange, dealers with offsetting holdings tend to trade with each other in what the authors call the *reversion of market inventory*. The market simulated in this thesis is similar to this approach in the sense that interdealer interactions are designed to accomplish reversion of dealers inventory. Moreover, this work's goal is not only to simulate the reversion behavior but to research how this feature combined with spreads trading impacts the the market quality.

2.3 Asymmetric Information and Strategic Behavior

This is a literature approach within the competitive liquidity providers framework as categorized by Biais et al. (2005). It assumes that asymmetric information gives rise to adverse selection. It focused on the clients and dealers interactions and the informational properties of trading. Similar to this thesis model, some authors assume that investors' orders follow a single order arrival process as in Copeland and Galai (1983b) and Glosten and Milgrom (1985). In this approach, every individual investor, based on a set of information, assigns a private valuation to a given asset. Once all investors define their private valuation, these are turned into orders. Under this approach, client trading activity takes place in the dealer market and the orders arrive individually as market orders[1] . In market orders a client inquires a dealer or group of dealers and dealers compete in price to execute the trade. The main implication of these models is that trading activity influences securities prices. Every trade reveals information about agents' expectation over the assets' payoffs and this information is incorporated into dealers beliefs. Consequently, once a market order is executed, market participants (mainly dealers) adjust their bid-ask spreads to reflect the new information. Moreover, recent literature developments (Buis et al., 2022) opt for a simulation approach in which the distribution of agents' valuation has a constant constant mean. This assumption ensures that agents supply and demand are price sensitive. This thesis uses this private valuation simulation approach in order to model supply and demand cycles arising from agents private valuation.

The model designed in this thesis do not incorporates dealers private valuations nor strategic behavior. This is because it focuses on the impact of different interdealer trading strategies rather than the agents' strategic behavior. However, this research incorporates market features such as single order arrival process, modelled as a function of investors' private valuation as in Copeland and Galai (1983b) and Buis et al. (2022). Dealers private val-

[1] A market order is a client request for quote that the client wants to be executed in a short time window and at prices close to current mid price

uation is avoided so the changes in dealers' bid-ask spreads are solely driven by the impact that investors' net supply has on dealers inventory risk. This choice responds to the attempt to isolate the interdealer trading strategies impact on risk sharing capacity. Furthermore, other market features such as sequential order between clients' order execution and interdealer activity are based on previous authors such as Vogler (1997) and Viswanathan and Wang (2005).

2.4 Market Design

Another market microstructure area of interest is market design. It refers to the rules and institutions that define how trading activity is conducted and how it can be improved to reach more efficient outcomes. As the approaches previously reviewed helped to define the way clients Interact with dealers, the market design literature is reviewed with the focus set on interdealer market design. From the welfare perspective Vayanos (1999) showed that higher welfare levels can be achieved by concentrating trading activity in a bilateral auction in comparison to splitting it in many moments. From an interdealer market design perspective, this leads to a better risk sharing capacity. This happens because all the possible risk offsetting trades are revealed at the same time, avoiding the issues of adverse selection due to asymmetric information (Copeland & Galai, 1983a) while improving the liquidity. The main condition is that dealers' orders arrive at the same time or in a short time frame so all dealers undergo the auction process without taking advantage of new information. This thesis' model is similar to both approaches as the interdealer market trading activity is conducted via uniform price call auction[2]. The aim of this market design is to isolate the effects of interdealer market trading strategies. This is accomplished by using a informational efficient and welfare enhancing interdealer market design as the bilateral auction.

[2]This type of auction process takes time at a specific time during the trading session. All participants send their buy and sell prices in a short time span before the auction starts and the auction is cleared at a single price. In the model described in this research this action takes place only in the interdealer market at the end of each trading session.

Chapter 3

Methodology

3.1 Market Design

By means of a simulation, this work describes an OTC market organized in a dealership structure coupled to a sequential interdealer market. In this OTC market, final investors or clients interact only with dealers in the dealer market, this thesis will refer to this process as Client to Dealer (D2C) interaction. Afterwards, dealers, besides trading with clients, trade with each other in the interdealer market, referred in this thesis as Dealer to Dealer (D2D) interaction. This means that final investors do not have access to the interdealer market. This market design resembles the way in which some actual OTC markets are organized. Among some of the most relevant examples are: the interest rate swaps market, the foreign exchange forwards market, and the government bonds market. Moreover, final investors have a private valuation l of each investable asset. This is a consequence of assuming that clients have a non-monotonous downward (upward) demand (supply) curve for each asset. Consequently, when the client order is likely to be executed at a level better than the private valuation, the client will send a market order to dealers. This market orders are commonly known as Requests for Quotes (RfQs) and contain the private valuation, direction, and volume of the clients' orders. The process through which the RfQs are modeled here is called Stochastic Order Arrival Process (SOAP) and in partially resembling previous research Buis et al. (2022) and is defined and described in the section 3.2.

D2C and Marginal Risk

In the D2C, each RfQ is assessed by the inquired dealers, whom in return retrieve a price that reflects assets' current market mid price $P^{mid}_{t,m}$ plus or minus a margin, depending on the direction of the trade. The market mid price is assumed to be the same for all dealers, while the margin, from dealers' perspective, is assumed to be the cost of bearing new market risk. The latter is a measure conditional on each dealer's risk exposure at the time of trade execution.

Dealers are assumed to be mean-variance risk averse agents. Consequently, the risk measure to which dealers are exposed to, is defined as the assets' price variance, and is measured as the variance σ^2 of historical price returns, following common market and regulatory practices. At an inventory level, assets' covariance structure is incorporated to account for the correlation between assets. More specifically, for an given dealer the inventory risk at time t is measured as

$$\sigma^2_{t,n} = W'_{t,n}\Sigma W_{t,n} \tag{3.1}$$

More specifically, this measure is the inventory risk of the n-th dealer at time t. while $W_{t,n}$ is a $1XM$vector containing the n-th holding on each each of the M investable assets at time t. The measure Σ represents the covariance matrix. In this work, dealers' inventory refers to the residual position on the investable assets that a dealer holds at any time t. It is worth highlighting that in this model an inventory is different from an investment portfolio in the sense that the latter is the result of an investment strategy, while the former is modeled as a residual holding resulting from both C2D and D2D interactions. In practice, dealers can hold a specific position reflecting a conviction about certain investment strategies. However, this is not the main role of dealers and the relevance and performance of dealers' active strategies is out of the scope of this work.

A specific order's marginal risk $\Delta\sigma^2_{t,n,i}$is estimated as the difference between the m-th dealer inventory's risk at time t as if the RfQ were to be executed and the current inventory risk. This difference is scaled by the m-th dealer's risk aversion coefficient γ_n

$$\Delta\sigma^2_{t,n,i} = \gamma_n[(W_{t,n} + RfQ_{t,i})'\Sigma(W_{t,n} + RfQ_{t,i}) - W'_{t,n}\Sigma W_{t,n}] \tag{3.2}$$

The first term inside the squared brackets in the right side of the equation represents the n-th dealer inventory risk as if the RfQ were to be executed. The second term inside the squared brackets in the right side of the equation represents the current inventory risk. The difference between the two terms is the gross marginal risk and is scaled by the risk aversion coefficient γ_n to estimate the n-th dealer marginal risk.

In the D2C interaction, dealers estimate each inquiry's marginal risk as in equation 3.2, the resulting value equates to the margin charged to clients over the mid price as in 3.3 and 3.4. As explained before, this marginal risk varies between dealers due to differences in risk aversion and inventory exposure. From a dealer perspective, there are only two possible outcomes from any executed RfQ. First, Positive marginal risk trades that lead to higher charged margin to clients, whom agree to the price whenever this is better than their private valuation l. These type of trades arise whenever the dealer engages in a long position ($v = 1$) in the asset and the asset's correlation with inventory's risk at time t is positive, or when a dealer engages in a short position ($v = -1$) in the asset and the asset's correlation to dealer's inventory risk at time t is negative. Second, negative marginal risk trades, that arise when by executing a trade the dealer engages in a long position in the asset and the correlation between the asset and dealer's inventory risk at time t is negative, or when a dealer engages in a short position in the asset and the correlation between the asset and dealer's inventory risk at time t is positive. In later scenario, RfQs are assumed to be executed at mid price ensuring that dealers do not trade at worse prices than mid price.

$$P_{t,m}^{bid,n} = P_{t,m}^{mid} - \Delta\sigma_{t,n,i}^2 \tag{3.3}$$

$$P_{t,m}^{ask,n} = P_{t,m}^{mid} + \Delta\sigma_{t,n,i}^2 \tag{3.4}$$

Net Supply

The aggregated market inventory on asset m at time t $S_{t,m}^{net}$ is equivalent to the clients' cumulative net supply until time t, and can be estimated as the sum of all dealers' holdings on asset m at the end of the D2C interaction as in 3.5. Net supply is assumed to follow a zero long term average with short term imbalances. These imbalances can be decomposed en two components, a stochastic one and a clients' reaction function to price shocks as explained in section 3.2. The long term aggregated balance implies that, in the long term the net supply $S_{t,m}^{net}$ gravitates around zero for each asset n. When $S_{t,m}^{net} = 0$, dealers will hold risk offsetting positions, allowing them to perceive a high benefit from risk sharing activity in the interdealer market leading to lower frictions in the D2D. However, when short term net supply imbalances arise (e.g. $S_{t,m}^{net} \neq 0$), the D2D risk sharing activity faces higher frictions. This is a consequence of dealers holding similar inventories which leads to fewer number of possible risk offsetting D2D trades.

$$S_{t,m}^{net} = \sum_{n=1}^{N} w_{t,m,n} \tag{3.5}$$

Here $w_{t,n,m}$ is the position of dealer n of asset m at time t.

D2D Interaction

The extent to which $S^{net}_{t,m}$ differs from zero plays a relevant role not only in the interdealer risk sharing capacity but also in D2D price discovery activity. When dealers hold offsetting inventories they will hedge their risk short time after C2D interaction and at prices close to mid market price. However, when dealers do not hold offsetting inventories, they will be willing to bear a cost to hedge their market risk in the D2D, driving prices away from previous mid price. As with C2D interactions, D2D trades are priced by dealers as a the trade's marginal risk as in equation 3.2. In this work, the D2D interaction is assumed to be conducted through a call auction process[1] that take place multiple times at the end of each trading session t. In this auction all dealers send a buying (bid) and selling (ask) price for each one of a set of predefined trades. Subsequently, bid and ask prices are ranked and all prices better or equal than the auction clearing price are executed. The specific details of the bilateral auction process are explained in section 3.2. This auction is also the mechanism through which the price discovery is undertaken, more specifically, the last auction on each asset defines the trading session's closing mid price at time t. Consequently, in this model contemporary price shocks are linked to over or under supply. Additionally, net supply imbalances can have an effect on subsequent periods giving rise to a supply driven price cycle that is compensated by the investors reaction to price shocks.

In brief, when dealers hold similar residual risk resulting from non zero client net supply[2], the D2D interaction will not lead to the reversion of market

[1] The use of a call auction as the trading mechanism of the D2D is because of its computational efficiency and the small number of parameters needed to simulate it. In contrast, actual interdealer markets operates under continuous trading mostly through intedearler brokers

[2] This is the case when the sum of all dealers' position on one specific asset is different from zero i.e. in aggregate dealers are either long or short the asset

inventory [3]. As consequence, the D2D auction will execute fewer risk reducing trades or execute trades that are risk reducing for one side of the market and risk increasing for the other side.

Package Based Hedging

When dealers want to hedge the undesired risk exposure from specific instruments, the obvious strategy to achieve that is by entering the exact opposite position on the same instrument. However, because of non zero net supply, that strategy is not always available for all the dealers. To overcome this issue, dealers use instruments that are highly correlated to the ones they want to hedge. Although this increases the number of possible hedging strategies, those highly correlated single instruments might not have a zero net supply as well. The way dealers respond to this problem is by combining multiple instruments in one single package, and the resulting package is highly correlated to the risk they want to hedge. This way dealers deal with the issues that arise from non zero net supply.

Spread Trading

One of the most common traded packages in fixed income markets are the spreads. These are defined as the combination of two different instruments that are traded simultaneously. The two instruments included in the package have an opposite direction i.e. dealer is long in one of the instruments and short in the other one. Is called spread because the price at which is traded is the difference or spread between the rates or prices of the two embedded assets. The main risk of this strategy is the instability of the covariance across time. However, changes in the correlation between assets is out of the scope of this thesis. Consequently, short term covariance stability is assumed. The aim of this assumption is to isolate the impact that D2D spread trading has over the risk sharing capacity and its impact on market quality.

[3] This is because the D2D can only eliminate the residual risk when dealers hold opposite positions on the asset

3.2 Market Simulation Setup

This section describes in detail the model assumptions and the simulation setup.

Stochastic Order Arrival Process (SOAP)

This is the first stage of the simulation framework and encompasses the clients' behavior that gives raise to the D2C interaction. This process starts by defining how clients form their own private valuation $l_{t,m}$ on each of the M available assets. The price level of each private valuation determines on which side of the market clients are (i.e. supply or demand) as shown in eq. 3.7. In the base case, $l_{t,m}$ is assumed to follow a normal distribution, $l_{t,m} \sim N(p^{mid}_{t,m}, \theta^2)$[4] for both sellers and buyers.

Once private valuations for sellers and buyers are sampled, clients' buying (selling) interests below (above) mid price (vertical gray line) at time t are sent in a random order as RfQs to a random subsample of dealers. This simulation setup assumes that each order's volume is bounded to one[5]. Trade direction is the sign of RfQ and is understood from the perspective of dealers. This means that a client buy (sell) RfQ implies that dealers will engage in a short (long) position, respectively. As dealers sit on the other side of the trade. Order arrivals are assumed to be independent, while the supply and demand can diverge in probability as $p^{mid}_{t,m}$ changes, as shown in eq. 3.8 and 3.9. The main implication is that in expectation higher prices lead to more sellers and less buyers ($p^{mid}_{t,m} > p^{mid}_{t-1,m}$ then $E[S^{net}_{t,m}] > 0$). It is also true that lower prices lead to less sellers and more buyers ($p^{mid}_{t,m} < p^{mid}_{t-1,m}$ then $E[S^{net}_{t,m}] < 0$). This way of defining the net supply dynamics ensures that the simulation accounts for the aforementioned net supply driven price cycles.

[4] θ^2 is the variance of the clients' private valuations, for simplicity it is assumed to be the same for all clients and assets across time

[5] In reality volumes have a multi-modal distribution but a volume of one is chosen to reduce the amount of parameters

For $l_{t,m}$ to follow a normal distribution around mid price it is defined as

$$l_{t,m,i} = p_{t,m}^{mid} + e_{t,i} \tag{3.6}$$

Where $e_{t,i} \sim N(0, \theta^2)$ and the underscore i represents the i-th client. Thus $l_{t,m,i}$ is the private valuation of the i-th investor on the m-th asset.

The $l_{t,m,i}$ are then classified between demand or supply requests for quote based on the market mid price at time t

$$RfQ_{t,m,i} = \begin{cases} l_{t,m,i}^{demand} & \text{if } l_{t,m,i} < p_{t,m}^{mid} \\ l_{t,m,i}^{supply} & \text{if } l_{t,m,i} > p_{t,m}^{mid} \end{cases} \tag{3.7}$$

While the $l_{t,m,i}$ probability of being a sell (supply) or buy (demand) order is defined by the following equations

$$P(l_{t,m,i}^{demand}) = P(l_{t,m,i} < p_{t,m}^{mid}) = \int_{-\infty}^{p_{t,m}^{mid}} f(l)\, dl \tag{3.8}$$

$$P(l_{t,m,i}^{supply}) = P(l_{t,m,i} > p_{t,m}^{mid}) = \int_{p_{t,m}^{mid}}^{\infty} f(l)\, dl \tag{3.9}$$

Where $f(x)$ is the probability density function that clients' private valuation l follows. This distribution is assumed to be the probability density function of the normal distribution for which the limits of integration are defined by the mid price at time t $p_{t,m}^{mid}$. This way of defining the probability of demand and supply ensures the inclusion of net supply cycles $E[S_{t,m}^{net}] \neq 0$

In the next step clients manifest their supply and demand interest to dealers via RfQs. In order to make the simulation closer to common market dynamics, each client inquires a random set of dealers. This set of dealers is stochastic in size and constituents. Each RfQ is expressed in terms of final investors' private valuation, volume and direction. In this stage, RfQ is transformed into a one dimensional vector of size M, and contains the size and direction of each investor's order. When an investor is a buyer (seller) of one unit of the m-th asset, from the perspective of the dealer this leads to a short (long) position. These vectors are defined as follows:

In a market where the total number of assets M is three, a RfQ vector in which client wants to sell one unit of the first asset is defined as

$$RfQ_{t,m,i} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \tag{3.10}$$

While a RfQ where the client wants to buy one unit of the second asset is defined as

$$RfQ_{t,m,i} = \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix} \tag{3.11}$$

This depicts that in the simulation process each RfQ is seen from dealers' perspective. The next stage of the simulation is the D2C interaction where dealers assess and price each of the RfQs. Additionally, This whole SOAP takes place in a random order for the n available assets.

C2D Interaction

Once a client's RfQ arrives to the dealership market, each one of the inquired dealers retrieve a price based on the marginal change in risk expected from the execution of the order as in 3.2. The retrieved price is defined as a margin around the current market mid price as in eq. 3.4 and 3.3. Given that a RfQ can have a negative $\Delta\sigma^2_{t,n,i}$ a dealer could, execute a trade at a cost. However, the margin charged by dealers is assumed to have a lower zero bound. The way in which prices retrieved by dealers are bounded and ranked depending on RfQ direction as in eq. 3.12. This rules ensure that the sole execution, in the D2C, is never economically detrimental for dealers. Additionally, what dealers receive as margin is an amount equivalent to the perceived risk once trade is executed.

The best price is defined by the following equations

$$p^{bid,ask}_{t,m,i} = \begin{cases} p^{mid}_{t,m} - min[max(\boldsymbol{\Delta\sigma}^2_{t,i}, 0)] & \text{if client sells} \\ p^{mid}_{t,m} + min[max(\boldsymbol{\Delta\sigma}^2_{t,i}, 0)] & \text{if client buys} \end{cases} \tag{3.12}$$

Here symbols in bold represent vectors, more specifically $\boldsymbol{\Delta\sigma}^2_{t,i}$ is a vector that contains the marginal risk of all the inquired dealers. This function ensures that the best bid and ask prices are the ones closer to mid price.

For the trade execution process, this work assumes that dealers engage in a competence a-la-Bertrand to define who executes the order. In this type of competition, the dealer that sends the tightest margin (i.e bid or ask closer to mid price at time t) is the one that executes the order. Moreover, if more than one dealer sends the same best price, the winner will be chosen randomly as in Vogler (1997). Another condition for the execution of the trade is that clients will accept the price only when it is better than its own private valuation $l_{t,m,i}$.

As clients RfQs, on the different available assets, go through the D2C, dealers inventories are updated with the new holdings. This new holdings can give rise to undesired risk for the dealers in which case the first option for dealers is to use client orders to offset the undesired risk. for instance, suppose that in a three assets market, at time $t = 1$, two dealers are inquired to undertake a long position in *asset two* (i.e client sells asset two). In such case the RfQ vector will be $RfQ_i = [0, 1, 0]$. Suppose as well that dealer one has the following inventory $W_1 = [0, 1, 0]$ and dealer two $W_2 = [0, -1, 0]$. When both dealers assess the $\Delta\sigma^2_{t,m,i}$ for the first one $\Delta\sigma^2_{0,1,i} > 0$ as once executed it will double its exposure to the second asset. In contrast, for dealer two $\Delta\sigma^2_{0,2,i} < 0$ as the trade execution will leave its inventory with no market risk exposure. Following eq. 3.12 given that the client buys, the first dealer will retrieve a $p^{bid}_{0,1,i} > p^{mid}_{t,m}$ while the price shown by dealer two is$p^{bid}_{0,1,i} = p^{mid}_{t,n}$. In which case dealer two will retrieve the best price and execute the RfQ. After the execution dealer one's inventory will have no changes and dealer two's inventory will be $W_2 = [0, 0, 0]$. This example illustrates how dealers compete a-la-Bertrand and how dealers use clients' inquires to hedge their market risk exposure.

Once all clients' RfQs for period t are exhausted, dealers can find themselves holding undesired risk leading to interdealer activity in the interdealer market or D2D interactions.

D2D Interaction

As short term net supply imbalances arise, the dislocated aggregated market inventory creates the incentives that lead to the risk sharing activity between dealers or D2D interaction. As presented in section 3.1 D2D is takes place through a call auction that follows the D2C interactions. This auction allows the market to find those trades that lead to the most efficient inventory allocation through the optimization of the trade-off between risk reduction and utility. The auction optimization is ensured by removing the zero bounds introduced in eq. 3.12[6] and letting dealers use the same pricing functions to determine which strategies lead to the highest risk sharing of the market.

More specifically, the simulation of the D2D call auction starts by estimating dealers' prices $p^{bid,ask}_{t,m,s}$ for all the s available strategies. This strategies are defined as vectors containing the size and direction of the assets involved, similar to RfQs vectors. In this stage of the simulation is where spread strategies can take place. These strategies are structured as a package of assets traded as one product. These strategies are called spreads as a result of how market participants quote them (i.e. spread packages are quoted in terms of the rate

[6]Unlike the D2C, in the D2D dealers sometime pay to reduce their risk, this resembles actual dynamics of interdealer markets

difference or price difference between the included assets).

Once all the strategies are priced by dealers, bids and ask from each strategy are ranked from higher to lower in the case of $p^{bid}_{t,m,s}$ and from lower to higher in the case of $p^{ask}_{t,m,s}$. Trades are executed as long as the $p^{bid}_{t,m,s} > p^{ask}_{t,m,s}$. This ensures that in each one of the strategies' auction the most number of trades are executed. This leads to the largest possible utility that can be obtained by each strategy. The auction utility perceived by each dealer is estimated as the difference between its own strategy's execution price and the clearing price as in eq. 3.14 and 3.13. The clearing price is defined as the average between the lowest bid $p^{bid}_{t,m,s}$ and the highest ask $p^{bid}_{t,m,s}$ for which the execution condition is met.

$$U^{long}_{t,m,s}(W_{t,m}, W_t, \Sigma) = \Delta\sigma^2_{t,m,s^{buy}} - p^{clearing}_{t,s} \tag{3.13}$$

$$U^{short}_{t,m,s}(W_{t,m}, W_t, \Sigma) = p^{clearing}_{t,s} - \Delta\sigma^2_{t,m,s^{sell}} \tag{3.14}$$

Once all the dealers' utility from each strategy is known the total utility of each D2D strategy is calculated via

$$U^{total}_{t,s}(W_t, \Sigma) = \sum_{m=1}^{M} \mathbb{1}_{t,m} * U^{long}_{t,m,s} + \sum_{m=1}^{M} \mathbb{1}_{t,m} * U^{short}_{t,m,s} \tag{3.15}$$

where $\mathbb{1}_m$ is an indicator function defined as

$$\mathbb{1}_m = \begin{cases} 1 & \text{If } p^{bid}_{t,m,s} > p^{ask}_{t,m,s} \\ 0 & \text{In any other case} \end{cases} \tag{3.16}$$

Each strategy's total utility is found by using eq. 3.15 and the strategy with the highest utility is then executed. This call auction process is carried out multiple times until the marginal utility from an additional auction its lower than a predefined marginal utility threshold. The definition of a utility threshold implies that dealers will share risk in the interdealer market as long as it materially increases the overall market utility. Once one of the auctions reaches the utility threshold the interdealer market goes through a final auction in which dealers find the closing price for each asset. This pricing auction is carried out once for each individual asset and the clearing price of each auction defines the closing market mid price $p_{t,m}^{clearing} = p_{t+1,m}^{mid}$.

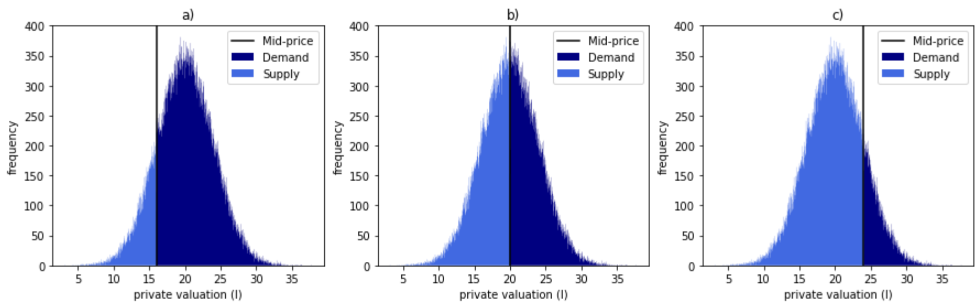
3.3 Going Through the Simulation

This section present in a detailed manner each of the steps of the simulation as described in the previous section.

SOAP and D2C

The first step of this stage, is the simulation of clients' private valuation l for each specific asset. Each subplot in figure 3.1 shows the distribution of clients private valuation for different mid prices. This simulated private valuations are then classified between supply or demand RfQs. The classification process follows the rules presented in eq. 3.7. In brief, private valuations l above current mid price are classified as demand interests while those below mid price are classified as supply interest. As can be seen from this figure, mid price level determines the probability of both supply RfQ^{supply} (in light blue) and demand RfQ^{demand} (in dark blue). Once all of the private valuations are classified they are transformed in to vectors of size $1XM$, where each row represents the inquired volume of each asset.

Figure 3.1: SOAP Sampling



Note: This figure displays the possible scenarios of demand and supply for different mid prices. plot a) shows the case when the mid price at time t is lower than the mean private valuation. plot b) shows the case when the mid price at time t is equal to the mean private valuation. plot c) shows the case when the mid price at time t is higher than the mean private valuation.

Assuming that this is a three asset market, the following vectors represent demand and supply interests for asset two (blue). The sign of the inquired volume is defined from the perspective of dealers. For instance, when a client demands an asset, dealers will sell that asset, which mean the dealers will engage in a short position, thus seen as a negative volume.

$$RfQ_i^{demand} = \begin{bmatrix} 0 \\ \text{-1} \\ 0 \end{bmatrix}$$

$$RfQ_i^{supply} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

Once private valuations are classified between demand and supply and RfQs are turned into vectors. Then these RfQs are sent to the dealer market in which the inquired dealers will estimate the marginal risk of each order based on their current inventory.

Lets suppose that the dealer market inventory W has five dealers and their inventories are:

$$W_t = \begin{bmatrix} 3 & \text{-1} & \text{-4} & 2 & 0 \\ 2 & \text{-2} & 3 & 1 & \text{-1} \\ 1 & 1 & 0 & \text{-2} & 1 \end{bmatrix}$$

Here each column represents a dealer inventory and each row represent each asset holding. For example, for asset two (blue), dealer two has a short position of -2, while for the same asset dealer four has a long position of 1.

Suppose that for the RfQ_i^{demand} the client asks two dealers, dealer one and three. The pricing process would start with each dealers addressing the marginal risk $\Delta\sigma^2_{t,n,i}$ as if the trade were to be executed as in 3.2. For each dealer, the first step is to evaluate the volume impact of the trade. In the case of dealer one this RfQ is a risk reducing trade given that its execution leads to a lower exposure to asset two. Dealers one inventory impact estimation is as follows

$$W_{t,1} + RfQ_i^{demand} = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ \text{-1} \\ 0 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix}$$

Once the inventory impact is known, the next step is to evaluate its risk impact. For the dealer one this is estimated as the difference between the execution of the new trade and the current market risk exposure. This is

$$\Delta\sigma^2_{t,1,i} = \begin{bmatrix} 3 & 1 & 1 \end{bmatrix} \Sigma \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 3 & 2 & 1 \end{bmatrix} \Sigma \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix}$$

In order to translate this to actual numbers suppose that the three assets' covariance matrix is

$$\Sigma = \begin{bmatrix} 0.00169 & 0.00146 & 0.00106 \\ 0.00146 & 0.00155 & 0.00136 \\ 0.00106 & 0.00136 & 0.00162 \end{bmatrix}$$

Then the marginal risk for dealer one is

$$\Delta\sigma^2_{t,1,i} = 0.0362 - 0.0524$$
$$\Delta\sigma^2_{t,1,i} = \text{-}0.0164$$

As can be seen the sign of the $\Delta\sigma^2_{t,1,i}$ indicates the risk impact of the trade execution. In theory, dealer one would be willing to execute this trade at a cost, by selling the asset two at a price lower than current mid price. However, as mentioned before, this thesis assumes that in the D2C dealers do not trade in detriment of their economic performance. This is achieved by imposing a zero bound to the price to ensure that the best price in the D2C interaction is the mid price.

With respect to dealer two, following the same process, its inventory impact would be

$$W_{t,2} + RfQ_i^{demand} = \begin{bmatrix} \text{-}1 \\ \text{-}2 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ \text{-}1 \\ 0 \end{bmatrix} = \begin{bmatrix} \text{-}1 \\ \text{-}3 \\ 1 \end{bmatrix}$$

In this case for dealer two the trade would be risk increasing as it enlarges dealer two short position on asset two from -2 to -3. In terms of marginal risk, the estimation process is the same followed by dealer two. The exact estimate in this case is $\Delta\sigma^2_{t,2,i} = 0.00795$. Once inquired dealers know the risk impact of the trade, the next step is to use this estimate to show a price to the client. This is done by finding the bounded marginal risks and then estimating each dealer ask price $p^{ask}_{t,n,i}$ as in eq. 3.12. Assuming that the current mid price for asset two is $p^{mid}_{t,2} = 20$, the price showed by dealers would be as follow

For dealer one

$$p^{ask}_{t,1,i} = p^{mid}_{t,n} + max(\Delta\sigma^2_{t,1,i}, 0)$$
$$p^{ask}_{t,1,i} = p^{mid}_{t,n} + max(-0.0164, 0)$$
$$p^{ask}_{t,1,i} = 20$$

For dealer two

$$p^{ask}_{t,2,i} = p^{mid}_{t,n} + max(\Delta\sigma^2_{t,2,i}, 0)$$
$$p^{ask}_{t,2,i} = p^{mid}_{t,n} + max(0.00795, 0)$$

$$p^{ask}_{t,2,i} = 20.00795$$

As dealers compete a-la-Bertrand then the executed price is the one closer to mid, in this case $min(p^{ask}_{t,1,i}, p^{ask}_{t,2,i}) = 20$, consequently this trade is executed by dealer one, who will the update its risk and inventory. The steps the same steps are followed when, instead of demand, the client supplies the asset. This whole process is executed for as many clients' RfQs are sent to the market. Once all the RfQs are quoted by dealers the D2D interaction takes place[7].

D2D Auction Process

D2D interaction is conducted through a bilateral auction that takes place after the D2C interaction. At each t the whole auction is executed multiple times

[7]Sometimes the best price is above the private valuation, then no trade is done

until it exhausts the utility perceived by dealers. This is ensured by executing the auction algorithm always that the dealers utility increases more than a predefined threshold. The auction algorithm is as follows

1. All dealers send each one's bid and ask price for all the available strategies.

2. Using prices from step 1. each s strategy's clearing price $p_{t,s}^{clearing}$ is estimated.

3. Te utility perceived by each dealer is estimated using steps 1. and 2. and eq. 3.15.

4. The strategy with the highest utility is executed as long as the utility increase perceived by dealers is above a predefined marginal utility threshold.

5. The inventory is updated for those dealers that executed the strategy.

6. The process starts again from step 1.

Auction Round Illustration

This sub section presents an example of an auction round, starting with the definition of strategies, followed by dealers pricing of a given strategy. Once strategy bid and ask prices are known the subsequent step is the estimation of the clearing price. This is followed by the utility estimation and the inventory update.

In this thesis two types of strategies are included in the D2D interaction i.e. single asset trades and spread trades. For the case of a single asset strategy S in vector form is

$$S^{buy} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$S^{sell} = \begin{bmatrix} -1 \\ 0 \\ 0 \end{bmatrix}$$

In the case of a spread trade the strategy in vector form is

$$S^{buy} = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

$$S^{sell} = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

To illustrate an auction execution process, assume that the initial inventory of each dealer

$$W_t = \begin{bmatrix} -6 & -4 & -4 & -4 & -6 \\ 6 & 6 & 7 & 6 & 5 \\ 3 & 3 & 0 & 0 & 4 \end{bmatrix}$$

In this bilateral auction all dealers send their bid and ask price, based on the marginal risk $\Delta\sigma^2_{t,n,s}$, for a given strategy. For example, if the strategy S^{buy} price for the first dealer is found by estimating the inventory impact and then the marginal risk of the strategy

$$W_{t,1} + S^{buy} = \begin{bmatrix} -6 \\ 6 \\ 3 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} -5 \\ 6 \\ 2 \end{bmatrix}$$

$$= \begin{bmatrix} \text{-5} & 6 & 2 \end{bmatrix} \Sigma \begin{bmatrix} \text{-5} \\ 6 \\ 2 \end{bmatrix} - \begin{bmatrix} \text{-6} & 6 & 3 \end{bmatrix} \Sigma \begin{bmatrix} \text{-6} \\ 6 \\ 3 \end{bmatrix}$$

This process is carried on by every dealer for the S^{buy} and S^{sell} in the same manner. Using the covariance matrix presented in the previous example, the buying and selling prices would be

$$\Delta\sigma^2_{t,s^{buy}} = \begin{bmatrix} 0.08642 \\ 0.06098 \\ 0.02484 \\ 0.02684 \\ 0.09980 \end{bmatrix}$$

$$\Delta\sigma^2_{t,s^{sell}} = \begin{bmatrix} 0.11053 \\ 0.08508 \\ 0.04894 \\ 0.05094 \\ 0.12391 \end{bmatrix}$$

In the next step $\Delta\sigma^2_{t,s^{sell,buy}}$ are ranked to find which dealers would trade the strategy. More specifically, bids are sorted from higher to lower and asks from lower to higher. Trades will be executed in every case that ranked bids are higher than ranked asks. This process is as shown next.

$$\Delta\sigma^2_{t,s^{buy}} = \begin{bmatrix} 5 & 0.099809 \\ 1 & 0.086429 \\ 2 & 0.060987 \\ 4 & 0.026841 \\ 3 & 0.024842 \end{bmatrix}, \Delta\sigma^2_{t,s^{sell}} = \begin{bmatrix} 3 & 0.048945 \\ 4 & 0.050944 \\ 2 & 0.085090 \\ 1 & 0.110531 \\ 5 & 0.123912 \end{bmatrix}$$

In blue are the prices for which ranked bids are higher than ranked asks, thus are executed. The execution in this trade means that the dealers five and one will buy the strategy and dealers three and four will sell it. The clearing price is defined as the middle point between lower traded bid and higher traded ask, in this case[8]

$$p_{t,s}^{clearing} = \frac{0.08643 + 0.05094}{2}$$

$$p_{t,s}^{clearing} = 0.06868$$

Once the clearing price is known the next step is to estimate the auction utility using eq. 3.15. This is the sum of the difference between each dealer price and the clearing for those that got cleared

The utility for the dealers that would engage in a long position on the strategy is

$$U_{t,s}^{long} = (0.099809 - 0.06868) + (0.086429 - 0.06868)$$

$$U_{t,s}^{long} = 0.04888$$

The utility for the dealers that would engage in a short position on the strategy is

$$U_{t,s}^{short} = (0.06868 - 0.048945) + (0.06868 - 0.050944)$$

$$U_{t,s}^{short} = 0.03747$$

The total strategy utility is the sum of both as shown next

$$U_{t,s}^{total} = U_{t,s}^{long} + U_{t,s}^{short}$$

[8]if no trade is executed then mid price is calculated used the best bid and best ask

$$U_{t,s}^{total} = 0.08635$$

This whole process is carried on for all the available strategies in the D2D and the one with the highest utility is executed. For instance, if the previous example were the one with the highest utility, then the new inventory would be

$$W_t = \begin{bmatrix} -5 & -4 & -5 & -5 & -5 \\ 6 & 6 & 7 & 6 & 5 \\ 2 & 3 & 1 & 1 & 3 \end{bmatrix}$$

where the numbers in blue are the ones that show the changes resulting from the strategy execution. Once the inventory is updated, the auction starts again until the utility dealers can harvest from the auction is exhausted.

Pricing Auction

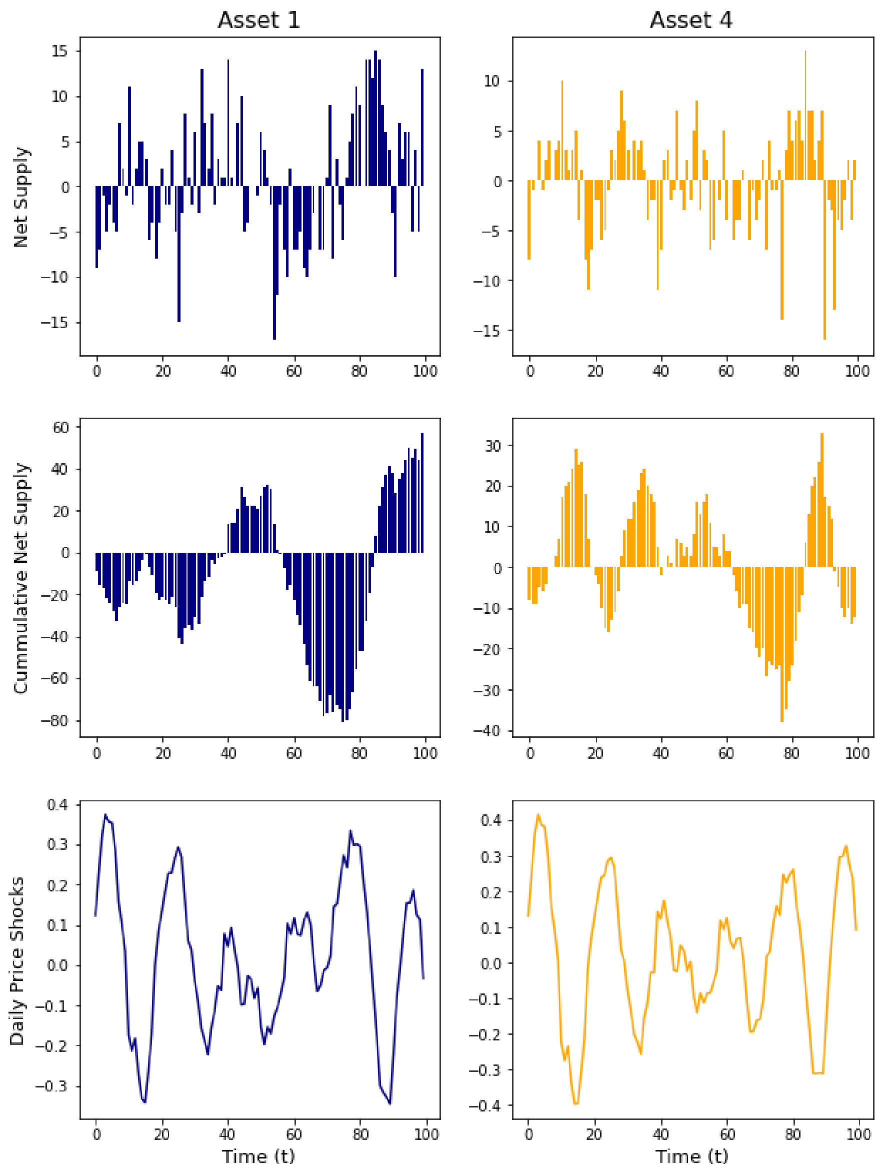
The next step after the D2D interaction is the pricing auction. In this auction dealers send bid and ask prices for every individual asset and the clearing price of each one is the closing mid price that will be the starting mid price of the next trading session $t + 1$. As explained in the SOAP this new mid price will define the probability of next trading session's supply and demand interest.

Complete Market Cycle

A complete simulation consists of T trading sessions where in each session, during the D2C interaction, N dealers quote I client interests. Once all the I interests are quoted, the D2D takes place once every t trading session, always after the D2C interaction. from the D2D interaction a new mid price for every asset is defined and the t+1 trading session starts. The aim of this section is to present, briefly, how the (net) supply and price dynamics interact with each other in this market set up.

Figure 3.2 shows for two assets how the net supply interacts with price shocks. As can be seen, cumulative net supply cycles are closely linked to price movements as defined in the previous section. This means that negative price shocks are more frequent or severe when there is excess of supply. The opposite is true as well for negative cumulative net supply. However, it can also be noticed that price still has a stochastic component. For instance, between trading session 20 and 40 for asset 1, price shock is positive when there is excess of cumulative net supply for that asset, this shows that the net supply cycle is not the only determinant of price behavior.

Figure 3.2: Simulation Dynamics



Note: This figure present a complete simulation cycle for two different assets. The covariance matrix used for this simulation is one with highly correlated assets. The first row present the net supply and the cumulative net supply. The last row shows the daily price shock. This figure shows the supply driven price cycles. low prices lead to a lower cumulative net supply while high prices and high prices lead to higher cumulative net supply.

3.4 Market Quality Metrics

In this section all the metrics used to measure market quality are defined and explained.

Utility

The first utility measure is the *clients utility*, and is estimated as the difference between execution price and private valuation for executed trades. At each time t, the cross asset client utility is added to find the total utility perceived by clients as in eq. 3.17.

$$U_t^{client} = \sum_{n=1}^{N} \sum_{i=1}^{I} \mathbb{1}_{t,n,i} * |l_{t,n,i} - p_{t,n,i}^{bid,ask}| \tag{3.17}$$

$$\mathbb{1}_{t,n,i} = \begin{cases} 1 & \text{If trade is executed} \\ 0 & \text{In any other case} \end{cases} \tag{3.18}$$

And average client utility

$$\overline{U}^{client} = \frac{1}{T} \sum_{t=1}^{T} U_t^{client} \tag{3.19}$$

With respect to dealers utility, it is measured as the margin charged to clients during the D2C plus the total utility obtained from the D2D auction process. Is measured as

$$U_t^{dealer} = \sum_{i=m}^{M} \sum_{i=1}^{I} \mathbb{1}_{t,m,i} * \Delta\sigma_{t,m,i}^2 + \sum_{s=1}^{S} \mathbb{1}_{t,s} * U_{t,s}^{total} \tag{3.20}$$

The utility from the second term on the right side of the equation $U_{t,s}^{total}$ refers to the one defined in equation 3.15 and its respective indicator function is defined as

$$\mathbb{1}_{t,m,i} = \begin{cases} 1 & \text{If dealer m executes the trade} \\ 0 & \text{In any other case} \end{cases} \tag{3.21}$$

And the indicator function in the second terms is defined as

$$\mathbb{1}_{t,s} = \begin{cases} 1 & \text{If auction's s-th strategy is executed} \\ 0 & \text{In any other case} \end{cases} \tag{3.22}$$

The average dealer utility is estimated as

$$\overline{U}^{client} = \frac{1}{T}\sum_{t=1}^{T} U_t^{client} \tag{3.23}$$

Liquidity

Bid-ask spread is used as a liquidity proxy and is defined as the average bid-ask spread at each time t clients can get for each of the available instruments. It is defined as the average of $p_{t,n,i}^{bid,ask}$ as in eq. 3.12. This average includes the cases in which the RfQs are not executed[9].

$$\overline{p}_{t,m}^{bid,ask} = \frac{1}{I}\sum_{i=1}^{I} p_{t,m,i}^{bid,ask} \tag{3.24}$$

Cross asset bid ask spread is estimated as

[9] In this case the best bid and best ask are used regardless of the trade not being executed

$$\overline{p}^{bid,ask} = \frac{1}{NT} \sum_{m=1}^{M} \sum_{t=1}^{T} \overline{p}_{t,m}^{bid,ask} \tag{3.25}$$

Given that standard deviations and bid-ask spreads are of similar magnitude averaging across assets is warranted

Price Behavior

In this sub section two groups of price behavior metrics are presented. The first group, measures the market quality from the perspective of price behavior. Metrics within this category are: price volatility, price extremes,and price stability. The second group of metrics evaluates how much the realization of simulated prices differs from input data. The two metrics in this category are price divergence and the price correlation divergence.

Price Volatility

Price volatility is one of the most frequently addressed measures in the field of market microstructure. This measures allow to capture the riskiness of an instrument as well as its stability across time. The volatility for a the m-th instrument is estimated as the standard deviation of price shocks

$$SD_m^{mid} = \sqrt{\frac{1}{T-1} \sum_{t=2}^{T} (p_{t,m}^{mid} - \overline{p}_m^{mid})^2} \tag{3.26}$$

Where $r_{t+1,m}^{mid}$ is the one period price return at $t+1$ and $\overline{r}_m^{mid}$ is the m-th asset average return. The cross asset price volatility is estimated as the average of the M assets volatility

$$\overline{SD}^{mid} = \frac{1}{M} \sum_{m=1}^{M} SD_m \tag{3.27}$$

This averaging is possible given that assets prices are of similar magnitude.

Price Extremes

Similarly to price volatility this metric aims to address the riskiness of an asset but from the perspective of a worse case scenario. It measures the maximum price shock (i.e. largest daily return) across time and across assets. Is defined as

$$r^{max} = max(\mathbf{r}_{t,m}^{mid}) \tag{3.28}$$

Price Divergence

Price Divergence is understood as the average difference between simulated mid prices and the initial mid price $p_{t,n}^{mid}$. Estimated as follows

$$d_m = \frac{1}{T}\sum_{t=1}^{T}(p_{t,m}^{mid} - p_{0,m}^{mid}) \tag{3.29}$$

Price Correlation Divergence

This is a control metric that helps to estimate how much the simulated prices' correlations differ from the actual prices correlation. Values close to one are a signal that both correlations are similar.

$$\rho^{diff} = \frac{1}{N}(\boldsymbol{\rho}^{input} - \boldsymbol{\rho}^{simulated}) \tag{3.30}$$

Net Supply Price Impact

As presented in the methodology, price and net supply are linked through the SOAP sampling. The following two metrics capture the strength of this link.

Correlation

This metric is estimated as the contemporary Pearson correlation coefficient between net supply and price shock.

$$\rho(S_{t,m}^{net}, r_{t,m}^{mid}) \tag{3.31}$$

Net Supply Beta

The price shocks $r_{t,m}^{mid}$ sensitivity to changes in net supply $S_{t,m}^{net}$ is estimated as the β_s coefficient from a linear regression. This regression is estimated as the follows

$$r_{t,m}^{mid} = \beta_s S_{t,m}^{net} + e_{m,t} \tag{3.32}$$

The higher the value of β_s the more sensitive the price shock to the changes in net supply is.

Auction

Auction Efficiency

This measure quantifies the efficiency of the auction process in terms of the number of cycles it has to go through. It also captures the extent to which new strategies lead to an increase of the risk reducing D2D activity.

Spread Trading Relevance

This metric disentangles the relevance of spread trading within the simulation, by measuring how intensive is the use of these strategies. Is measured as the number spread trades executed in a complete auction process as a proportion of the total number of auction rounds.

$$S_t^{relevance} = \frac{\#Executed\,Spread\,Trades_t}{\#Auction\,Rounds_t} \tag{3.33}$$

The higher its value the more intensive the use of spread trading strategies during D2D interaction

Risk Reduction

Measures the average inventory risk reduction that dealers experience as a consequence of the D2D interaction

$$\boldsymbol{\Delta\sigma^{2,}}_t^{auction} = \boldsymbol{\sigma}_{t,n}^{2,pre\,auction} - \boldsymbol{\sigma}_{t,n}^{2,post\,auction} \tag{3.34}$$

The more negative the value of the risk reduction metric the better the auction risk reduction capacity.

Inventory Risk

Value at Risk

Value at Risk aims to capture riskiness of dealers inventories in extreme cases. Is estimated using a parametric approach, using as input each dealer's inventory and the covariance matrix to find the volatility of the portfolio. The estimation is as follows

$$VaR_{t,n}^{\alpha} = \sigma_{t,n}\, z_{\alpha} \tag{3.35}$$

Parameter z_{α} indicates the z-score i.e. number of standard deviation, and the subscript α indicates the confidence level of the estimation. For instance in this work a 1% alpha is used, meaning that the estimation confidence level is 99%.

Balance Sheet Usage

This measure is a proxy of how intensive is the balance sheet use of dealers. In addition, given that both long and short holdings cause a capital charge, this metric is also a proxy of the capital consumption of dealers. Estimates as

$$BS_{t,n} = \sum_{m=1}^{M} |w_{t,n,m}| \tag{3.36}$$

The higher the value of the Balance Sheet Usage the higher the capital consumption

Net Total Inventory

Net Inventory is a measure of diversification risk as it captures the risk of dealers as if the correlation were to drop to zero. and is estimated as the absolute value of the total holdings in each asset. It is estimated as

$$w_{t,n}^{net} = |\sum_{m=1}^{M} w_{t,n,m}| \tag{3.37}$$

The higher the value of net inventory the higher the diversification risk a dealer bears.

Chapter 4

Simulation Results

4.1 The Benefits of Spread Trading Strategies

This section presents the results from the simulation of the market described in section 3.1. The simulation is run twice, one including spread trading and the other one excluding it. For this simulation the input covariance matrix is empirically estimated from a one-year sample of swap rates from the European swaps market. The use of these instruments is motivated by their high correlation (see fig. 4.1) which benefits from spread trading strategies. Table 4.1 shows a summary of euro swaps daily returns.

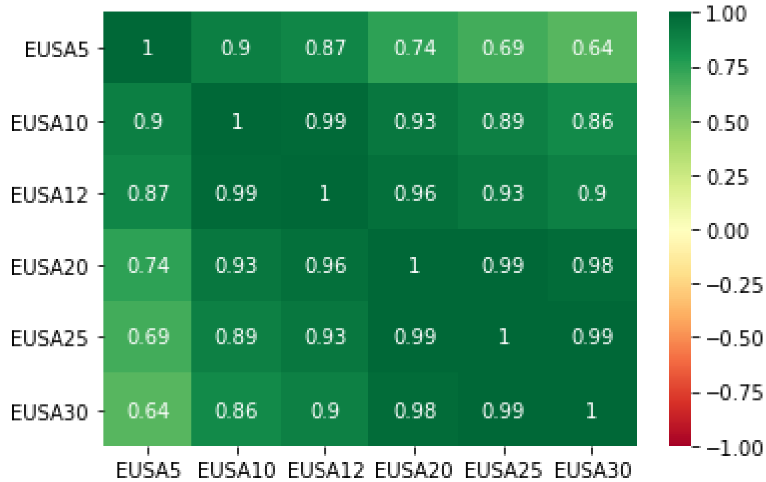
	EUSA5	EUSA10	EUSA12	EUSA20	EUSA25	EUSA30
Mean	0.0079	0.0072	0.0070	0.0058	0.0053	0.0050
Std	0.0412	0.0394	0.0389	0.0388	0.0393	0.0404
Max	0.14	0.109	0.1255	0.123	0.124	0.129
Min	-0.16	-0.148	-0.136	-0.1185	-0.124	-0.134

Summary of Euro swaps market rates' daily returns from 2021-05-11 to 22-06-10 for the 5 years, 10 years, 12 years, 20 years, 25 years, and 30 years tenors.

Table 4.1: Euro Swaps Summary

For this simulation market quality metrics are presented in table 4.2. According to these results, the use of spread trading strategies in the D2D market

Figure 4.1: Euro Swaps Correlation Heatmap



lead to a general improvement of the market quality when measured by liquidity, market risk, price volatility, and risk sharing capacity.

Because when spread trading is introduced[1], dealers bear a lower inventory risk[2] and given that the D2C quoting process is linked to the inventory risk, bid-ask spreads are improved i.e. clients can trade at tighter bid ask spreads. More specifically, an statistically significant reduction of 6.33% of the average inventory risk[3] is reflected in a significant reduction of the bid-ask spread (5.98%). Moreover, the lower inventory risk leads to a significantly lower price volatility (6.75% lower) and price extremes (8.14% lower).

Improvements in price behavior and liquidity are explained by the non-linear relationship that client quoting and price setting mechanisms have with inventory risk. Due to the quadratic nature of the chosen risk measure, lower inventory risk leads to lower marginal risk while higher inventory risk leads to

[1]The practical consequence of introducing spreads is the increase of the number of D2D tradeable strategies

[2]Inventory risk is measured as the average VaR across dealers inventories

[3]All the measures presented in the table are sample means of multiple simulation realizations

a higher marginal risk. Because the marginal risk is the main determinant of price shocks and bid ask spreads, when inventory risk is lower price shocks and bid ask spreads are lower as well. From an economic perspective, this means that when dealers bear lower inventory risk they are willing to take additional risk. In contrast when bearing higher inventory risk, dealers are less willing to take additional risk. Moreover, to take additional risk when inventory risk is already higher dealers require larger margins, which is expressed through the wider bid ask spreads and higher price volatility.

Another relevant result is that when spread trading is introduced, dealers make a less intensive use of their balance sheet[4]. spread tradings drives this enhancement via better allocation of dealers inventories. This is because spread trading is capable to either find more D2D risk offsetting trades or to better reallocate risk, thus enhancing the D2D risk reducing capacity.

Due to tighter bid-ask spreads and lower inventory risk it would be expected that spread trading could be risk enhancing for dealers and clients. However, although utility of clients and dealers is slightly higher when spread trading is introduced the improvement is not statistically significant.

For this set of results the market is simulated 100 times ($K = 100$) each one over 100 trading sessions ($T = 100$) (10000 D2C and D2D rounds) and 50 client interests are quoted in each round.

[4]this can be inferred from the significant lower balance sheet use (37.16% lower) observed when spread trading is introduced

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.136	3.134	0.00200	0.064%
		(0.00338)	(0.00373)		
	Dealer Utility	0.238	0.237	0.00117	0.496%
		(0.00371)	(0.0044)		
Liquidity	Bid-Ask Spread	0.069	0.073	-0.00437	-5.978%
	Bid	0.035	0.036	0.00117	-5.181%
		(0.00036)	(0.00051)		
	Ask	-0.034	-0.037	0.00117	-6.773%
		(0.00036)	(0.0005)		
Price Behavior	Price Volatility	0.088	0.094	-0.00633	-6.735%
		(0.00201)	(0.00295)		
	Price Extremes	0.201	0.219	-0.01780	-8.138%
		(0.00566)	(0.00724)		
	Price Stability	0.789	0.804	-0.01453	-1.808%
		(0.00506)	(0.00837)		
	Price Divergence	0.034	0.023	0.01109	47.730%
		(0.00773)	(0.00682)		
	Price Correlation Divergence	1.064	1.055	0.00956	0.907%
		(0.00417)	(0.00651)		
Net Supply Price Impact	Correlation	-0.187	-0.184	-0.00307	1.668%
		(0.00461)	(0.00473)		
	Beta	-0.003	-0.003	0.0	
		(8e-05)	(9e-05)		
Auction	Spread Trading Relevance	0.681			
		(0.00106)			
	Auction Efficiency	13.614	8.245	5.37	65.126%
		(0.05997)	(0.05152)		
	Risk Reduction	-0.0238	-0.0237	0.00117	0.496%
		(0.00037)	(0.00044)		
Inventory Risk	Value at Risk	0.265	0.283	-0.01792	-6.329%
		(0.00602)	(0.00588)		
	Balance Sheet Usage	21.325	33.935	-12.61	-37.159%
		(1.05108)	(0.76812)		
	Net Total Inventory	3.030	3.290	-0.26	-7.903%
		(0.28748)	(0.30823)		

Table 4.2: Spread Trading Benefits

4.2 Robustness Tests

Increased Dealer Competition

Spread trading benefits on market quality hold when competition between dealers increases. This test is conducted by increasing the number of dealers in the simulation. More specifically, a 50% more dealers, which means going from 8 dealers in the base case to 12 dealers in the increased competition scenario. In general, the risk-to-price transmission mechanism, described in the bases case, holds when dealers competition is increased. Although benefits from spread trading are significant the degree to which it improves market quality is lower for inventory risk and price behavior. Spread trading impact hold because the heterogeneity of dealers inventories is still present. This heterogeneity ensures that D2D interaction is benefited by the increased number of tradeable strategies resulting from spread trading. However, given that client RfQs remain at the same level (50 per instrument per D2C round) not in every D2D interaction all the dealers enter the auction with exposure to all the assets, thus reducing the effectiveness of spread trading. This can be observed by a general lower impact of spread trading on market quality.

It is relevant to note that when instead of comparing spread trading with non spread trading, one compares the difference between the base case scenario and higher competition scenario, the increased competition improves the bid ask spreads and the price behavior metrics as well as leading to a lower inventory risk. The later is because the same amount of clients' RfQs are split between a larger number of dealers[5].

[5]This is relevant because the robustness test also allows to validate the consistency of the model

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.135	3.135	-0.00050	-0.016%
		(0.00324)	(0.00278)		
	Dealer Utility	0.338	0.336	0.00247	0.735%
		(0.00395)	(0.00514)		
Liquidity	Bid-Ask Spread	0.056	0.05854	-0.00281	-4.795%
	Bid	0.028	0.029	0.00117	-4.867%
		(0.00025)	(0.00035)		
	Ask	-0.028	-0.029	0.00117	-4.722%
		(0.00027)	(0.00036)		
Price Behavior	Price Volatility	0.069	0.073	-0.00376	-5.130%
		(0.00147)	(0.00219)		
	Price Extremes	0.163	0.166	-0.00341	-2.049%
		(0.00465)	(0.00532)		
	Price Stability	0.849	0.855	-0.00631	-0.738%
		(0.00367)	(0.00502)		
	Price Divergence	0.034	0.028	0.00621	22.251%
		(0.00772)	(0.00806)		
	Price Correlation Divergence	1.069	1.063	0.00616	0.580%
		(0.00328)	(0.00418)		
Net Supply Price Impact	Correlation	-0.157	-0.157	0.00004	-0.026%
		(0.00451)	(0.00413)		
	Beta	-0.002	-0.002	0.0	-1.994%
		(6e-05)	(6e-05)		
Auction	Spread Trading Relevance	0.687			
		(0.0009)			
	Auction Efficiency	15.153	9.586	5.57	58.081%
		(0.05494)	(0.05376)		
	Risk Reduction	-0.0338	-0.0336	0.00117	0.735%
		(0.00039)	(0.00051)		
Inventory Risk	Value at Risk	0.197	0.204	-0.00674	-3.307%
		(0.00346)	(0.00383)		
	Balance Sheet Usage	15.189	29.701	-14.51	-48.861%
		(0.62485)	(0.60912)		
	Net Total Inventory	2.242	2.265	-0.02	-1.042%
		(0.21695)	(0.22381)		

Table 4.3: Increased Dealers Competition

Reduced Dealer Competition

Spread trading has no material impact when dealers competition is low. Following a similar approach as in the previous test, a lower competition between dealers is simulated by reducing the number of dealers in the market. More specifically, a 75% reduction which is achieved by setting the number of dealers in two instead of eight. In this case spread trading has no major impact in market quality as the risk-to-quoting transmission mechanism is not anymore materially different between the two strategies. This is explained by the lack of spread trading activity due to the homogeneity of dealers inventories. The similarity between inventories arise as the two dealers quote the same requests from clients thus engaging in the same inventory positions. The lower spread trading activity in comparison with the base case scenario can be observed in the relevance of spread trading metric, which is 53% in the reduced competition scenario while in the base case it is 68%. In addition, other metrics as the balance sheet usage and the net total inventory help to show how similar the inventories are with and without spread trading when competition is low.

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.127	3.120	0.00710	0.228%
		(0.004)	(0.00321)		
	Dealer Utility	0.018	0.016	0.00180	11.416%
		(0.00039)	(0.00043)		
Liquidity	Bid-Ask Spread	0.158	0.158	-0.00023	-0.145%
	Bid	0.079	0.079	0.00117	0.064%
		(0.00057)	(0.00056)		
	Ask	-0.079	-0.079	0.00117	-0.354%
		(0.00053)	(0.00063)		
Price Behavior	Price Volatility	0.217	0.216	0.00046	0.212%
		(0.00308)	(0.00356)		
	Price Extremes	0.535	0.545	-0.00945	-1.733%
		(0.01169)	(0.01481)		
	Price Stability	0.411	0.413	-0.00134	-0.325%
		(0.01038)	(0.00867)		
	Price Divergence	0.014	0.035	-0.02020	-58.302%
		(0.00653)	(0.00646)		
	Price Correlation Divergence	0.977	0.978	-0.00056	-0.057%
		(0.00035)	(0.00034)		
Net Supply Price Impact	Correlation	-0.323	-0.320	-0.00293	0.917%
		(0.00394)	(0.00382)		
	Beta	-0.012	-0.012	0.0	
		(0.00016)	(0.00017)		
Auction	Spread Trading Relevance	0.539			
		(0.00244)			
	Auction Efficiency	4.147	2.835	1.31	46.276%
		(0.01811)	(0.01429)		
	Risk Reduction	-0.0018	-0.0016	0.00117	11.416%
		(4e-05)	(4e-05)		
Inventory Risk	Value at Risk	0.612	0.558	0.05369	9.623%
		(0.0254)	(0.02134)		
	Balance Sheet Usage	67.708	68.983	-1.28	-1.848%
		(3.10328)	(2.86558)		
	Net Total Inventory	5.375	5.167	0.21	4.032%
		(0.55872)	(0.49717)		

Table 4.4: Reduced Dealer Competition

Changes In Private Valuation Distribution Parameters

The aim of this section is to test the stability of the simulation's results to changes in the volatility parameter of the clients' private valuations.

Higher Volatility

Changes in price elasticity of end users can be addressed by modifying the client private valuation's volatility parameter θ^2. In this specific robustness test, the impact of a lower price elasticity is simulated by increasing the value of θ^2. In general, a higher θ^2 leads to a higher impact of spread trading on market quality. Because a lower price elasticity of end users leads to longer net supply cycles, dealers hold similar inventories for longer periods. As described in the methodology chapter, dealers benefit the most from spread trading when non zero net supply is present. Therefore, when spreads are introduce to the D2D and at the same time the end users' price elasticity is reduce, the outcome is a greater impact of spread trading on market quality than in the base case scenario. This is observed in liquidity, price behavior, and inventory risk.

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	5.425	5.422	0.00300	0.055%
		(0.00679)	(0.00626)		
	Dealer Utility	0.300	0.306	-0.00574	-1.879%
		(0.00386)	(0.00513)		
Liquidity	Bid-Ask Spread	0.119	0.133	-0.01391	-10.426%
	Bid	0.065	0.072	0.00117	-10.150%
		(0.00076)	(0.00098)		
	Ask	-0.055	-0.061	0.00117	-10.750%
		(0.00081)	(0.00093)		
Price Behavior	Price Volatility	0.146	0.160	-0.01308	-8.201%
		(0.00372)	(0.00463)		
	Price Extremes	0.336	0.356	-0.01982	-5.571%
		(0.00722)	(0.0082)		
	Price Stability	0.909	0.915	-0.00526	-0.575%
		(0.00209)	(0.00186)		
	Price Divergence	1.083	1.119	-0.03550	-3.173%
		(0.01585)	(0.01762)		
	Price Correlation Divergence	1.086	1.091	-0.00511	-0.468%
		(0.00243)	(0.0017)		
Net Supply Price Impact	Correlation	-0.135	-0.135	0.00003	-0.019%
		(0.0047)	(0.00426)		
	Beta	-0.004	-0.004	0.00028	-0.425%
		(0.00013)	(0.00013)		
Auction	Spread Trading Relevance	0.668			
		(0.00103)			
	Auction Efficiency	14.263	8.777	5.49	62.504%
		(0.05678)	(0.06262)		
	Risk Reduction	-0.0300	-0.0300	0.00117	-0.058%
		(0.00039)	(0.00051)		
Inventory Risk	Value at Risk	0.299	0.370	-0.07085	-19.146%
		(0.00679)	(0.01098)		
	Balance Sheet Usage	24.800	35.960	-11.16	-31.034%
		(1.01014)	(0.76176)		
	Net Total Inventory	3.605	4.825	-1.22	-25.285%
		(0.33663)	(0.53292)		

Table 4.5: Higher Private Valuation Volatility

Lower Volatility

When θ^2 is low leading to a high price elasticity of end users, the impact of spread trading is not anymore relevant. When price elasticity of end users is high, the net supply cycles are shorter. This means that the client orders are more often in the opposite position of dealers inventories. As a result, dealers use the clients' orders to offset their risk exposure, this shift in inventories positions reduces the relevance of the D2D interaction as a risk reducing mechanism. At the same time it drives away the benefits of D2D spread trading activity. This is why the market quality with and without spread trading under high price elasticity of end users is not as relevant as in the base case or when elasticity is lower.

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	1.589	1.589	0.00000	0.000%
		(0.00163)	(0.00209)		
	Dealer Utility	0.207	0.204	0.00277	1.359%
		(0.00198)	(0.00229)		
Liquidity	Bid-Ask Spread	0.055	0.055	-0.00054	-0.970%
	Bid	0.027	0.027	0.00117	-0.387%
		(0.00019)	(0.00022)		
	Ask	-0.027	-0.028	0.00117	-1.545%
		(0.0002)	(0.00021)		
Price Behavior	Price Volatility	0.071	0.072	-0.00082	-1.145%
		(0.00112)	(0.00132)		
	Price Extremes	0.175	0.180	-0.00469	-2.611%
		(0.00431)	(0.00431)		
	Price Stability	0.656	0.660	-0.00367	-0.557%
		(0.00585)	(0.00596)		
	Price Divergence	-0.005	0.000	-0.00571	-1196.133%
		(0.00319)	(0.00374)		
	Price Correlation Divergence	1.061	1.058	0.00223	0.211%
		(0.00437)	(0.0033)		
Net Supply Price Impact	Correlation	-0.242	-0.244	0.00120	-0.491%
		(0.00421)	(0.0043)		
	Beta	-0.003	-0.003	0.00001	-0.320%
		(6e-05)	(6e-05)		
Auction	Spread Trading Relevance	0.683			
		(0.00106)			
	Auction Efficiency	13.113	7.934	5.18	65.284%
		(0.03466)	(0.04924)		
	Risk Reduction	-0.0207	-0.0204	0.00117	1.359%
		(0.0002)	(0.00023)		
Inventory Risk	Value at Risk	0.190	0.194	-0.00421	-2.169%
		(0.0037)	(0.00378)		
	Balance Sheet Usage	19.215	31.656	-12.44	-39.302%
		(0.73479)	(0.59039)		
	Net Total Inventory	1.844	2.106	-0.26	-12.463%
		(0.17375)	(0.19396)		

Table 4.6: Reduced Private Valuation Volatility

Adding Randomness to D2C Interaction

Given that in practice dealers do not have the same information or modeling techniques, their private valuations have an idiosyncratic component. This begs the question of how relevant the impact of spread trading is when the simulation account for this idiosyncratic differences. This included by introducing a idiosyncratic random term to eq. 3.2

$$\Delta\tilde{\sigma}^2_{t,n,i} = \Delta\sigma^2_{t,n,i} + e_{t,n} \tag{4.1}$$

By adding randomness to the quoting process of the D2C interaction, the effect that spread trading has on market quality is diluted. This is because including a stochastic component to the D2C quoting process reduces the relevance of inventory's marginal risk as determinant of order execution. This leads to a more random allocation of the net supply between dealers and a more random bid ask spread. Consequently, the risk reducing effect of spread trading that is still present (-2.17% lower VaR with spread trading) is not completely transmitted to the D2C interaction. However, there is still an impact on market quality, as spread trading leads to: tighter bid ask spread, lower price volatility, higher D2D risk sharing capacity, less intensive use of dealers' balance sheet and smaller net total inventories. However, the impact of spread trading on these metrics is not as strong as in the base case. This points to the relevance of heterogeneity between dealers private valuation.

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.132	3.139	-0.00660	-0.210%
		(0.00331)	(0.00351)		
	Dealer Utility	0.240	0.229	0.01075	4.691%
		(0.0029)	(0.00312)		
Liquidity	Bid-Ask Spread	0.068	0.069	-0.00117	-1.690%
	Bid	0.034	0.035	0.00117	-1.319%
		(0.0003)	(0.00038)		
	Ask	-0.034	-0.035	0.00117	-2.060%
		(0.00032)	(0.00038)		
Price Behavior	Price Volatility	0.088	0.090	-0.00115	-1.287%
		(0.00179)	(0.00229)		
	Price Extremes	0.204	0.201	0.00250	1.241%
		(0.00483)	(0.00671)		
	Price Stability	0.793	0.793	-0.00003	-0.004%
		(0.00585)	(0.00587)		
	Price Divergence	0.027	0.028	-0.00040	-1.458%
		(0.00912)	(0.00921)		
	Price Correlation Divergence	1.053	1.065	-0.01127	-1.059%
		(0.0052)	(0.00454)		
Net Supply Price Impact	Correlation	-0.187	-0.185	-0.00156	0.843%
		(0.00429)	(0.00471)		
	Beta	-0.003	-0.003	0.00004	-0.313%
		(7e-05)	(8e-05)		
Auction	Spread Trading Relevance	0.677			
		(0.00101)			
	Auction Efficiency	13.551	8.156	5.39	66.147%
		(0.05236)	(0.04797)		
	Risk Reduction	-0.0240	-0.0229	0.00117	4.691%
		(0.00029)	(0.00031)		
Inventory Risk	Value at Risk	0.256	0.242	0.01427	5.894%
		(0.00557)	(0.00522)		
	Balance Sheet Usage	21.248	34.310	-13.06	-38.072%
		(0.85562)	(0.72279)		
	Net Total Inventory	3.015	2.369	0.65	27.265%
		(0.25444)	(0.25606)		

Table 4.7: D2C Quoting Randomness

Including a Penalty for Balance Sheet Intensive Use

Traders not only care about the risk of their portfolio but also about their cost of inventory. This cost can be proxied by measuring the balance sheet use[6]. Moreover, this metric can also proxy for market risk from the perspective of correlations instability. Given that this can be a material risk under market stress scenarios it is also relevant to test its impact as if it were to be accounted for into dealers pricing. This is done by modifying eq. 3.2 as follows

$$\Delta\tilde{\sigma}^2_{t,n,i} = \Delta\sigma^2_{t,n,i} + \Delta BS_{t,n,i} \tag{4.2}$$

Where $\Delta BS_{t,n,i}$ is the marginal increase of balance sheet use as if a trade or strategy were to be executed compared with the current BS. This metric will increase the margin charged if the BS increases and reduces the margin when BS decreases. As can be seen in table 4.8 the incorporation of ΔBS in dealers' pricing equation drives out most of the spread trading benefits. This is because balance sheet use is one of the main benefits of spread trading. Once dealers account for this in their pricing, the D2C and D2D lead to similar balance sheet use. This can be from the balance sheet use result in table 4.8. Because for dealers is more difficult to find other dealers with the exact offsetting position in a specific spread, they will more often trade offsetting single assets. This will lead to a lower inventory risk in the case when spread trading is not included. Therefore, the risk-to-price transmission mechanism works better when spreads are not traded.

[6]This is because the inventory cost has a direct relation with the size of the inventory, which is what balance sheet use metric measures. This metric is presented in the methodology section

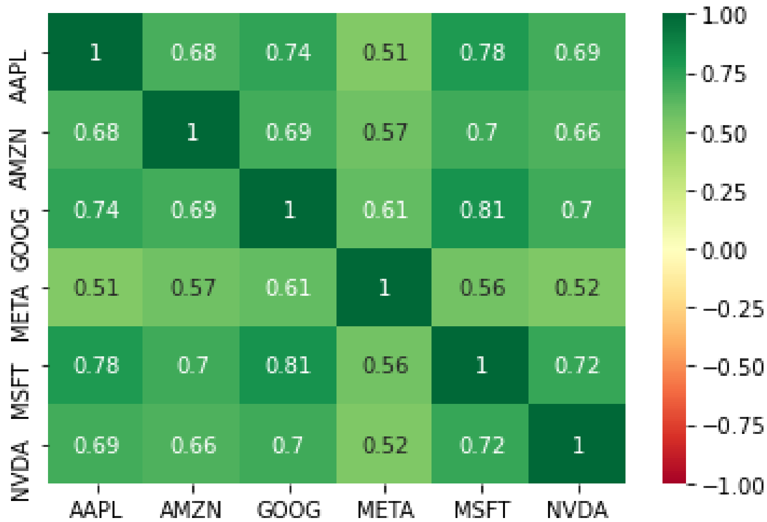
Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.137	3.139	-0.00200	-0.064%
		(0.00265)	(0.00269)		
	Dealer Utility	0.520	0.533	-0.01299	-2.439%
		(0.00492)	(0.00508)		
Liquidity	Bid-Ask Spread	0.079	0.076	0.00344	4.523%
	Bid	0.040	0.038	0.00117	4.417%
		(0.00029)	(0.00027)		
	Ask	-0.040	-0.038	0.00117	4.630%
		(0.00029)	(0.00026)		
Price Behavior	Price Volatility	0.102	0.097	0.00560	5.796%
		(0.00171)	(0.00151)		
	Price Extremes	0.244	0.232	0.01155	4.976%
		(0.00502)	(0.00527)		
	Price Stability	0.812	0.804	0.00837	1.041%
		(0.00393)	(0.00401)		
	Price Divergence	0.033	0.022	0.01064	48.457%
		(0.00614)	(0.00636)		
	Price Correlation Divergence	0.987	0.998	-0.01108	-1.110%
		(0.00635)	(0.00602)		
Net Supply Price Impact	Correlation	-0.197	-0.201	0.00321	-1.602%
		(0.00319)	(0.00321)		
	Beta	-0.003	-0.003	-0.00011	-0.322%
		(6e-05)	(6e-05)		
Auction	Spread Trading Relevance	0.650			
		(0.00097)			
	Auction Efficiency	12.291	13.099	-0.81	-6.165%
		(0.03784)	(0.06297)		
	Risk Reduction	-0.0235	-0.0227	0.00117	3.671%
		(0.00022)	(0.00022)		
Inventory Risk	Value at Risk	0.253	0.243	0.00932	3.830%
		(0.00464)	(0.00394)		
	Balance Sheet Usage	16.558	16.586	-0.03	-0.173%
		(0.55942)	(0.56703)		
	Net Total Inventory	2.848	2.611	0.24	9.047%
		(0.22868)	(0.18712)		

Table 4.8: Balance Sheet Use Penalty

Spread Trading in the Equity Market

So far all the analysis have been conducted using euro denominated swap rates, however the covariance matrix for other asset classes is not the same as in euro swaps. This raises the question about the spread trading impact for a different asset class. Moreover, is relevant to evaluate the results with assets with lower correlations given the relevance of correlation in spread trading. The chosen asset class is US equities, more specifically technology related companies such as: Apple Inc., Amazon, Google (Alphabet), Microsoft, and Nvidia. The correlation heatmap is presented in the figure below

Figure 4.2: Equities Correlation Heatmap



As can be seen correlations are still positive but lower when compared to correlations between the euro swaps. Table 4.9 shows how relevant are the high correlations for the spread trading to improve the market quality. These results show that when correlations between assets are low spread trading lose effectiveness. This is because when correlations are high, spreads help dealers to overcome non zero net supply issues. In contrast, when correlation between assets are low, spreads can not anymore help dealers to overcome non zero net supply issues[7]. Therefore, the inclusion of spread trading do not leads to a better market quality. In fact spread trading can lead to a lower market quality when the assets' correlations are low. This can be seen in table 4.9 where bid ask spread, price volatility, and inventory risk are higher when spreads are introduced.

[7]This is because when correlation are low between different assets, the cross asset and package based hedging strategies are not as effective as when correlation are high

Market Feature	Quality Metric	With Spread Trading	Without Spread Trading	Difference	Difference (%)
Utility	Client Utility	3.136	3.138	-0.00280	-0.089%
		(0.00385)	(0.00343)		
	Dealer Utility	0.121	0.114	0.00704	6.178%
		(0.00179)	(0.00211)		
Liquidity	Bid-Ask Spread	0.022	0.021	0.00096	4.495%
	Bid	0.011	0.011	0.00117	3.643%
		(0.00038)	(0.00041)		
	Ask	-0.011	-0.010	0.00117	5.380%
		(0.00038)	(0.00041)		
Price Behavior	Price Volatility	0.015	0.014	0.00096	6.869%
		(0.00046)	(0.00072)		
	Price Extremes	0.032	0.030	0.00213	7.036%
		(0.00116)	(0.00153)		
	Price Stability	0.946	0.932	0.01429	1.534%
		(0.00259)	(0.00554)		
	Price Divergence	0.038	0.030	0.00823	27.431%
		(0.00611)	(0.00821)		
	Price Correlation Divergence	1.307	1.284	0.02255	1.756%
		(0.00732)	(0.01299)		
Net Supply Price Impact	Correlation	-0.109	-0.102	-0.00714	7.029%
		(0.00546)	(0.00588)		
	Beta	-0.001	-0.001	-0.00003	-0.057%
		(4e-05)	(4e-05)		
Auction	Spread Trading Relevance	0.566			
		(0.00147)			
	Auction Efficiency	13.556	14.903	-1.35	-9.037%
		(0.06616)	(0.10501)		
	Risk Reduction	-1209.3223	-1138.9539	0.00117	6.178%
		(17.93632)	(21.11059)		
Inventory Risk	Value at Risk	81.266	70.993	10.27312	14.471%
		(1.50355)	(1.69977)		
	Balance Sheet Usage	20.163	18.680	1.48	7.936%
		(0.68676)	(0.80182)		
	Net Total Inventory	7.083	6.390	0.69	10.837%
		(0.69118)	(0.59826)		

Table 4.9: Equities Spread Trading

Chapter 5

Methodology Discussion

The aim of this chapter is to briefly discuss the assumptions made during the implementation of the simulation and its implication on the relevance of the obtained results.

As it has been presented and justified throughout this thesis, several assumptions have been made to define the simulation's methodology. The reason of this assumptions range from computational efficiency to model parsimony. However, I am confident that the implemented version of this methodology is sufficiently well design so it resemble an OTC market in which is possible to isolate the impact of spread trading. Moreover, the aim of this research is to be a first approximation to the comprehension of the implications of different interdealer trading strategies. As the obtained results are coherent with most of the expected implications of spread trading I believe that those results will hold under more sophisticated approaches as well.

With the aim to present the reasoning behind the most relevant assumptions, next I discuss the justification, benefits, and drawbacks

1. **Dealers quadratic loss aversion**: In practice, although dealers behave as risk averse agents, the margin charged to take additional risk is

not likely to increase exponentially[1]. However, it is true that as the inventory exposure to a specific risk or to a highly correlated one increases the margin charged does as well. Moreover, when the dealer's exposure to that specific risk is already high, is reasonable to think that the margin charged is likely to increase more than linearly. The later scenario is captured by the quadratic loss aversion assumption. This is because the client volumes are bounded to 1 and the marginal risk is conditional on the current dealer inventory. Therefore, when a dealer has a high exposure to a specific risk the quadratic loss aversion captures the non linear margin increase charged for taking additional risk.

2. **Zero bound on D2C margins**: As mentioned before, this assumption captures an economic rationale of the relationship between clients and dealers. In this relationship dealers accept to take a risk, from client orders, in exchange for a margin. However, when a client order is risk reducing the margin charged is not usually a cost for the dealer[2] . What more often happens is that dealers quote this type of requests at a price close to mid price, only in some occasions dealers execute through mid. Moreover, when they do execute through mid price it is not far from mid price. This is why the zero bound on D2C margins reflects a common dynamic of actual OTC markets.

3. **Call auction instead of continuous D2D trading**: In actual OTC markets, D2D interactions take place in a semi-continuous manner. One of the assumptions of this thesis is that D2D interactions are modeled using a non continuous call auction per trading session. However, the simulation can be seen as an intraday multiround model[3]. From this perspective it partially overcomes the non continuous assumption. On the other hand, the decision of using a call auction process responds to

[1] For instance, if a dealer charges a 10% margin for 100 units of risk, it is not likely that the same dealer will charge more than twice, say a 30% margin, for 200 units of risk

[2] In this context the word cost refers to a trade executed through mid price. For instance dealer selling at a price lower than mid or buying at a price higher than mid

[3] This means that each time t is not necessarily one day but can be seen as a fraction of one trading session T

its informational and computational efficiency. The informational efficiency is a consequence of the concentration of D2D trading activity in a specific point in time, in which dealers send their prices simultaneously. The main benefit of its informational efficiency is that it allows to isolate the D2D spread trading from other D2D phenomena. This isolation feature is relevant because this is, from the best of my knowledge, the first attempt to formalize the impact of spread trading on market quality. While the computational efficiency means that this process is significantly less computational intensive and can be implemented using a smaller amount of parameters.

4. **Utility-based auction sequentially**: Assuming an utility driven order for the auctions, within the D2D call auction, arises from the aim to give an economic rationale to the auctions sequentially. Another option is to assume a random order between the auctions. However, this randomness could lead to meaningless results as it would ignore that dealers prioritize the hedging of their larger risk exposures.

5. **Sequentiality between D2C and D2D**: In real OTC markets the order and frequency between D2C and D2D interactions is not warranted to be one by one sequential[4]. However, one of the main triggers of D2D interaction is the execution of client orders. This mechanism works as follows, in a first stage dealers take risk by executing clients orders, the next step is to hedge that risk. This hedging process can be done by using client orders or by trading in the D2D. Because client flow is uncertain and dealers are risk averse, dealers assist to the interdealer market to hedge the risk. This shows how there is some sequentiality between the D2C and the D2D. Although, the assumption captures some of the D2D-D2C dynamic, it is still a simplification of actual markets behavior.

6. **Price sensitive order arrival process**: As presented previously in this thesis, the use of a price sensitive order arrival process is an attempt

[4] This means that in actual markets is not the case that the client orders will all be quoted and then the D2D will commence

to incorporate the elasticity of clients' net supply to price shocks, in the context of financial markets.By introducing this dynamic it is possible to induce different degrees of distress in dealers inventories. In practice, it is common to observe that D2C net supply is one of the drivers of inventory distress. This warrants the necessary conditions to analyse how the D2D spread trading helps dealers to overcome the non zero net supply issue.

Chapter 6

Conclusions

Main results suggest that in an OTC market where dealers' inventory risk is the main determinant of price discovery, the market quality generally improved by spread trading. This benefits are perceived by a higher market liquidity, lower price volatility, lower average inventory risk, and less intensive use of dealers' balance sheet. Spread trading has a passive impact on market quality because of improved interdealer risk sharing capacity. Such an enhancement is a consequence of an increased number of tradeable strategies (i.e. spreads) of highly correlated assets. This additional packages allow dealers to use of the high correlations to hedge their inventory risk when the exact opposite position is not available. This allows dealers to overcome the issue that arises from the non zero net supply cycles. Moreover, spread trading impact on market quality hold under a several relevant scenarios. These scenarios are: increased dealer competition, changes in price elasticity of final users, and heterogeneity of dealers private valuation. In other tests such as the use of equities' covariance matrix, spread trading does not lead to a better market quality. However, this is coherent with the fact that lower correlations reduce the effectiveness of package based hedging. Although in most of the cases the results are as coherent, when balance sheet use is incorporated in the pricing formula, the results diverge from the expected impact of spread trading. This points to the limitations of the design of this specific simulation set up, as mentioned in the discussion chapter.

Much has been studied about the relationship that market quality has with market design and agents behavior. However, from the best of my knowledge, the impact of interdealer spread trading strategies has not been previously studied. Therefore, this research is a first step towards the understanding of how the interdealer's trading strategies have an impact on the overall market quality. Further research could reach more conclusive finding by making this simulation closer to actual OTC markets. Some of these modification could be: the inclusion of strategic behavior of dealers and end users, the incorporation of a more realistic sequentiality between D2C and D2D interactions, and the modification of the D2D trading mechanism from a call auction to a continuous trading process.

The practical relevance of this work lies on the understanding of the benefits of using certain trading strategies in the interdealer market. This benefits are widely accepted by market participants but this thesis adds a more formal understanding of why spread trading benefit the market as a whole. In addition, this research proposes one possible transmission mechanism able to explain how spread trading improves the market quality.

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