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Master of Science (M.Sc) in Banking and Finance

“Comparative analysis of Back to Back vs Dark Pool STP execution models in OTC Markets”

Ονοματεπώνυμο φοιτητή: Βαμβουλής Ευστράτιος (MXAN1802)

Επιβλέπων Καθηγητής: Νικόλαος Κουρογένης, Καθηγητής
Μέλη επιτροπής: Χ. Στεφανάδης, Καθηγητής, Σ. Αναγνωστοπούλου, Αναπλ. Καθηγήτρια

Student Name: Efstratios Vamvoulis (MXAN1802)

Supervisor: Nikolaos Kourogenis, Professor
Members of the Committee: C. Stefanadis, Professor, S. Anagnostopoulou, Assoc. Professor

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Abstract

The aim of this thesis is to present and compare two different models of handling trading flow in OTC Forex retail Market. I will present and describe two discrete Straight Through Processing (STP) models that retail aggregators or brokers use to handle retail client trading flow via two different variations. A back-to-back approach, where all trading flow is externalized to the market via associated liquidity providers and an Own Liquidity model where the firm acts as the primary liquidity pool and operates as principal counterparty in all transactions

Initially we will present an overview of currency markets microstructure as well as describe some real-world systems. Then we will present the retail forex market microstructure, participants as well as how it is linked to the interbank market. Later on, we will compare the two models in three segments. At first, we will examine how and why each model affects execution time and how this is related with market volatility and price discovery.

Then we will compare the two models, based on the available data, n terms of speed of execution, best execution in price terms and finally we will measure daily market risk exposure in each model using the analytic or parametric Value at Risk methodology and examine any relationship with the retail client’s profit/loss performance.

Key words: retail forex, liquidity, market risk, market microstructure, over the counter, OTC, value at risk.

Στόχος της παρούσας διπλωματικής εργασίας είναι η παρουσίαση και σύγκριση δύο διαφορετικών μοντέλων διαχείρισης της ροής συναλλαγών στη λιανική αγορά OTC Forex. Θα παρουσιάσω και θα περιγράψω δύο διακριτά μοντέλα Straight Through Processing (STP) που χρησιμοποιούν οι επενδυτικές εταιρίες στο χώρο του λιανικής ή οι μεσίτες για να χειριστούν τη ροή συναλλαγών πελατών λιανικής μέσω δύο διαφορετικών αποκλίσεων. Μια προσέγγιση back-to-back, όπου όλες οι ροές συναλλαγών εξωτερικεύονται στην αγορά μέσω συνδεδεμένων παρόχων ρευστότητας και ενός μοντέλου ίδιας ρευστότητας όπου η εταιρεία ενεργεί ως κύριος αντισυμβαλλόμενος σε όλες τις συναλλαγές

Αρχικά θα παρουσιάσουμε μια επισκόπηση της δομής των αγορών συναλλάγματος καθώς και κάποια πραγματικά μοντέλα αγοράς. Στη συνέχεια θα παρουσιάσουμε τη δομή της λιανικής αγοράς συναλλάγματος, τους συμμετέχοντες καθώς και τον τρόπο σύνδεσής της με τη διατραπεζική αγορά. Έπειτα, θα συγκρίνουμε τα δύο μοντέλα με βάση τρία βασικά χαρακτηριστικά. Αρχικά θα εστιάσουμε στο χρόνο εκτέλεσης συναλλαγών του κάθε μοντέλου και πώς αυτό σχετίζεται με την μεταβλητότητα της αγοράς και την ανακάλυψη βέλτιστων τιμών

Στη συνέχεια θα συγκρίνουμε τα δύο μοντέλα, λαμβάνοντας υπόψιν τα διαθέσιμα δεδομένα, σε όρους ταχύτητας εκτέλεσης, βέλτιστη εκτέλεση τιμής και τέλος θα μετρήσουμε την ημερήσια έκθεση στον κίνδυνο αγοράς σε κάθε μοντέλο χρησιμοποιώντας την αναλυτική ή παραμετρική μεθοδολογία Value at Risk και θα εξετάσουμε τυχόν γραμμική σχέση του με την ημερήσια απόδοση κέρδους/ζημίας των πελατών.

Contents

Chapter 1: Introduction

1.1 Introduction to Forex Market

The foreign exchange market is the generic term for the worldwide institutions that exist to exchange or trade currencies. Foreign exchange is often referred to as "forex" or "FX." The foreign exchange market is a worldwide decentralized over-the-counter (OTC) financial market for trading currencies. Unlike the Stock Market, the forex market does not have a physical central exchange like the NYSE does at 11 Wall Street. Without a central exchange, currency exchange rates are made, or set, by market makers. There is no clearing house where orders are matched. Rather, trading is done 'off-exchange' or over-the-counter directly between two parties. FX dealers and market makers around the world are linked to each other around-the-clock via telephone, computer, and fax, creating one cohesive market. Since there is no centralized exchange, competition between market makers prevents monopolistic pricing strategies. If one market maker attempts to drastically skew the price, then traders simply have the option to find another market maker. Moreover, spreads are closely watched to ensure market makers are not whimsically altering the cost of the trade. Many equity markets, on the other hand, operate in a completely different fashion; the New York Stock Exchange, for instance, is the sole place where companies listed on the NYSE can have their stocks traded. Centralized markets are operated by what are referred to as specialists; market makers, on the other hand, are the term used in reference to decentralized marketplaces. Since the NYSE is a centralized market, a stock traded on the NYSE can only have one bid-ask quote at any time. Decentralized markets, such as foreign exchange, can have multiple market makers – all of whom have the right to quote different prices.

During the 1970's the FX market was dominated by bank brokers. However, deregulation and electronic trading has made the FX market the most liquid market in the world and more easily accessible to smaller investors. Central banks remain powerful in this system; however, their influence has fallen from previous levels. Furthermore, the National Futures Association (NFA) and the Commodity Futures Trading Commission (CFTC) were established in the 1970's and the 1980's to protect individual market participants.

The first venture into electronic trading in foreign exchange markets was the launch of Reuter's "Monitor Dealing Service" in the early 1980's, which was later replaced by Reuters Dealing 2000-1 in 1989. The earliest systems allowed for communication between foreign exchange dealers with a single counterparty but did not serve as a matching system between numbers of potential counterparties. In 1992, however, this changed when Reuters launched Dealing 2000-3, a true electronic brokering system that automatically matched buy and sell quotes from dealers. Next, the Minex Corporation, a Japanese group of brokers and bankers set up its own system in April 1993. In September 1993, EBS (Electronic Brokering Service) was formed by a group of large dealing banks and launched its trading system. Once Minex Corporation transferred its business rights to EBS in 1996, the foreign exchange market was left with two major inter-dealer electronic brokering systems. Order matching systems are much more reliable, and faster, allowing traders to conduct many simultaneous trades, rather than one or two over the phone.

Average traders can now trade alongside the biggest banks in the world, with virtually similar pricing and execution. What used to be a game dominated and controlled by the “big boys” is slowly becoming a level playing field where individuals can profit and take advantage of the same opportunities as big banks. FX is no longer a “good old boys” club, which means opportunity is abound for aspiring online currency traders.

In the last 25 years, increasing globalization has had a profound impact on the foreign exchange market, resulting in staggering growth as well as an impressive rise in the number and diversity of players. The market has expanded from one of banks trading predominately amongst each other to one in which many different kinds of financial and non-financial institutions all participate for a variety of reasons. There have been many contributing factors to the growth of the foreign exchange market but the major developments that are worth noting are:

1) Advancement in technology and

2)The continuing growth of international and cross-border capital movement, i.e., foreign investment.

The participants in the FX market can be organized into a ladder. To better understand what we mean, here is a neat illustration:

Figure 1-Forex Market Hierarchy

At the very top of the forex market ladder is the interbank market. Composed of the largest banks in the world, the participants of this market trade directly with each other ("bilaterally") or through voice or electronic brokers (such as EBS Market and Reuters Matching). Next on the ladder are the hedge funds, corporations, retail market makers, and retail ECNs. Since these institutions do not have tight credit relationships with the participants of the interbank market, they have to do their transactions via commercial banks. This means that their rates are slightly higher and more expensive than those who are part of the interbank market. At the very bottom of the ladder are the retail traders.

The foreign exchange or forex market is the largest financial market in the world – larger even than the stock market. Trading activity in the foreign exchange market reached an all-time high of \$5.3 trillion in April 2013, 35% higher than in2010 and a few years later it reached a daily volume of \$6.6 trillion, according to the 2019 Triennial Central Bank Survey of FX and OTC derivatives markets. Below, in Figure 2, we can see a chart from Bank of International Settlements that illustrates volume evolution of Forex Market from 2004 until 2019. Note that, values are adjusted for local and cross-border inter-dealer double-counting (ie "net-net" basis.), The category "other FX products" covers highly leveraged transactions and/or trades whose notional amount is variable and where a decomposition into individual plain vanilla components was impractical or impossible and Non-US dollar legs of foreign currency transactions were converted into currency amounts at average exchange rates for April of each survey year and then reconverted into US dollar amounts at average April 2019 exchange rates.

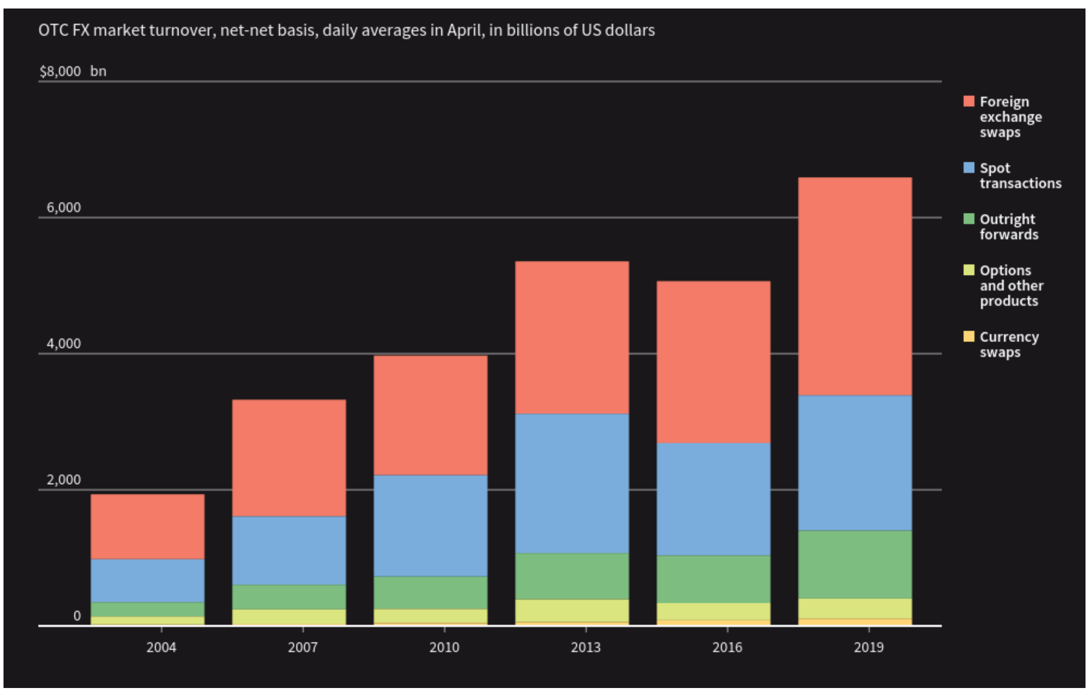


Figure 2-OTC foreign exchange turnover. Sources: Euromoney tradedata; Futures Industry association, The options clearing corporation, BIS derivatives statistics. Foreign exchange futures and options traded worldwide. Source: Bank of international settlements. Ritvik Carvalho |REUTERS GRAPHICS

There is a reason why forex is the largest market in the world: It empowers everyone from central banks to retail investors to potentially see profits from currency fluctuations related to the global economy. The reasons for forex trading are varied. Speculative trades – executed by banks, financial institutions, hedge funds, and individual investors – are profit-motivated. Central banks move forex markets dramatically through monetary policy, exchange regime setting, and, in rare cases, currency intervention. Corporations trade currency for global business operations and to hedge risk.

1.2 Main scope

The aim of this Master's thesis is to review initially, the overall Currency Markets microstructure and how they function by presenting real-world systems, then present the microstructure of retail Forex market specifically in details. Based on this review, we will present two discrete execution and order management models brokers use to handle the generated trading flow from their respective clients.

Specifically, we will compare two broker systems, that also act as dealers (broker/dealer retail aggregators), and the methodologies that are used by the aggregators to handle trading flow generated by its retail clients trading activity, as well as what advantages/disadvantages each system imposes both on brokers and clients as well. The first type of these systems relies on processing client order flow directly to market liquidity pools "outside" the broker simply by passing along inter-bank spot prices, without interfering in quoted prices. The second type of models uses Own liquidity pool execution by the broker, acting as a market-making Dealer aggregator and handling his risk over the client generated exposure on a later stage. Again, in terms of prices and in regard to the examined model, the aggregator will be acting as price taker, without interfering in quoted prices.

The main focus is given on how each of these systems affects the speed of execution and the reasons that affect this parameter. Additionally, we will compare how executed prices are affected between the two models and the key drivers behind this parameter. Finally, we will assess advantages and disadvantages for the broker in terms of market risk, that each model imposes using variance covariance value at risk. Specifically, we will compare the dollarized value at risk of the exposure the broker holds compared to published statistics regarding client profit/loss ratios.

For the aforementioned topics, besides the related literature which will be presented below, we will use real execution data and model design parameters provided by a broker that operates in the Forex and CFD OTC market, Triple A Experts Investment Services S.A.

1.3 Review of related literature

There is an extensive literature regarding Currency Market Microstructure.
Initially we will refer to "The Microstructure of Currency Markets" (2012) by Carol Olser and Xuhang Wang to provide an overview of currency market, by describing the currencies and instruments traded and highlighting the market's two-tier institutional structure, in which dealers provide liquidity to customers in one tier and to each other in the second tier.

Consequently, based on "Market Architecture and Design" (2013) by Massimiliano Marzo, we will present Real-World systems on how OTC models work from a general perspective. A broad market classification distinguishes between market-based exchanges, where orders are placed by customers or dealers on an organized exchange, or over the counter (OTC) markets. Order matching is conducted bilaterally, off-exchange. A specific market is represented by Alternative Trading Systems (ATS) also known as dark pools or markets with nondisplayed liquidity. We will present an overall approach to this Market architecture and its' trading mechanics alongside with their corresponding characteristics.

On the other hand, Retail Forex Market structure is not very well documented. John Forman III (2016), makes though, a comprehensive presentation and analysis of the segment of OTC market microstructure, which we will use to link our models with. Primary parties and participants, linking with the inter-bank Market, as well as Retail Spot Forex trading mechanics will help us present, understand and analyze both of our models in comparison with whole market structure and philosophy.

Furthermore, based on "An Introduction to Value at Risk" (2013) by Moorad Choudhry and Fourth Edition, 1996 of Risk Metrics by JP Morgan and Reuters we will calculate the variance covariance (analytic or parametric method) Value at Risk (VaR) for the entire Portfolio based on the exposure or the order Book at specific timestamps, by decomposing the financial instruments and specifying distributions. For example, the most widely used analytic method, JPM organ 's Risk Metrics, assumes that the underlying distributions are normal. With normal distributions all the historical information is summarized in the mean and standard deviation of the returns. Finally, we will calculate the Daily Value at Risk and compare it with retail client monthly performance and use it as part of our comparative analysis between the models.

Chapter 2: Presentation of Currency Markets.

2.1 Presentation of Currency Markets Microstructure

2.1.1 Currency Markets Microstructure

When it comes to currency markets, the U.S Dollar and the Euro account for the majority of the traded volume. The next most actively traded instruments are the Japanese yen and British pound. Microstructure research concentrates on spot and forward currency trading, which typically accounts for roughly half of what has formally been identified as foreign exchange trading. Foreign exchange swaps dominate the rest of the foreign exchange market. These instruments are similar to repurchase agreements because they combine a spot transaction with a forward reversing transaction. Banks mainly use foreign exchange swaps for overnight position management. Other foreign exchange instruments include currency swaps and options. The foreign exchange market is far more lightly regulated than most equity or bond markets. Governments hesitate to regulate local trading practices because currency trading can take place anywhere, and trading operations, which pay well and are environmentally clean, can simply move elsewhere.

The foreign exchange market is at core a two-tier market. In one, customers trade directly with their dealers, in the other, dealers trade with each other. The customer market is a quote-driven or over-the-counter (OTC) market, in which most individuals or institutions needing foreign currency trade with specialized dealers.

Dealers (Liquidity Providers) trade very actively among themselves. Electronic trading, that was introduced to the interdealer market around 1990 eliminated voice brokers and replaced most direct interdealer trades., and within a decade, two major electronic limit order markets, Electronic Broking Service (EBS) and Reuters, dominated interdealer trading. Electronic trading naturally increased transparency in the interdealer market as it became far easier for dealers to learn the market price at a given moment and trading transformed the market's industrial organization. Each big bank now offers its customers a multitude of single-bank trading platforms, with each platform tailored to a specific customer type. The massive investment in trading infrastructure required to develop and support these trading platforms introduced economies of scale. This, in turn, brought a dramatic increase in market concentration among dealers. The foreign exchange market's increased concentration has, in turn, brought a major change in the way dealers managed inventory. Historically, dealers managed inventory by interdealer trades since customer trades arrived relatively infrequently and interdealer trades are fast and inexpensive. At large banks, the time between customer trades has fallen dramatically because of the overall expansion of currency trading and industry consolidation. Thus, large dealers now typically warehouse inventory for the brief interval of time until they can lay it off on other customers. At large banks, the rise in profits from internalized customer trades has helpfully offset a decline in speculative profits from interdealer trading. Dealers have also changed the way they quote prices. Historically, dealers did not usually shade prices based on their inventory, lowering prices when inventory was high and vice versa because of a reluctance to give other dealers information about their position. Now that dealers rely more heavily on customer trades for inventory management, those concerns have diminished, and price shading has reportedly become standard practice. The behavior of small dealers has also changed. Because the technology infrastructure required for strong customer relationships is expensive to develop and maintain, many smaller dealers now simply license this technology from larger dealers, a practice known as white labeling. Beyond the major dealing banks, the three other providers of foreign exchange liquidity are global custodian banks, retail aggregators, and high-frequency traders. Retail aggregators, in which we will be focusing, are Internet-based platforms that enable small individual investors to participate in the foreign exchange market. This allows the aggregator to pass on to their customers the small bid-ask spreads of the interdealer market. Some aggregators act as dealers, trading on a principal basis with customers, others act as brokers, trading on an agency basis and some act in both ways. Though retail aggregators commonly allow customers higher, they tightly control their risk by imposing margin requirements and liquidating positions instantaneously when margin calls are not met. Competition from these very low-cost liquidity providers has been a major factor encouraging banks to internalize customer trades.

Liquidity demanders in the foreign exchange market include corporations, retail investors, and financial institutions. Financial institutions include regional and smaller banks, central banks, high-leverage asset managers such as hedge funds, and low-level asset managers such as pension funds, endowments, and mutual funds. Regional and smaller banks are often customers of the major banks for trades in the most liquid currency pairs. Liquidity demanders vary in their motives for trading currencies. Financial customers rely on foreign currencies mainly as a store of value because they use currencies to generate future returns. Corporate customers, by contrast, rely on foreign exchange mainly as a medium of exchange because they use foreign currencies to buy and sell goods and services. For corporate customers, implementing the costly risk protections associated with speculative trading is inefficient. As in most OTC markets, foreign exchange customers historically had difficulty gaining up-to-the-minute market information. Trades between dealers and customers need not be reported, given the lack of regulation, and purchasing real-time interdealer prices is costly. Market transparency increased dramatically, however, with the arrival of electronic trading. Customers can now follow the interdealer prices online at low cost throughout the trading day. On request-for-quotes (RQF) systems, customers can compare quotes from multiple dealers simultaneously. Large institutional customers can even offer liquidity to the market on certain electronic trading platforms, rather than simply demanding liquidity from dealers. The improved transparency has, in turn, brought heightened competition among dealers and reduced bid-ask spreads. Since the arrival of retail aggregators around 2000, retail investing has increased dramatically worldwide and may already represent up to 10 percent of trading. Retail currency traders concentrate in the major currencies, generally trade intraday, adopt high leverage, and are unprofitable. The lack of profitability may reflect a lack of market-relevant information.

2.1.2 A look into Real-World Systems

Market architecture is directly determined by the characteristics of trading protocols. In general, markets are structured according to two fundamental mechanisms: order-driven or quote-driven. Order-driven markets leave more room to direct interactions between agents operating in the market. In quote-driven markets, orders are handled by intermediaries. The market is called as hybrid when both systems coexist within the same market structure. Evolving markets and trading systems have created several innovations in how orders are handled. This chapter will examine OTC architecture by reviewing the various approaches characterizing the relationship among various agents in the market: dealers, brokers and customers. Distinctions exist among three types of market structure: dealer to client or D2C, dealer to dealer or D2D, and alternative trading systems or ATS, such as Dark Pools.

In a D2C market, brokers have the role to bridge the gap between dealers and clients, mainly by utilizing multi-broker dealer electronic trading platforms, which are provided by brokers. In an OTC context, D2C markets are quote based by means of either a Request for Quote (RFQ) or a Request for Stream (RFS). The RFQ markets are specific platforms where quoted prices are generated based on a request made by a broker or a customer. For example, if a trader requires a limit order from a dealer, this is equal to placing an order directly on the dealer's private order book. In RFS, brokers or customers require a stream of updates in place of a single on-off quote. After the dealer makes the update, the trader may or may not accept the dealer's quotes and wait until the next quote updates.

Abroad distinction exists between an Electronic Communication Network (ECN) or a Crossing Network (CN) and an Alternative Trading System (ATS) or "dark pool." Both ECNs and ATSs are characterized as off-exchange trading venues. ECN is the first mechanism known to be an off-exchange trading venue. Before then, off-exchange trading was possible only via interdealer without participating clients. The ECNs or CNs differ from the Electronic Order Book (ELB). An ELB plays a role in aggregating orders and displaying limit orders (i.e., the quantity traders are willing to buy and sell at different prices). The CNs do not display orders, but they aggregate nondisplayed liquidity across exchanges and allow a match between buy and sell orders at the prevailing midpoint quote. In some sense, ECNs or CNs play the role of liquidity aggregator among exchanges and orders.

Dark pools are trading systems where orders and trading are not publicly displayed. In several contexts, dark pools passively match buyers and sellers at the midpoint offer. In other cases, dark pools operate purely as nondisplayed limit order books where orders are executed according to time and price priority. Dark pools should not be confused with other nondisplayed liquidity sources, such as a simple broker-dealer internalization procedure where a broker or a dealer handles orders as a principal or an agent. The main distinction between these two aspects is that in a dark pool customer-to-customer trades are possible, while in the broker-dealer internalization system, a broker or dealer works as an intermediary. In Figure 3 below, we can see how the market is organized both with Electronic Communication Networks and Alternative Trading Systems (Dark Pools). Note that this exhibit shows market organization with the interactions among the various types of agents and trading venues.

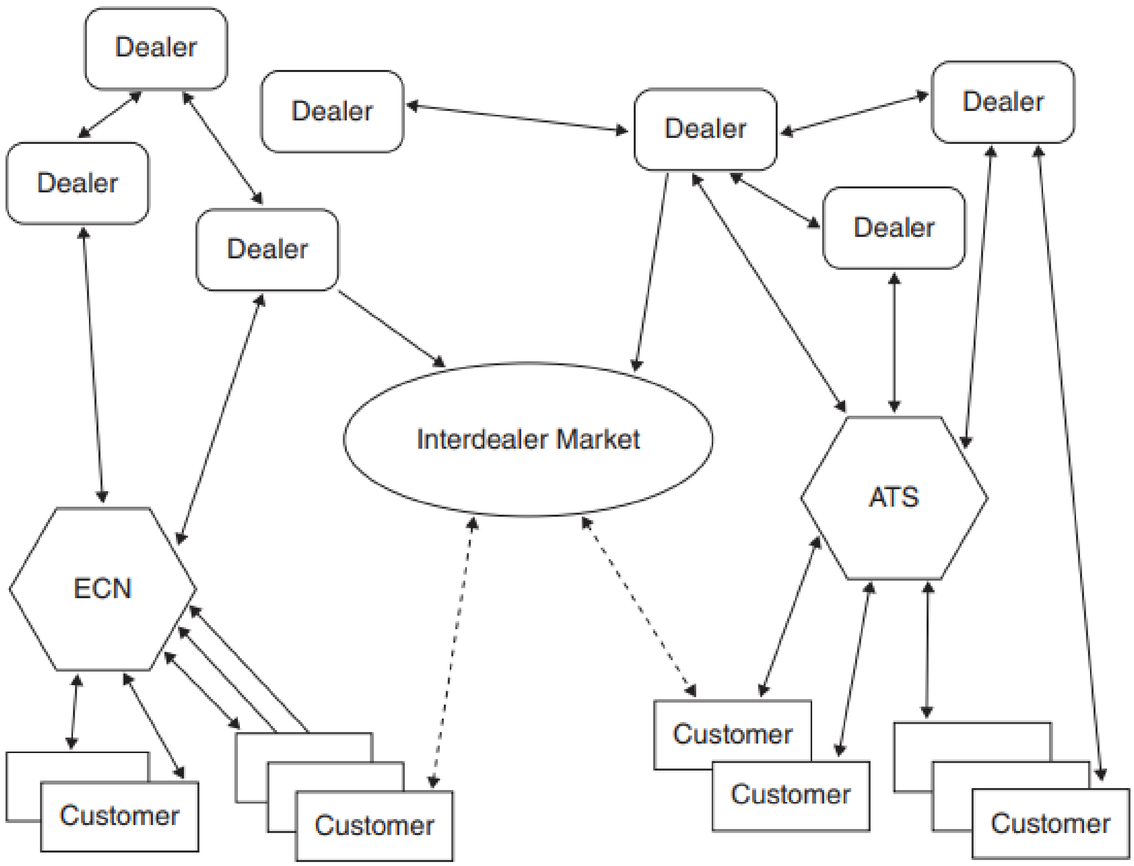


Figure 3-Market Organization with Electronic Communication Networks and Alternative Trading Systems (ATS). Source: Adapted from Johnson (2010).

2.2 Presentation of Retail Forex Market Microstructure

2.2.1 Retail Forex Market Overview and Participants

Retail forex trading has only been active in earnest since around the year 2000 (King et al., 2012), facilitated by the development of online trading platforms made available by retail aggregators, which allow for smaller minimum transaction sizes than commonly traded in the inter-bank and futures markets. Previously, the retail segment was considered too small to be economically interesting by banks.

Through the aggregators, the retail market also has a decentralized multiple-dealer structure in a fashion similar to the inter-bank market, with an array of institutions providing pricing and transactional capacity. The difference, however, is that the aggregators are largely price takers. Those using a dealer model may simply pass along inter-bank spot prices received from liquidity providers (generally inter-bank dealers), perhaps with a spread mark-up (King and Rime, 2010). Those using a pure broker model merely provide access to an electronic communication network (ECN) where orders are matched in an exchange-like system. The ECN model is the less frequently applied of the two. That said, however, it must be noted that aggregators do not necessarily operate in a single-model fashion. For a number of reasons (redundancy of systems, risk management, etc.) any given aggregator may operate multiple models side-by-side. The retail spot forex market looks rather like the institutional spot market in that it features a number of price-making entities servicing a larger group of price-taking ones. However, much of the exchange rate pricing in the retail market is simply passed down from the inter-bank arena. The retail forex structure is thus effectively a step removed from the inter-bank market. As a result, it is not as meaningful as a price discovery mechanism. The figure 4 below provides a basic indication of the relationship between the different parties.

Figure 4-Retail Forex Market Structure

The primary parties in the retail forex market

The schema above illustrates the parties participating in retail forex market and how the association between them works. Those who hold, or may hold, net positions appear in rounded boxes, while non- position-holding entities are in rectangles. Solid arrows indicate the direction of order flow. Single direction dotted arrows indicate the direction of price dissemination, indicating price-maker/taker relationships. Double-direction arrows indicate two-way price flow.

The survey done by CitiFX (CitiFX, 2010a, CitiFX, 2010b) provides some information as to the make-up and motivation of the population of participants in the retail spot forex market. Just under 91% of respondents describe themselves as individual non-professionals, and just shy of 83% listed speculation as their main reason for trading currencies. About 9% say hedging is their primary focus. In retail forex trading, hedging has a more extreme connotation. It has come to mean putting on opposing positions in the same currency pair. For example, if one were long 100,000 EUR/USD, a hedge in this usage of the term would entail going short 100,000 EUR/USD. By any normal definition this would be considered an offsetting transaction which closes one's position (no residual risk of any kind). Some aggregators do not force net accounting, however, so investors are able to have such opposing positions show as simultaneously open in their accounts. The CitiFX survey indicates 25.9% of respondents usually trade using hedging in this definition of the term. This may mean the aforementioned 9% who describe themselves as being hedgers is an overstatement due to confusion as to the definition of the term. Such a conclusion tends to be supported by the fact that only 8.7% of respondents indicate position holding periods longer than a few days (43.3% indicate generally holding for a few hours or less), which is the time horizon in which one would expect to see traditional hedgers operate. As a result, it is probably safe to say more than 83% of individual investors can be classified as speculators.

2.2.2 Linking Retail Forex to the Inter-Bank Market

The involvement of liquidity providers in offering pricing and transactional capacity to the retail aggregators links the retail spot forex market with the broader currency market, as those providers are mainly inter-bank dealers. Without them, retail forex would effectively be a self-contained construct – a kind of virtual market as per the bucket shop discussion above. In many ways that remains largely the case in as much as individual investor positions are matched against either each other or against dealer aggregators. There are investor position imbalances, however, where retail traders are collectively either net long or short a given currency pair. This implies the existence in the retail forex system of one or more institutions holding a net position which offsets the aggregate individual investor imbalance. To a certain degree, that is handled by those aggregators acting in market-making dealer roles, at least within the constraints of their risk management policies. The liquidity providers are the institutions at the end of the retail imbalance chain. Through the orders passed directly to them by the dealer/broker aggregators, they have immediate exposure to the imbalances which develop. This is furthered by any hedging capacity they provide to the market-making aggregators. To the extent these imbalances are not handled through internalization it is then expected that they offset them externally. While the liquidity providers cannot create exact contract offsets outside the retail market because of the non-deliverable nature of retail forex contracts, they can reasonably hedge externally any exchange rate exposure which develops. This liquidity provider internalization motivates questions as to how much of an impact the noted retail imbalances have on the inter-bank market. Since there no published figures regarding total retail spot forex open position volume like the Commitment of Traders report published weekly by the CFTC, it is hard to know the imbalances across the market. Rime and Schrimpf (2013) suggest that retail trading accounts for only 3.8% of spot market turnover in terms of the flows which actually reach the bank dealer level. The rest are internalized by liquidity providers, as well as lower down the channel in the retail platforms.10 This implies a limited impact on exchange rates at the inter-bank level. Further, liquidity providers largely view retail investors as uninformed, so are generally more willing to hold their net positions in inventory (King et al., 2012) than perhaps would be the case with institutional counterparties, assuming they are not internalized against interbank customer flows. Evidence of retail investors being uninformed is provided by Menkhoff et al. (2016) who find that individual investor flows are a strongly negative indication with respect to exchange rates, so the liquidity providers would seem to be well justified in internalizing those imbalances. That said, large imbalances in some of the less liquid currency pairs and imbalances hitting at times when general market liquidity is low could see retail flows exert a short-term influence on exchange rates. This is particularly true in the case of a "hot potato" effect among inter-bank dealers (Lyons, 1997).12 Further, to the extent that liquidity providers are able to ascertain which group(s) of retail investors are informed - providing them with a kind of private information, as suggested by Lyons (2001) - they will be less inclined to hold their inventory and more likely to attempt to quickly offset their exposure to such players externally. Thus, even as uninformed or noise traders (Black, 1986), retail forex investors may have some impact on exchange rates as suggested by Long et al. (1990) and Kogan et al. (2006).

2.2.3 Retail Forex Market Trading Mechanics

While nominally called a spot market, retail forex operates differently than the inter-bank spot version. The latter involves transactions in which the exchange of one currency for another is set to occur on a settlement date in the near future (1-2 business days) at a specific exchange rate. It is functionally very like a short-dated forward contract. Unless a later agreement offsets this transaction, the two parties will do the agreed upon exchange, at the designated rate, when the appointed day and time arrives. No exchange of currency ever takes place in the retail forex market. This is not to say, however, that retail spot forex is a cash-settled futures or non-deliverable forward (NDF) market, though it can be viewed very similarly to both in certain ways. A retail spot forex transaction starts in a manner similar to one in the inter-bank market with an agreement to do a future exchange. There is never any settlement, however. Instead, at the end of each trading day - assuming no offsetting intervening transaction - the agreement is automatically rolled forward to the next available settlement date. The result is that these quasi-forward contracts are perpetual, with no expiration or delivery date. Since there is no exchange of currency, retail spot forex trading is completely focused on the movement of exchange rates.

These are quoted in the same standard XXX/YYY fashion as seen in the inter-bank market whereby XXX is 3-letter ISO 4217 (a.k.a. SWIFT) code for the base currency, and YYY is similarly the code for the quote currency. The reading of these exchange rates is that one unit of the base currency is worth N units of the quote currency. For example, EUR/USD is the exchange rate between the euro and the US dollar, where the former is the base and the latter the quote. Thus, a reading of 1.2000 for EUR/USD would indicate €1 as being worth $1.20. When entering into a retail spot forex position, as in the case of futures and NDFs, the investor posts margin equivalent to some fraction of the value of the transaction. This is not a down payment on a loan for the purchase of an asset, as is the case of margin deposits in the stock market. Rather it is a deposit to reduce the aggregator’s credit risk in the case of customer losses from adverse exchange rate movements, as in the futures market. Similar to the case of the futures market, positions in retail spot forex are subject to mark-to-market accounting. This is done in real time on a continuous basis, which allows for a wrinkle in the margin call mechanism. When an investor’s account equity (cash minus open position losses) falls below the required maintenance margin level, rather than issuing a request for additional funds, as is the traditional case in the futures and equity markets, the aggregator in most cases simply closes out the investor's position(s) with immediate effect. This takes place no matter when during the trading day it happens. These automatic forced closures further reduce the aggregator's credit risk, and actually serve to prevent the investor from going into a negative equity situation in all but the most extreme situations. The result is the ability of the aggregator to provide greater leverage to the investor than would otherwise have been prudent.

As we mentioned above, retail forex is based on obligations rather than asset transfers. This means there must be opposing long and short sides to all open positions. Where a retail aggregator acts in a dealer fashion it is nominally the counter-party to all customer positions, with the aggregator hedging positional imbalances externally as per its risk management policies. Where the aggregator operates in a broker fashion, while legally it may still be official counter-party, the effective counter-party will be external - a liquidity provider, another aggregator, the customer of another aggregator matched via an ECN, or some combination of them. Regardless of the model, for each customer long there must either be a customer or an institution short on the other side somewhere in the market, and vice versa. That means every change in exchange rates is at once financially benefitting one party and harming another by the same amount. This translates that the Market, overall, is a zero-sum game. This can be presented by the following profitability functions for the two counterparties to every transaction:

$$L = P_T - P_0 \quad (1)$$
$$S = P_0 - P_T \quad (2)$$

Where:

L is the gain/loss for the long
S is the gain/loss for the short
P_0: is the spot exchange rate at time t=0
P_T: is the spot exchange rate at time t=T

Both of these transaction functions are offsetting, resulting in a simple zero-sum game to each position: L+S=0 (3)

Chapter 3: Presentation of the Discrete Execution Models

3.1 Presentation of "Back-to-Back" STP Model

The first of the two models on which our thesis will be focusing, which we will refer as "Back-to-Back" (or matched principle) transaction type, the Broker is acting as a retail aggregator in a broker fashion. The broker connects retail clients with Liquidity Providers by simply passing through prices to retail clients. That means that the Broker does not manipulate offered prices in respect with prevailing liquidity in the inter-bank market.
Exposure generated from retail client order flow in not internalized and is passed through it's liquidity providers (STP). That being said, although the aggregator remains the legal counterparty for the retail client, the order and it's associated exposure is hedged to an external liquidity provider who in turn becomes the counterparty for the respective market risk.
As whole retail spot forex features bid-ask pricing, the same happens with the inspected model. Since all orders are "market orders" (even Limit orders, when activated, they automatically become market orders), they put the customer in a price-taker position, regardless the aggregator is acting as dealer or merely passing through prices from a liquidity provider as in our case. If the aggregator used Electronic Communications Networks

Regarding the related model's trading mechanics, retail clients send order requests to trading servers which on their side transfer them to the execution engine to be processed. The execution engine consists of three major components.

1. Price aggregation mechanism. Price aggregator collects all available Top of Book (TOB) prices from the available Liquidity Providers connected with the Broker. The aggregator collects and stores these prices at any given time to be offered for filling incoming orders (trading requests). As we described above, there is no intervention in these (raw) prices and are passed through to clients.
2. Order Management System (OMS). The OMS processes the incoming requests based on the best price available and instrument availability. This means that the OMS will process the request at the best available price from the connected liquidity providers assuming instrument trading availability in the respective liquidity providers.
3. Risk Management Component/System (RMS). In this specific model, since the retail aggregator acts in a broker fashion and internalizing occurs, the RMS is limited to performing only operational risk management. This means that the RMS is checking and validating trading requests based on the stability of the system. Since there is no Market exposure and thus no Market risk, the RMS is validating proper price availability from the liquidity providers. Additionally, it checks the health of the connections with the respective

LPs. Furthermore, it makes margin level checks and initial money management validations based on funds availability prior sending flow to a liquidity pool.

Figure 5 below shows the connection schema between the several components.

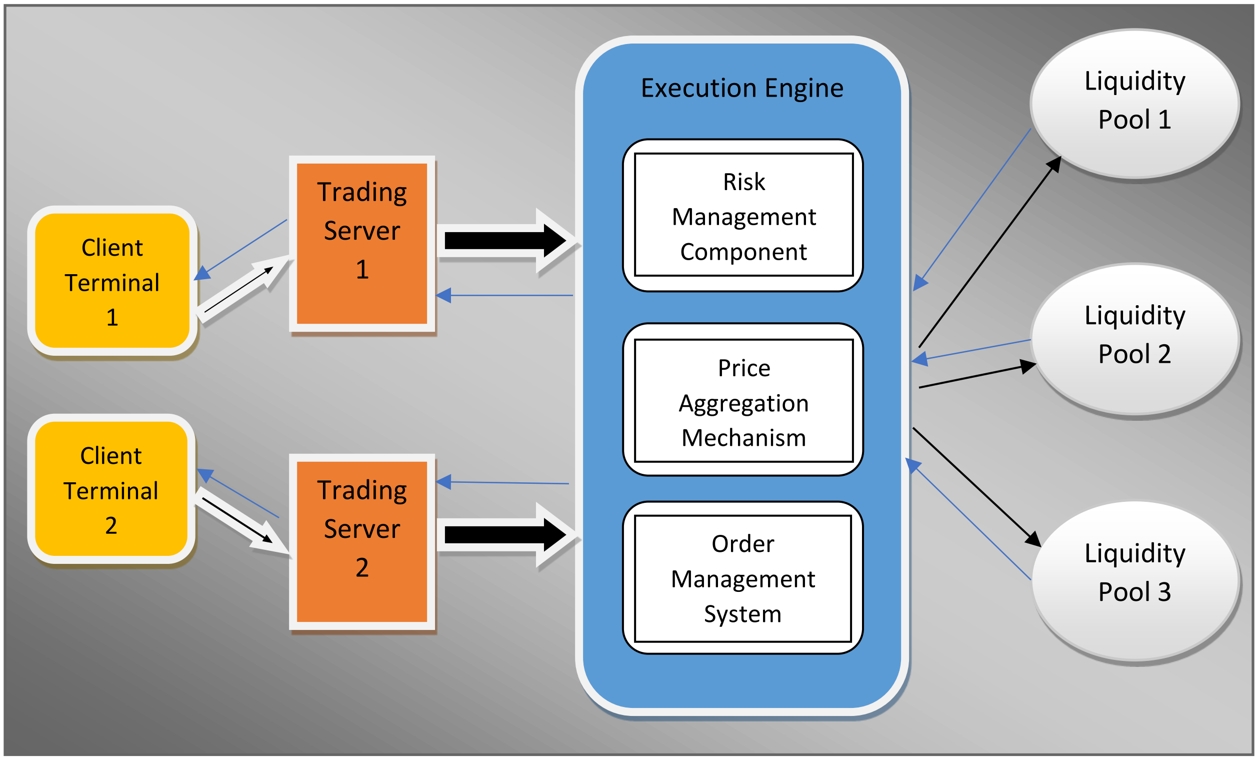


*Figure 5- **Back-to-Back STP Model Trading Architecture.** Black arrows indicate Orders flow. Blue arrow indicate price stream flow*

In order to better understand the model, we will use a simple example. Assuming a retail client want to go Long (Buy) 100,000 EURUSD. Client transmits his order from his terminal to the trading server who in turn passes it through the broker-aggregators execution engine. Sine the aggregator is not internalizing flow, the market risk is zero, thus the Risk Management component only performs recent price availability validations, as well as trading functionality availability from it's liquidity providers, containing it's role to operational risk. The price aggregator, that collects available prices, receives the following quotes from its Providers:

EUR/USD	Bid	Ask	Spread
LP1	1.10526	1.10531	0.00005
LP2	1.10531	1.10536	0.00005
LP3	1.10525	1.10529	0.00004

Table 1-Spread Example between LPs

Following, the order management system, having collected the all the necessary information mentioned above from its associated components will transmit the order request to the Liquidity provider that offers the best available price all other constraints held constant. In our case it will select to transmit the trading request to LP1 at the ask rate of 1.10529. Only after the LP1 has confirmed the trading request at that price level, the OMS will confirm the request to the retail client at the confirmed price and eventually open the trade. The retail aggregator receives the commission for the service (from now own presented as "C"), regardless of the outcome of each trade. Also the retail aggregator charges retail clients overnight rollover cash settlements for maintaining the respective positions that remain open in a respective LP, who in turn, charges the retail aggregator in the same manner. This means that equations (1) and (2) practically no longer offset, thus creating a negative-sum game for the retail clients.

3.2 Presentation of "Own Liquidity" Model

In the "Own Liquidity" model the retail aggregator uses the same components and philosophy as the "Back-to-Back" (matched principle) model presented earlier but is primarily internalizing the order flow generated by its clients by executing order in internal "Own" Liquidity and becomes the execution counterparty. The aggregator again is passing prices from the liquidity providers to the clients who are once more price takers. As a result, the majority of transactions see the customer on the wrong side of the bid-ask spread. An adjustment therefore needs to be made to Equations 1 and 2 to reflect bid-offer pricing:

$$L = P_{b,T} - P_{a,0} \quad (4)$$

$$S = P_{a,0} - P_{a,T} \quad (5)$$

Where:

$P_{b,0}$ and $P_{a,0}$ are respectively the bid and ask spot exchange rates at time t=0

$P_{b,T}$ and $P_{a,T}$ are respectively the bid and ask spot exchange rates at time T

In this case both long and short positions could end up losing, as the market might fail to move sufficiently in order one of the two side to be able to overcome the bid-ask spread. E.g. if a trade opens and closes without any market move, the trade will end up negative by the amount of the spread at the time. If take into account the commissions charged, equation (3) no longer holds and must be adjusted as follows:

$$L + S = (P_{b,T} - P_{o,0}) + (P_{b,0} - P_{o,T}) - C \quad (6)$$

Again, the market will be a negative-sum game for the majority of investors. Since the market as a whole remains a zero-sum game, there must be a positive offsetting to the negative client side. This is the aggregator acting in a market-making manner (as well as the liquidity providers), who collect both spread, rollover and any commissions charged.

In terms of trading mechanics and architecture, below is a diagram that illustrates how flow is processed in the examined model. As we can see, the similarities (as described also in the first paragraph) are many. In both models the main execution and price feed engine remain the same. The key difference is that orders are executed internally in an OWN liquidity pool, in respect with the aggregators risk management policy.

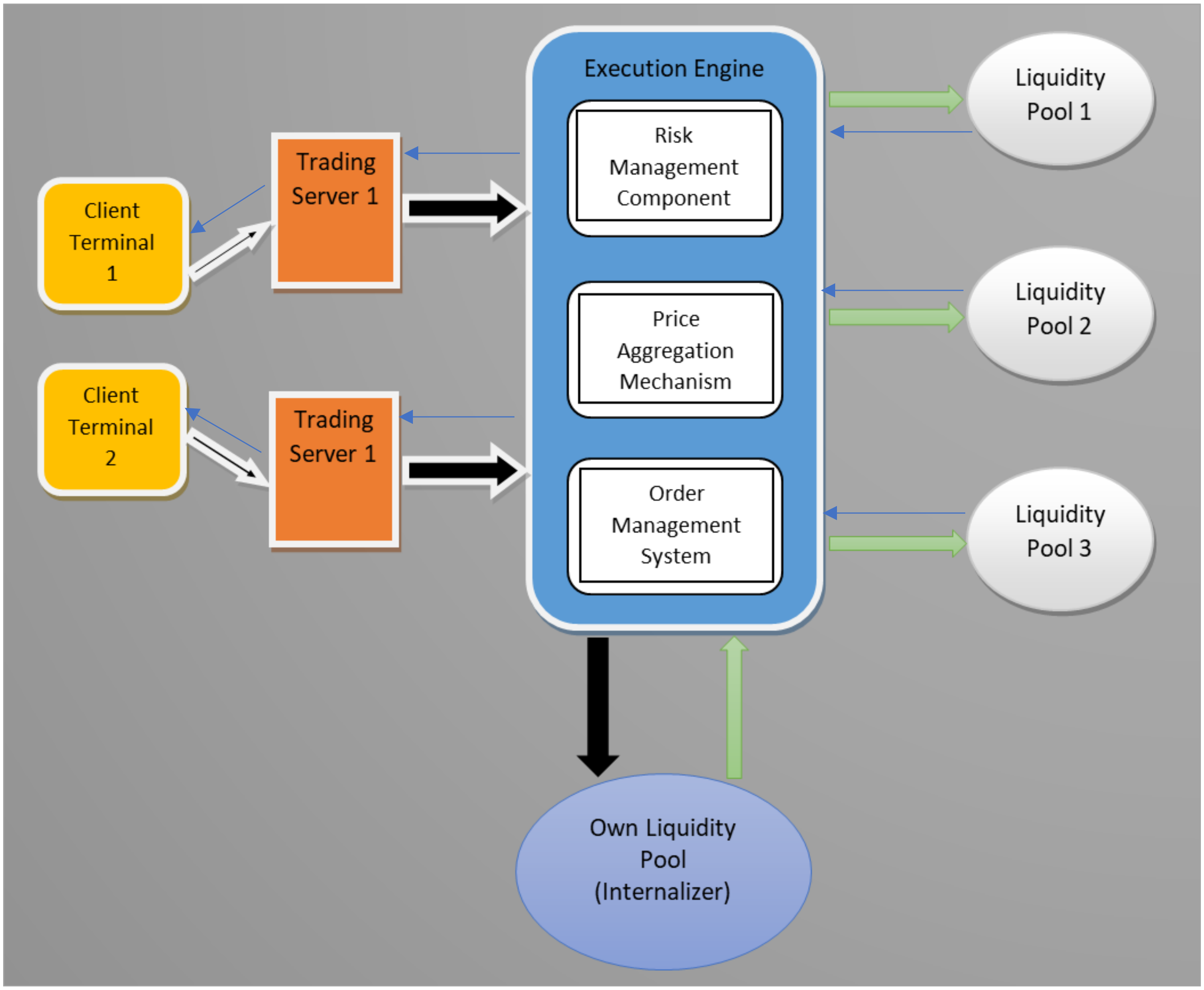


*Figure 6-**Own Liquidity Mode Trading Architecture.** Blue arrows indicate price feed flow. Black arrows indicate client order flow. Green arrows indicate externalized (hedged) client exposure.*

A point worth noting here is that in this model, since prices are passed from the liquidity provider directly to the clients, internalized flow tends to receive the order price rather than the market price. This means that the execution prices usually do not take into account market depth and available demand/supply levels in the market. This can prove both beneficial or against the retail client. To explain this better we will use an example. As we explained in our previous model, the price aggregation mechanism receives various prices and decides to "give" the best available price to the retail side and execute the order to the respective liquidity provider. Let's assume that in the time t the best available ask price for EUR/USD is Pt for an amount of e.g. 100,000 units and the next available price is at the same time is Pt,2=Pt+c for the next 100,000 units. A retail client makes a trading request to buy an amount 150,000 units of EUR/USD at time t at price Pt. According to the prevailing market depth availability he will eventually get from the liquidity provider, the average price which will be (Pt+ Pt,2)/2= Pt+c/2. This difference in executed price (ask) would be worse than the initial request and is what is called negative slippage. The exact opposite scenario, e.g., the executed price is better than the requested is called positive slippage and would be in benefit of the retail client. It can happen under the exact same principle. At the moment of the request, the liquidity provider can offer a better price to the aggregator and in turn to the aggregator's retail end client. In an internalizing model though (in most cases) this would not be the case though. Retail clients would get the requested prices at the time of the initial request and any price drifts, if they were to occur, would originate from any price latency within the system itself, thus benefiting clients from illiquid market moments or depriving them similar benefits when the market prices are more competitive than they appear.

Another point worth noticing in regards on how this model works is the consistency it can or may internalize the trading flow. Because the retail aggregator act in a market making principle and can internalize its flow that doesn't mean this is exactly the case. As we mentioned this operating principle works in respect with a firm's risk management policy, so there are practically three ways this can occur.

1. The aggregator internalizes into OWN liquidity all of its retail client generated flow for the full lifetime cycle of all trades.
2. The aggregator internalizes a part of its retail client generated flow and the remaining exposure is sent to an external liquidity in the way we described in our previous model.
3. Last, the aggregator is actively managing the generated exposure from its clients trading flow, both by internalizing and hedging externally within the same lifecycle of the trades. E.g. internalizing initially and hedging on a later stage and vice versa.

The image below presents how the aggregator can hold the trading exposure overall. The importance of this will be analyzed on a later section, where we will connect the models to any related market risk exposure.

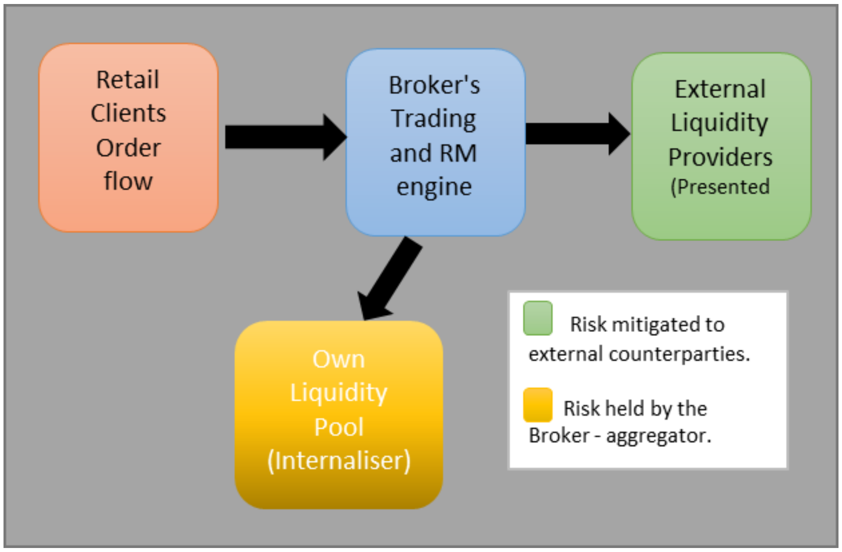


Figure 7-Internalization vs Externalization of Risk

Chapter 4: Empirical Performance

In this chapter we will some key conditions in each model. We will focus on the average execution time each model requires to process a trade request both in coverage terms and round turn. By the term “coverage time” we mean the required time a request takes to receive a positive confirmation from the liquidity pool either it is an external liquidity provider or an own liquidity pool. The term “round turn” is used to specify the time needed for a request to be processed both by the liquidity pool and the trading server, thus returning a response to the end user (retail client). This will allow us to distinguish if any of the two models is more competitive in terms of execution speed and the importance of this factor.

On the next sub-section, we will review best execution parameters. How competitive are the existing liquidity providers in terms of offered prices, as well as whether best execution is met in each of our examined models.

Finally, we will investigate any possible market risk exposure each of the model might be subject to and compare it with historical retail client performance to perform a basic cost-benefit analysis.

4.1 Speed of Execution Comparison

To review the execution time for each model we have collected data for 1.7 million trading requests executed to external liquidity providers for the examination of our “Back-to-Back model” and 0.6 million trading requests executed in the own liquidity model. The reported times are in milliseconds. The table below, alongside with visual graph, displays average, both coverage and roundtrip execution times for the Own liquidity and Back-to-Back model.

Month	*Average of CoverageTime - External*	*Average of RoundTrip - External*	*Average of CoverageTime - OWN*	*Average of RoundTrip - OWN*
Jun-20	894.2	1447.4	295.2	405.5
Jul-20	1092.3	1459.7	283.4	389.8
Aug-20	1412.5	1901.9	361.0	474.8
Sep-20	1301.5	1901.7	444.4	562.9
Oct-20	861.8	1268.0	466.7	579.0
Nov-20	811.4	1259.3	267.4	381.2
Dec-20	943.6	1243.4	462.9	599.1
Jan-21	923.6	1338.7	333.0	473.7

Feb-21	869.8	1467.2	274.2	437.9
Mar-21	732.8	1462.9	165.6	277.7
Apr-21	209.3	721.5	108.6	198.9
May-21	242.8	1167.9	85.5	173.5
Jun-21	235.4	1148.8	83.2	175.8

Table 2-Avg CT vs RT execution Time

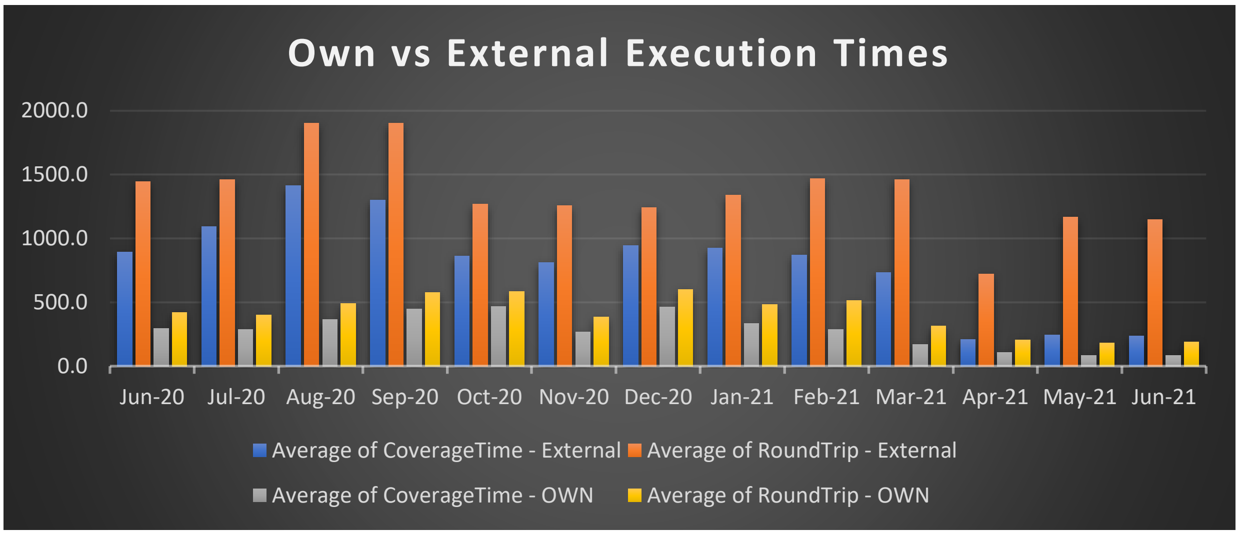


Figure 8-Own vs External Execution Times

Regarding the "Own Liquidity Model", we can see from the data table that average coverage execution time per month varies from 83.2 milliseconds up to 466.7 milliseconds with a total average for the period of 279.3 milliseconds. Consequently, roundtrip times vary from 173.5 up to 599.1 milliseconds, averaging in total 394.6 milliseconds. It is expected roundtrip times to be higher than coverage times. As we mentioned roundtrip times are the time a request needs to return a positive response to the final request listener, which the trading server, thus more messages to be processed until the final confirmation. On the other hand, it is clear, from the data, that the Back-to-Back model has much higher response times, with total average coverage time for the examined period as much high as 810.08 milliseconds and roundtrip times averaging 1368.33 milliseconds.

A part of this difference between the two models is due to network latency. Execution models, whose engines rely on external network factors, such as distance from target servers (liquidity provider's server) and other hardware factors like speed and capacity of all intermediate network lines. But one of the most important factors to add latency to execution times is the way the external liquidity provider handles incoming request. Since we do not have the data to back any hypothesis, we can only assume one of the following scenarios. The external liquidity provider acts in a broker principle. This would mean that the liquidity provider handles requests similarly to our back-to-back model, sending his turn, requests externally to the market (other LPs) and adding in this way additional layers of validations and “travel” time. Another scenario is that the liquidity acts in a market maker principle. In this case although we would expect faster response times than in the first case, we cannot account for additional execution parameters imposed by the liquidity provider. Although in our Own liquidity model, requests receive only price confirmation, for the price available at the internal system at the time of the request, this may not be the case for the liquidity provider. An LP acting in a market making principle may possibly aggregate prices from multiple sources before confirming a trading request from his end. Also, it has been observed that many LPs that act in the same principle (as well as retail aggregators) add time bumps to trading requests to simulate external execution from their end or “protect” themselves from high frequency or abusive traders that try to exploit latency arbitrage. The third hypothesis, is that the liquidity provider operates in a hybrid way combining more than one models, applying characteristics of the whole spectrum of execution possibilities.

Following, we present a table with distinct max and min execution times per month. We can see that max coverage observations for our back-to-back model (columns tagged as “external”) are consistently higher to those of the Own liquidity model, both for coverage and roundtrip time, with the latter being 2 to 3 times less than the first. When it comes to the min values, we see the “Own” model having values as low as 0 for various months both for coverage and roundtrip times, which is expected since execution lifecycle takes place internally. For the back-to-back model, we would not expect to see times as low as zero. Having values like this both for coverage and roundtrip back our hypothesis that the liquidity provider can act both in a market making as well as in a broker principle, consequently affecting the performance of our model. Again, without external data from the liquidity providers, it is not possible to perform any validations and back any of our hypothesis.

Month	*Max of Coverage Time-OWN*	*Min of Coverage Time-OWN*	*Max of Coverage Time-External*	*Min of Coverage Time-External*	*Max of RoundTrip-Own*	*Min of RoundTrip-OWN*	*Max of RoundTrip-External*	*Min of RoundTrip-External*
Jun-20	8624.0	0.0	21869.0	0.0	10640.0	31.0	22141.0	0.0
Jul-20	8484.0	0.0	21531.0	63.0	10515.0	31.0	22093.0	109.0
Aug-20	8516.0	0.0	22078.0	0.0	10438.0	47.0	22134.0	47.0
Sep-20	8609.0	0.0	22031.0	62.0	10594.0	31.0	22141.0	94.0
Oct-20	8609.0	0.0	22091.0	31.0	10563.0	31.0	22123.0	63.0
Nov-20	8625.0	0.0	21999.0	62.0	10219.0	30.0	22110.0	94.0
Dec-20	8594.0	0.0	21813.0	62.0	10547.0	31.0	22125.0	109.0
Jan-21	8625.0	0.0	32923.0	62.0	10563.0	31.0	34688.0	109.0
Feb-21	8625.0	0.0	32641.0	31.0	10688.0	16.0	35516.0	62.0
Mar-21	8234.0	0.0	32954.0	15.0	10360.0	31.0	35611.0	46.0
Apr-21	8625.0	0.0	12313.0	13.0	10157.0	32.0	32344.0	31.0
May-21	4360.0	31.0	15063.0	15.0	10032.0	46.0	35079.0	31.0
Jun-21	5001.0	31.0	18547.0	15.0	7421.0	62.0	35563.0	31.0

Table 3-Max & Min Execution Times

Having presented and reviewed all available execution time data for the period 06/2020 to 06/2021 it is clear that "Own Liquidity" model is on average far more superior in terms of execution speed. Expected or not, it is an advantage over the "back-to-Back" model, as traders can more efficiently exploit fast moving markets during market events like news releases and price volatility spikes. Despite this advantage, it is still unclear which of the models is more competitive versus the other. In the chapters to follow, we will review additional parameters that will help us enhance our comparative analysis, such as best execution and market risk exposure.

4.2 Best Execution Analysis between the models

4.2.1 Introduction

In this section we will review and compare quality of execution in terms of available vs executed prices between the two discreet models for the period of one year. More specifically we have collected real execution data between June 2020 and June 2021 for the most popular Forex pairs (EURUSD, GBPUSD, USDJPY, EURCHF & USDCHF) in terms of transactions and executed volume in comparison with the average month on month spread per forex pair in each LP.

4.2.2 Spread comparison

Before presenting the results of the collected data, I would like to describe how the spread is presented in the Forex market. The spread for each forex pair is presented in pips (percentage in points). In a forex pair as pip is calculated the penultimate digit in its quoted price. E.g., assuming the prevailing price for EURUSD in a given time id bid 1.05132 and ask is 1.05138, then the spread would be 0.6 pips or 0.6 basis points.

The systems continuously receive, collects and stores price data from the available liquidity providers through its' price aggregation mechanism. The review we are performing will not be on a bid on bid or ask on ask basis but rather on a bid-ask difference comparison between the available liquidity providers. The same approach will be used to compare later on executed requests each month for the examined period in relation to the available average spreads. Below we can see two tables presenting the average monthly spread for each liquidity provider. For reasons of confidentiality, we have removed the original names of the LP entities and labeled them as "LP1" and "LP2" respectively.

LP1	*Jun-20*	*Jul-20*	*Aug-20*	*Sep-20*	*Oct-20*	*Nov-20*	*Dec-20*	*Jan-21*	*Feb-21*	*Mar-21*	*Apr-21*	*May-21*	*Jun-21*
EURUSD	0.4	0.3	0.4	0.4	0.4	0.3	0.4	0.4	0.3	0.4	0.3	0.3	0.4
GBPUSD	0.6	0.5	0.5	0.6	0.6	0.5	0.8	0.6	0.6	0.6	0.5	0.5	0.6
USDJPY	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5
EURCHF	0.7	0.5	0.7	0.6	0.6	0.8	0.6	0.7	0.6	0.7	0.5	0.5	0.8
USDCHF	0.5	0.5	0.4	0.5	0.6	0.5	1.0	0.5	0.5	0.8	0.5	0.5	0.6

Table 4-LP1 Average Spreads

LP2	*Jun-20*	*Jul-20*	*Aug-20*	*Sep-20*	*Oct-20*	*Nov-20*	*Dec-20*	*Jan-21*	*Feb-21*	*Mar-21*	*Apr-21*	*May-21*	*Jun-21*
EURUSD	0.4	0.5	0.6	0.5	0.5	0.4	0.4	0.4	0.4	0.5	0.4	0.4	0.4
GBPUSD	0.8	0.8	1.0	1.1	1.1	1.1	1.3	1.0	1.0	0.9	0.9	0.9	0.9
USDJPY	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.5	0.5	0.4
EURCHF	0.9	0.7	0.9	1.0	0.9	1.0	0.9	0.9	0.7	0.8	0.8	0.9	1.0
USDCHF	0.6	0.6	0.7	0.8	0.8	0.7	0.8	0.7	0.6	0.7	0.7	0.7	0.7

Table 5-LP2 Average Spreads

As we can see, the liquidity provider labeled as "LP1" has consistently more competitive spreads (smaller) on a month-on-month basis for every examined forex pair than liquidity provider "LP2". This can result from various reasons such as, the method each Liquidity provider uses to aggregate and stream prices, commercial reasons as well as the principle in which they operate. Meaning that if the liquidity provider acts in a market making principle, he could be constructing the streamed prices according to its' model restrictions and/or strategy. On the table below we can see a more detailed spread price comparison between LP1 and LP2.

LP1 vs LP2	*Jun-20*	*Jul-20*	*Aug-20*	*Sep-20*	*Oct-20*	*Nov-20*	*Dec-20*	*Jan-21*	*Feb-21*	*Mar-21*	*Apr-21*	*May-21*	*Jun-21*
EURUSD	-0.04	-0.15	-0.2	-0.11	-0.11	-0.12	-0.06	-0.06	-0.08	-0.1	-0.09	-0.1	-0.02
GBPUSD	-0.23	-0.3	-0.47	-0.52	-0.54	-0.55	-0.57	-0.45	-0.39	-0.31	-0.39	-0.45	-0.3
USDJPY	-0.04	-0.11	-0.13	-0.13	-0.09	-0.1	-0.13	-0.01	-0.06	-0.07	-0.1	-0.12	0.08
EURCHF	-0.19	-0.17	-0.22	-0.35	-0.29	-0.2	-0.28	-0.22	-0.13	-0.15	-0.3	-0.44	-0.24
USDCHF	-0.12	-0.13	-0.22	-0.31	-0.18	-0.18	0.21	-0.14	-0.17	0.09	-0.21	-0.21	-0.15

Table 6-LP1 vs LP2 Average Spread

From the table above we can see that in most Forex pairs every month, the spread difference (Spread LP1-Spread LP2) is in favor of LP1. This means that LP1 has consistently more competitive spread per forex pair on average for every month of the examined period. The only cases where LP2 is more competitive in terms of average spread are Dec-2020, Mar-2021 and Jun-

2021 for the pairs USDCHF and USDJPY respectively. In Figure 9 below we can see these differences visualized

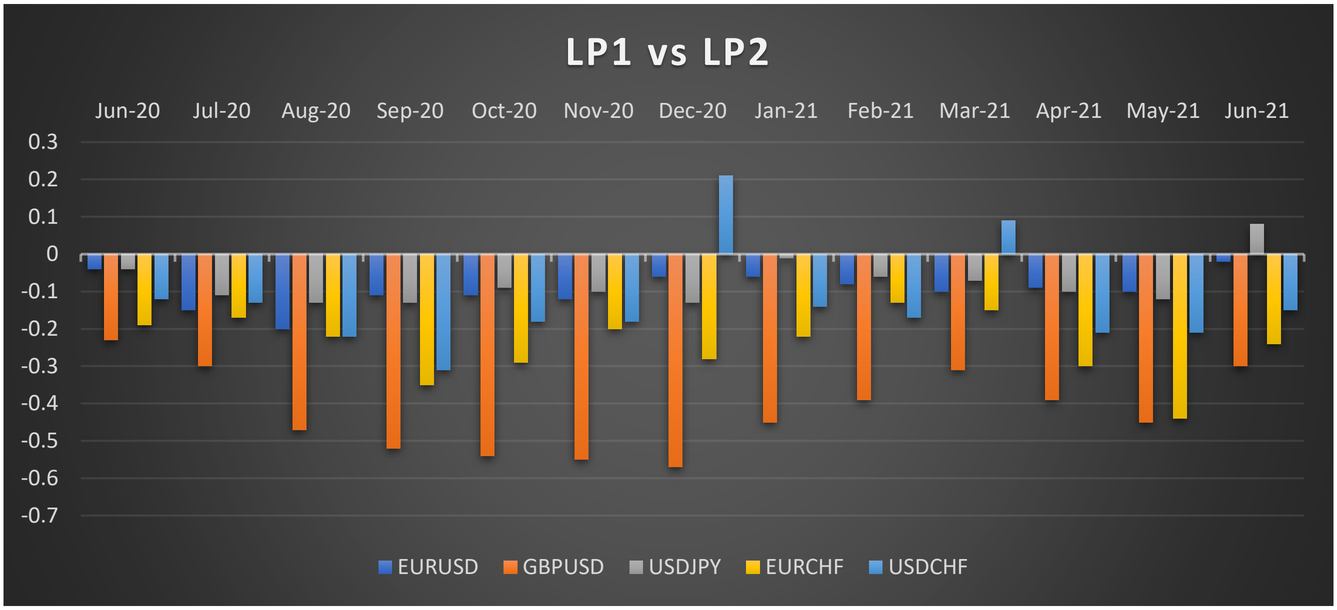


Figure 9-LP1 vs LP2 Spread Difference

4.2.3 "Back-to-Back" Model Price Execution Data

In the review of the "Back-to-Back" execution model we have collected approximately 500K executed trades with details like the external liquidity provider where the order was executed (LP1 or LP2), prevailing spread in each liquidity provider at the time of the trade. Again, as in the previous section the data refer to the top 5 forex pairs (EURUSD, GBPUSD, USDJPY, EURCHF, USDCHF). The main scope is to validate that the majority of executed trades has been directed to the liquidity provider with the most completive spread and thus, best execution conditions (in price terms) have been met. In the table below we can see the number of trades executed per forex pair per month and in which external liquidity provider they executed, as well as a visual representation.

Symbol	**EURCHF**		**EURUSD**		**GBPUSD**		**USDCHF**		**USDJPY**	
Month/LP	LP1	LP2	LP1	LP2	LP1	LP2	LP1	LP2	LP1	LP2
Jun-20	1175	576	12605	9476	12032	4657	4472	2487	1214	461
Jul-20	314	101	12096	4920	12786	2708	671	277	1560	372
Aug-20	384	72	13214	3562	11188	1521	1342	226	1491	362

Sep-20	598	222	16566	6487	10713	1211	1238	109	1732	603
Oct-20	2470	426	13971	5379	8490	838	1309	266	1268	347
Nov-20	3121	722	12962	4305	9980	975	1085	161	2409	597
Dec-20	2307	731	8482	4073	7359	1173	886	201	2159	550
Jan-21	3725	910	8044	4653	6951	1288	1117	232	2486	1105
Feb-21	1651	2871	14173	7289	5613	784	428	371	1298	494
Mar-21	567	1049	19947	10549	6227	1591	610	774	732	381
Apr-21	1029	193	10677	7703	8519	2147	780	206	1321	703
May-21	1200	334	10818	9538	6279	1502	649	188	1405	818
Jun-21	370	218	11088	10644	6014	1728	828	592	977	1082

Table 7-Number of Executed actions per LP

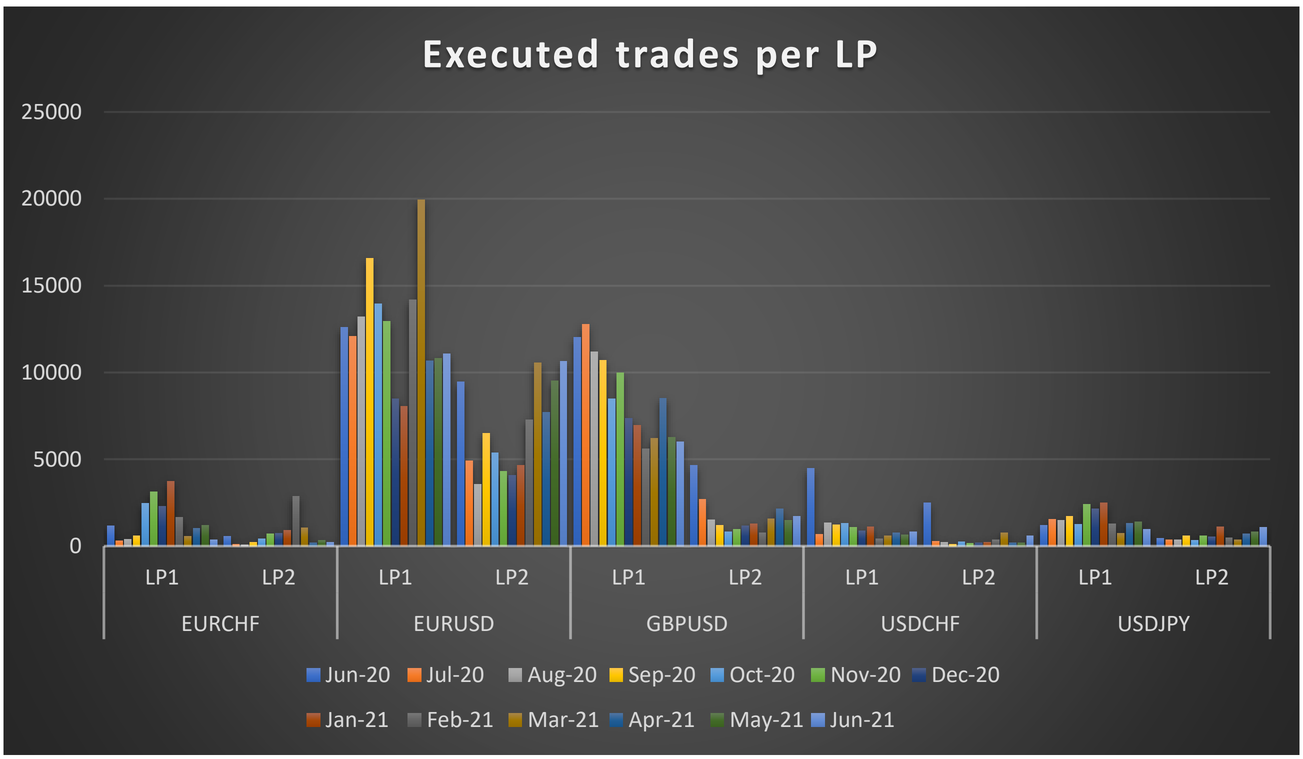


Figure 10-Number of Executed Trades per LP -Graph

Now let's compare these data with the average spread data from the previous section. Although the approach we will follow can be used for all examined pairs, in our example, we will focus only in EURUSD. More specifically we will see if the majority of transactions for EURUSD was executed for each month to the liquidity provider with the best average spread. The table below is a representation of the combined regarding EURUSD.

Month	Spread LP1	Spread LP2	Spread Diff	LP1 Trades	LP2 Trades	% Trades
Jun-20	0.35	0.39	-0.04	12605	9476	57%
Jul-20	0.32	0.47	-0.15	12096	4920	71%
Aug-20	0.36	0.56	-0.2	13214	3562	79%
Sep-20	0.43	0.54	-0.11	16566	6487	72%
Oct-20	0.35	0.46	-0.11	13971	5379	72%
Nov-20	0.31	0.43	-0.12	12962	4305	75%
Dec-20	0.37	0.43	-0.06	8482	4073	68%
Jan-21	0.35	0.41	-0.06	8044	4653	63%
Feb-21	0.33	0.41	-0.08	14173	7289	66%
Mar-21	0.35	0.45	-0.1	19947	10549	65%
Apr-21	0.32	0.41	-0.09	10677	7703	58%
May-21	0.30	0.40	-0.1	10818	9538	53%
Jun-21	0.35	0.37	-0.02	11088	10644	51%

Table 8-Table - EURUSD Execution Review

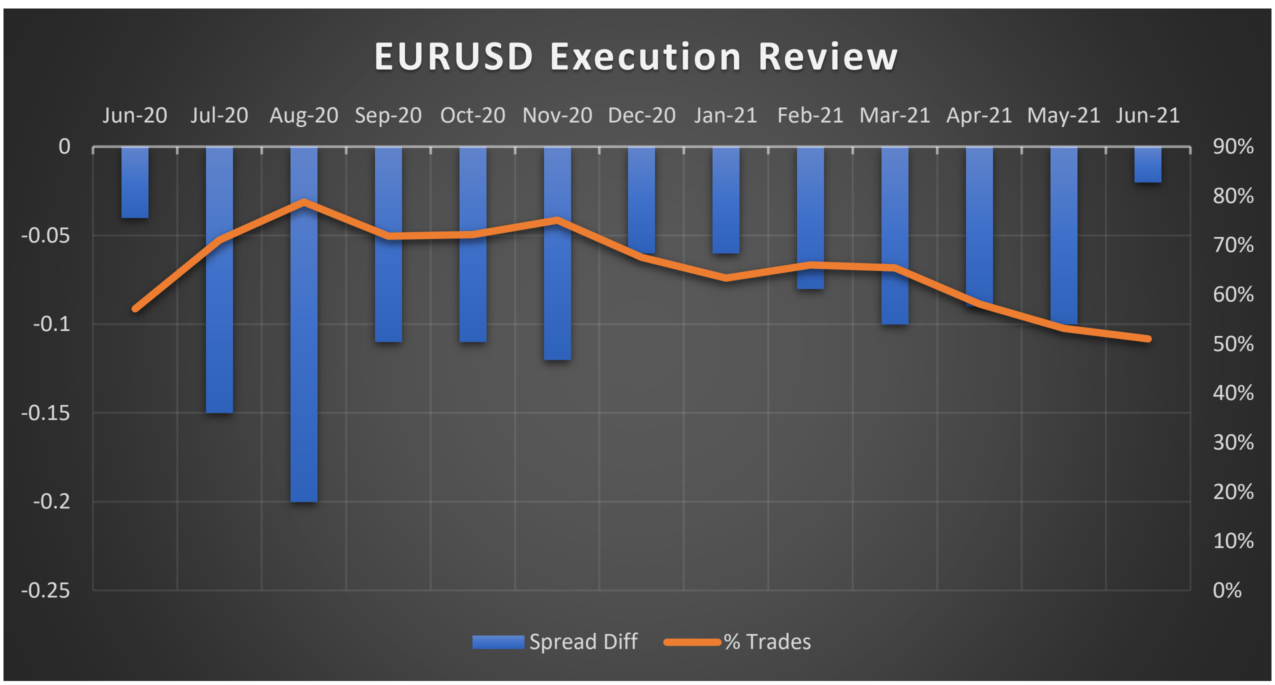


Figure 11-Graph - EURUSD Execution Review

As we can see, the majority of the transactions for EURUSD, are executed to the LP with the lower average spread (LP1 in this case). We can see that the more marginal the spread difference becomes between the two distinct liquidity providers the percentage of trades executed to each LP drifts towards 50% and vice versa. On June 2021 when the spread difference reaches its' lowest level, we see that the distribution of trades between the LPs is almost even (51%/49%). This trend is visually presented in the graph above.

To summarize, we can see from the presented data, that execution in a “Back-to-Back” model under straight through processing conditions, meaning there is no manual intervention to the system and all trading requests are processed automatically in respect with the best available price, works fairly consistently. Various drifts in the reported data can be observed, either in specific cases and/or in specific time ranges. These cases though are not consistent can occur due to various reason closely related to system limitations or liquidity availability at the time of a request. For example, if at the time of the incoming request the liquidity provider with the best spread is unavailable, the system will route the trade to the next available liquidity provider (e.g., LP2), executing though in a worst price than initially available.

4.2.4 OWN Liquidity Model Price Execution Data

In this model the retail aggregator is internalizing the trading flow executing order in its OWN liquidity pool (in House execution). The execution data we use as sample are all trades in the aforementioned forex pairs (EURUSD, GBPUSD, USDJPY, USDCHF, EURCHF) that consist on about 190K trades, all of them executed in own liquidity pool, for the period between June 2020 and June 2021. Despite the fact that these trades have not executed in an external LP, the prices used for execution are again from LP1 and LP2, streamed through the system with the exact same price aggregation mechanism. As we mentioned in our Own model description in Chapter 3.2 trading requests are executing in the order price (price available to end user terminals at the request time) and not necessarily the best available price at the given time.

Fx Pair	EURCHF			EURUSD			GBPUSD			USDCHF			USDJPY		
Month/Avg Spread	Avg LP1_spread	Avg LP2_spread	Avg OWN_spread	Avg LP1_spread	Avg LP2_spread	Avg OWN_spread	Avg LP1_spread	Avg LP2_spread	Avg OWN_spread	Avg LP1_spread	Avg LP2_spread	Avg OWN_spread	Avg LP1_spread	Avg LP2_spread	Avg OWN_spread
Jun-20	0.8	1.0	0.9	0.4	0.4	0.4	0.6	0.8	0.6	0.5	0.8	0.5	0.4	0.5	0.4
Jul-20	0.6	0.7	0.6	0.3	0.5	0.3	0.5	0.8	0.5	0.5	0.6	0.5	0.4	0.5	0.4
Aug-20	0.7	0.9	0.7	0.4	0.5	0.4	0.5	1.0	0.5	0.5	0.7	0.5	0.4	0.6	0.4
Sep-20	0.8	1.1	0.8	0.4	0.5	0.4	0.6	1.1	0.6	0.5	0.9	0.5	0.5	0.6	0.5
Oct-20	0.6	0.9	0.6	0.4	0.5	0.4	0.6	1.1	0.6	0.5	0.8	0.5	0.4	0.5	0.5
Nov-20	0.7	0.9	0.7	0.3	0.4	0.3	0.5	1.1	0.6	0.6	0.8	0.6	0.3	0.5	0.4
Dec-20	0.7	1.0	0.7	0.4	0.4	0.4	0.7	1.3	0.8	0.6	0.8	0.6	0.4	0.5	0.4
Jan-21	0.8	1.0	0.8	0.3	0.4	0.4	0.6	1.1	0.6	0.6	0.8	0.6	0.4	0.5	0.5
Feb-21	0.7	0.9	0.7	0.3	0.4	0.3	0.6	0.9	0.6	0.5	0.7	0.5	0.4	0.4	0.4
Mar-21	0.6	0.8	0.7	0.3	0.4	0.3	0.6	0.9	0.6	0.6	0.8	0.6	0.4	0.4	0.4
Apr-21	0.7	0.8	0.7	0.3	0.4	0.4	0.5	0.9	0.6	0.5	0.7	0.5	0.4	0.4	0.4
May-21	0.8	1.2	0.8	0.3	0.4	0.3	0.5	0.9	0.5	0.6	0.8	0.7	0.3	0.4	0.4
Jun-21	0.6	0.8	0.6	0.4	0.4	0.4	0.6	0.8	0.6	0.5	0.6	0.5	0.5	0.5	0.5

Table 9-Average Executed Spread Comparison

In the table above we can see a comparison between the average spread between external liquidity providers and Own liquidity. Since Own liquidity is not a price feed source, but rather an execution pool, its spread should match either LP1 or LP2. Any drifts from these values can occur though due to latency between the initial feed source and re-distributing these prices to own liquidity for execution, but they are close to zero (from 0.01 to 0.1 basis points). Since in this case all executed trades have been routed to OWN liquidity, the average own spread is actually the average spread executed retail client orders received for the period. As we can see below, the average own spread matches the LP1 average spreads, which from the previous section proved to be the most competitive on an average basis for the examined symbols during the reference period. So, based on the available data, it would be safe to assume that although best execution is not met by default from the system, in contrast with the first model, when clients are streamed the more competitive pricing from the existing sources, average execution tends to be in the best available price. On top of this, it would be useful to mention again (as in section 3.2) that orders executed on "order price" rather than "liquidity price" most of the times benefit retail clients at expense of the retail aggregator.

Fx Pair	*EURCHF*		*EURUSD*		*GBPUSD*		*USDCHF*		*USDJPY*	
Month/Avg Spread	LP1 vs Own spread	LP2 vs Own spread	LP1 vs Own spread	LP2 vs Own spread	LP1 vs Own spread	LP2 vs Own spread	LP1 vs Own spread	LP2 vs Own spread	LP1 vs Own spread	LP2 vs Own spread
Jun-20	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.3	0.0	0.0
Jul-20	0.0	0.1	0.0	0.1	0.0	0.3	0.0	0.1	0.0	0.1
Aug-20	0.0	0.2	0.0	0.2	0.0	0.5	0.0	0.2	0.0	0.2
Sep-20	0.0	0.3	0.0	0.1	0.0	0.5	0.0	0.3	0.0	0.1
Oct-20	0.0	0.3	0.0	0.1	0.0	0.5	0.0	0.2	0.0	0.1
Nov-20	0.0	0.2	0.0	0.1	0.0	0.5	0.0	0.2	0.0	0.1
Dec-20	0.0	0.2	0.0	0.1	0.0	0.6	0.0	0.2	0.0	0.1
Jan-21	0.0	0.2	0.0	0.1	0.0	0.4	0.0	0.1	0.0	0.0
Feb-21	0.0	0.2	0.0	0.1	0.0	0.4	0.0	0.2	0.0	0.0
Mar-21	0.0	0.2	0.0	0.1	0.0	0.3	0.0	0.2	0.0	0.1
Apr-21	0.0	0.1	0.0	0.0	0.0	0.3	0.0	0.2	0.0	0.1
May-21	0.0	0.4	0.0	0.1	0.0	0.4	0.0	0.1	0.0	0.0
Jun-21	0.0	0.2	0.0	0.0	0.0	0.3	0.0	0.1	0.0	0.0

Table 10-Average Execution Spread Differences

4.3 Market Risk Exposure

4.3.1 Introduction

In this chapter we will examine what is the market risk exposure each model is subject to. Since the Back-to-Back model externalizes all of its volume, we assume no market risk (market risk is zero), but rather only operational risk, which cannot be quantified with the available data. Thus, we will focus on market risk exposure that occurs for Own liquidity model, which as we analyzed earlier internalizes the trading volume. To define market risk exposure, we will use Value at Risk methodology (VaR). VaR is a measure of market risk. It is the maximum loss which can occur with X% confidence over a holding period of t days. VaR is the largest likely loss from market risk (expressed in currency units) that an asset or portfolio will suffer over a time interval and with a degree of certainty selected by the user. It is essential to mention that VaR only captures risks that can be quantified. Therefore, it does not measure other risks that an investment firm (in our case a retail aggregator) will be exposed to, such as liquidity risk or operational risk. In our examination we will use the variance–covariance, parametric or analytic method. This method assumes the returns on risk factors are normally distributed and the correlations between risk factors are constant.

4.3.2 Data decomposition

The analytic method assumes that financial instruments can be decomposed or 'mapped' into a set of simpler instruments that are exposed to only one market factor. In our case, we have broken assets down to net amount per market side (buy or sell) per day for the period 2020-2021. The exposure snapshot is extracted per day at the end of day (EOD) and price data for each asset are also EOD closing daily prices. The asset prices used to calculate VaR and the exponential weighted moving average EMWA (as we will describe later in this section), consist of the 90 trading days with ending reference date 26th May 2022 (end of April).

Below is a sample representation of both.

Date	Symbol	Side	Amount	Avg Price
1/1/2020	AUDCAD	BUY	209000	0.941691875
1/1/2020	AUDCAD	SELL	70000	0.904446857
1/1/2020	AUDCHF	BUY	122000	0.685031849
1/1/2020	AUDCHF	SELL	111000	0.6717695
1/1/2020	AUDJPY	BUY	258000	80.3601413
1/1/2020	AUDJPY	SELL	439000	74.58762963

Table 11-End Of Day Exposure Snapshot

Symbol	Time	ask_open	ask_high	ask_low	ask_close
EURUSD	4/29/2022 0:00	1.05036	1.05932	1.05024	1.05498
EURUSD	4/28/2022 0:00	1.05544	1.05653	1.04718	1.05033
EURUSD	4/27/2022 0:00	1.06431	1.06549	1.05148	1.05546

EURUSD	4/26/2022 0:00	1.07128	1.07389	1.06354	1.0643
EURUSD	4/25/2022 0:00	1.08098	1.08124	1.06971	1.07128

Table 12-End Of Day Prices sample

4.3.2 Calculation of VaR

Now we will present the calculation steps for the VaR values to extract daily EOD market risk exposure for the period 01/2020 to 12/2021. We will calculate VaR at a 99% confidence interval with a z-score of 2.33 standard deviations. The general equation that will be used to calculate VaR for the entire portfolio is the following:

$$VaRp = \sqrt{\sum_{i=1}^{n} VaR_i{}^2 + \sum_{i=1}^{n} 2 * VaRi * VaRj * Pij_{\,i}}$$

Where:

$VaRp = Value\ at\ Risk\ of\ the\ portfolio$

$VaRi = Value\ at\ Risk\ of\ asset\ i$

$VaRj = Value\ at\ Risk\ of\ asset\ j$

$n = number\ of\ assets$

$Pij = corellation\ between\ asset\ i\ and\ j$

VaR for each asset will be calculated according to the following formula:

$$VaRi = FVi * Avg\ ri * \sqrt{\sigma_{1,t+1}} * 2.33$$

Where:

FV = Face Value of asset i

$Avg\ ri = Average\ of \log Returns\ of\ asset\ i$

$\sigma_{1,t+1} = volatility\ forecast\ in\ t-1$

All the calculation steps can be found in the respective file "Portfolio Risk". We will create a daily table with Net Face Value in dollar terms. Conversions have been done using latest respective rate snapshot. Sample of the exposure table can be found below.

		BUY	*Avg BUY*	*SELL*	*Avg SELL*	***NET FV***
1.0733	**EURUSD**	1968000	1.1103	6046000	1.0913	4376917
1.2618	**GBPUSD**	5353000	1.2286	1273000	1.2206	5148062
127.11	**USDJPY**	503000	107.8642	369000	107.405	134000
0.7158	**AUDUSD**	54000	0.6939	339000	0.6431	398156
160.40	**GBPJPY**	1366000	133.1729	442000	130.429	1165885
8.3674	**NGAS**	16000	2.2959	1000	1.75	34985
32865	**US30**	1	24528.6000	5	23621.70	93580
12555	**NAS100**	9	9464.5444	1	9383.40	75798

Table 13-Daily End Of Day Exposure in US dollars

Next, following Risk Metrics forecasting methodology using the exponentially weighted moving average model (EWMA) to forecast variances and covariances (volatilities and correlations) of the multivariate normal distribution. To capture the dynamic features of volatility is to use an exponential moving average of historical observations where the latest observations carry the highest weight in the volatility estimate. the exponentially weighted moving average model depends on the parameter λ $(0 < \lambda < 1)$ which is often referred to as the decay factor. This parameter determines the relative weights that are applied to the observations (returns) and the effective amount of data used in estimating volatility. In our case we will use decay factor of 0.95, since for 1% tolerance level (99% confidence interval) and 90 observations, this is the value suggested by Risk Metrics (see table below).

daily returns

	Days of historical data at tolerance level:			
Decay factor	**0.001%**	**0.01%**	**0.1%**	**1 %**
0.85	71	57	43	28
0.86	76	61	46	31
0.87	83	66	50	33
0.88	90	72	54	36
0.89	99	79	59	40
0.9	109	87	66	44
0.91	122	98	73	49
0.92	138	110	83	55
0.93	159	127	95	63
0.94	186	149	112	74
0.95	224	180	135	90
0.96	282	226	169	113
0.97	378	302	227	151
0.98	570	456	342	228
0.99	1146	916	687	458

Table 14-Risk Metrics decay table. The number of historical observations used by the EWMA model

The 1-day Risk Metrics volatility forecast is given by the expression:

$$\sigma_{1,t+1} = \sqrt{\lambda\sigma_{1,t-1}^2 + (1-\lambda)r_{1,t}^2}$$

Where:

$$\lambda = decay\ facotr$$
$$\sigma_{1,t-1}^2 = volatility\ forecast\ in\ t-1$$
$$r = logarithmic\ return\ in\ time\ t$$

Based on the above we have calculated volatility forecast for every instrument that our End of Day portfolio consists on.

In the next step we calculate the necessary matrices. First, we will construct Correlation matrix between the instruments based on the 90-day logarithmic returns. We use the CORELL function available in Excel. Then we construct 2*p*VaRi*VaRj matrix for all the instruments the portfolio consists on. Below are samples from both matrices.

	EURUSD	GBPUSD	USDJPY	AUDUSD	USOilSpot
EURUSD	0.00337%	0.58%			
GBPUSD	0.69	0.00389%	0.62%		
USDJPY	(0.11)	(0.10)	0.00313%	0.56%	
AUDUSD	(0.11)	(0.10)	(0.06)	0.00507%	0.71%
USOilSpot	0.08	0.17	0.10	0.19	0.07865%
NGAS	(0.11)	0.05	(0.07)	0.16	0.24
US30	0.21	0.35	0.02	0.49	(0.08)
NAS100	0.21	0.32	0.04	0.51	(0.09)
GBPJPY	0.43	0.66	0.68	0.41	0.20
GER30	(0.05)	(0.07)	(0.14)	(0.13)	(0.04)
USDCHF	(0.55)	(0.52)	0.42	(0.55)	(0.13)

2pVaR*VaR	EURUSD	GBPUSD	USDJPY	AUDUSD	USOilSpot
EURUSD					
GBPUSD	1,342,122,921				
USDJPY	(132,366,236)	(210,422,790)			
AUDUSD	(18,957,847)	(30,137,315)	(12,912,670)		
USOilSpot	-	-	-	-	
NGAS	(21,541,853)	19,172,992	(15,089,444)	5,230,755	-
US30	166,468,089	493,201,561	18,705,003	62,278,129	-
NAS100	8,071,108	22,194,073	1,702,756	3,204,277	-
GBPJPY	1,892,612,993	5,350,070,478	3,451,304,127	294,687,553	-
GER30	(3,651,358)	(9,925,528)	(13,250,326)	(1,721,423)	-
USDCHF	(215,027,662)	(364,936,238)	186,228,236	(35,121,572)	-

*Figure 12-Corelation & 2*p*VaRi*VaRj matrices used to calculate daily Value at Risk.*

Based on the above, we have calculated daily EOD Value at Risk. We can see from the chart below a representation of the results for the 2 year period that the Value at risk can vary from \$35k up to \$1.23 million for the Own Liquidity model.

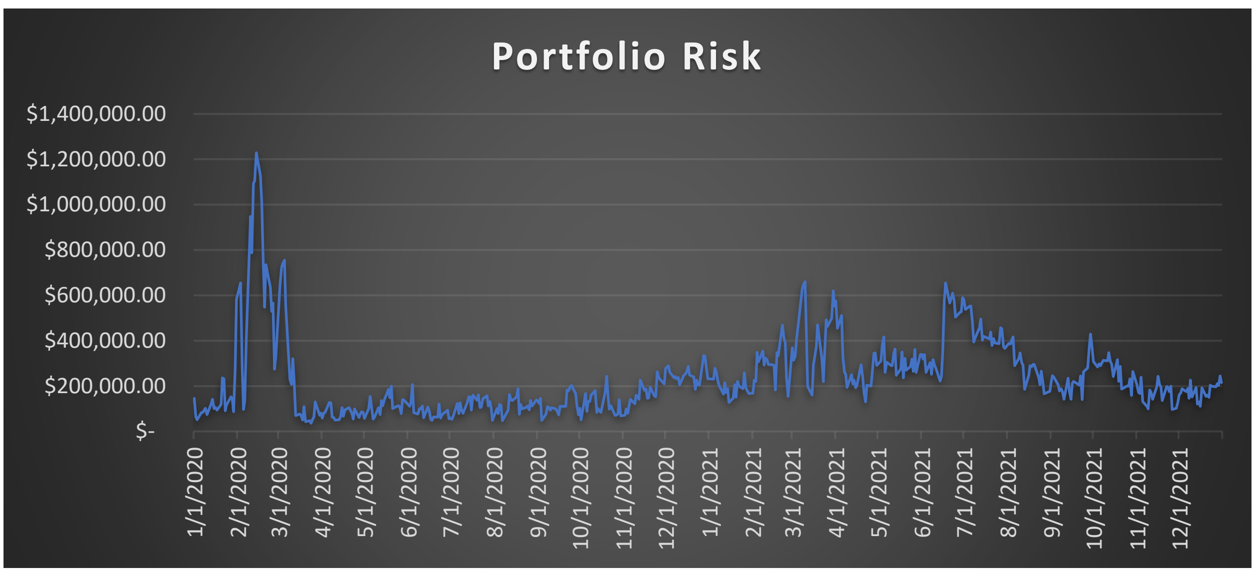


Figure 13-Daily EOD VaR Chart

Now we want to investigate if there is any linear relationship between the size of the daily EOD value at risk and the daily percentage of winners vs losers. We will examine the following linear multiple regression equation using R:

$$Y = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

Where:

Y = Portfolio Risk

X_1 = Percentage of Winning Accounts

X_2 = Percentage of Losing Accounts

The dataset we will use for our linear regressions analysis will be daily EOD VaR values and daily percentages of profitable and losing accounts for the period of 2 years (from 01/01/2020 to 31/12/2021). The from of dataset can be seen in the sample table below.

Date	*PortfolioRisk*	*PercentProfitableAccounts*	*PercentLosingAccounts*
1/1/2020	145803.99	71	29
1/2/2020	64673.08	71	29
1/3/2020	51130.3	72	28
1/6/2020	82758.37	65	35
1/7/2020	83976.87	58	42
1/8/2020	93932.9	64	36
1/9/2020	102003.28	41	59
1/10/2020	73704.63	70	30
1/13/2020	122573.15	56	44
1/14/2020	141970.81	68	32
1/15/2020	101364.73	71	29
1/16/2020	106523.5	65	35

Table 15-Data Sample used for the regression analysis

For a our test, the null and alternative hypotheses are:

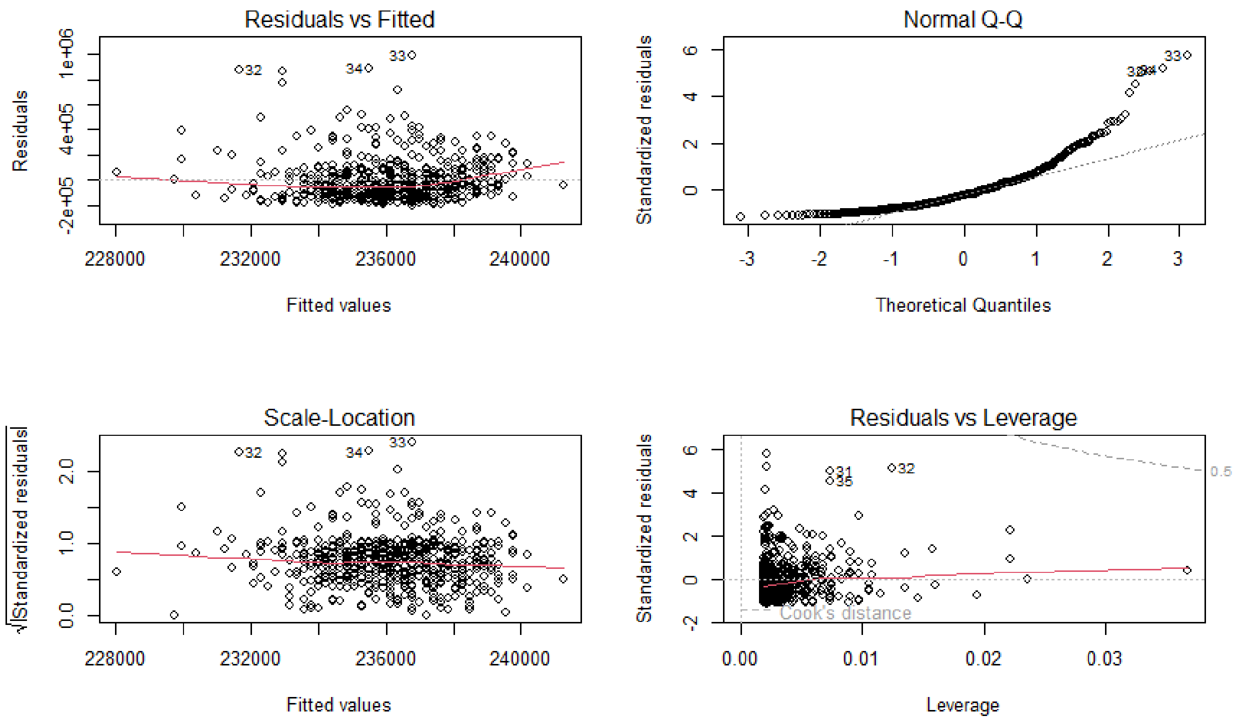
H0:$\beta 1=0$ (there is no (linear) relationship between the variables)

H1:$\beta 1\neq 0$ (there is a (linear) relationship between the variables)

Below we can find the regression results.

```
Call:

lm(formula = PortfolioRisk ~ PercentLosingAccounts, data = mydata)

Residuals:

   Min      1Q  Median      3Q     Max

-200850 -122726  -40052   59664  992140

Coefficients:

                 Estimate Std. Error t value Pr(>|t|)

(Intercept)         242952.5    28330.9   8.576   <2e-16 ***

PercentLosingAccounts   -212.9      850.0  -0.251    0.802

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 172500 on 521 degrees of freedom

Multiple R-squared:  0.0001204,  Adjusted R-squared:  -0.001799

F-statistic: 0.06276 on 1 and 521 DF,  p-value: 0.8023

>summary(model$coefficients)

    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.

  -212.9  60578.4 121369.8 121369.8 182161.2 242952.5

> summary(model$residuals)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.

-200850 -122726  -40052       0   59664  992140
```

We can see that the multiple R-squared is extremely low and close to zero, meaning it cannot explain sufficiently the percentage of the variance in the dependent variable that the independent variables explain collectively. Additionally, the p-value is higher than 0.05, thus we cannot reject the null hypothesis. To further support this, we can see below the residuals vs fitted plot and the scale-location plot. In both cases it appears that residuals are not randomly scattered around the 0 line.



Despite the fact that we did not observe any linear relationship between daily percentage of losers, winners and value at risk, this does not mean that this means that there is no association between market risk exposure and retail client profit/loss. The profitable-losing accounts data we used are daily percentages on distinct accounts. They do not take into account the actual profit-loss sizes. This means that e.g. a percentage of losing accounts 30% might represent the 90% of the generated retail client daily profit and loss. Since we do not have the evidence data to support this, it remains an assumption.

Chapter 5: Conclusions

We have compared two models of handling trading flow in OTC Forex retail Market side by side, comparing data on execution speed, best execution and overall market risk exposure, to identify advantages and disadvantages between the two models.

The speed of execution comparative analysis showed us that, the own Liquidity model is clearly a much faster model than the Back-to-Back liquidity model. In our analysis of the data, we examined both coverage and roundtrip times. In both cases we saw that the Own Liquidity Model was 2 or 3 times lower than Back-to-Back model. Even in the case of extreme prices (min, max values per month), the data suggested the same pattern of results. Speed of execution is important, as it gives an edge to high frequency and volatility spike trader to exploit short-term opportunities in the market. Slower execution can create gaps in such trading strategies, leading to failure in implementation and consequently loses for the retail clients.

The best execution analysis was more marginal. From the data comparison we observed that the Back-to-Back model operated in respect with best price availability, thus offering in a consistent basis the best (on average) price discovery. On the other hand, we saw marginal drifts in the Own Liquidity model in comparison with the Back-to-Back model. Prices on executed trades were in most cases matching the best available prices, but we saw periodic (on a month basis) drifts up to 0.1 points from best price.

Regarding Market Risk exposure. As we mentioned in the relevant section, Back-to-Back model assumes no market risk. All exposure is instantly externalized outside the retail aggregator's (broker) trading book. If any market risk arises, this would be due to failure of fully or partially externalizing trading flow due to systemic technical failures. Since we do not have data to measure the exposure amount or the frequency of these failures, we assume zero Value at Risk and thus zero market risk. The Own Liquidity model on the other hand internalizes the generated trading volume. We calculated the associated market risk, by computing the daily end of day value at risk that the aggregator carries in its books. The values varied from tens of thousands up to over a million for one day period. There is no winner or loser in this case. The ascension of risk is something clearly related with risk appetite and the balance sheet size of the retail aggregator. In general terms internalization can lead to significant revenue streams for the brokers. This is because they become direct counterparties to all transactions, in a market, where the majority of the retail clients tend to eventually lose money in the long term. Thus, a broker that can sustain carrying negative effect from the associated market risk for a long period, might eventually benefit in the long term.

Overall, it is difficult to distinguish one model against the other. Both models have their advantages and disadvantages, and it is subject to the retail aggregator's business policy and financial strength which of the two could be more beneficial.

Appendix

Code used for data extraction and relevant R scripts

```
mydata <- read.csv('E:\\RegressionDataSet.CSV', header = TRUE)
model <- lm(PortfolioRisk ~ PercentLosingAccounts+PercentProfitableAccounts, data
= mydata)
summary(model)
cor(mydata$PercentProfitableAccounts, mydata$PercentLosingAccounts)
hist(mydata$PortfolioRisk)
plot(PortfolioRisk ~ PercentLosingAccounts, data=mydata)
plot(PortfolioRisk ~ PercentProfitableAccounts, data=mydata)
par(mfrow=c(2,2))
plot(lm(PortfolioRisk ~ PercentLosingAccounts+PercentProfitableAccounts, data =
mydata))
par(mfrow=c(1,1))
summary(model$coefficients)
summary(model$residuals)
```

R Multiple linear regression script

```
SELECT
COUNT(DISTINCT(t.`Account`)) "Total Accounts Traded",
SUM(IF(t.`NET P/L` = "Profit", 1, 0)) AS "Profitable Accounts",
ROUND((SUM(IF(t.`NET P/L` = "Profit", 1, 0)) / COUNT(DISTINCT(t.`Account`)) *100
),0) "% of Profitable Accounts",
SUM(IF(t.`NET P/L` = "Loss", 1, 0)) AS "Loosing Accounts" , ROUND((SUM(IF(t.`NET
P/L` = "Loss", 1, 0)) / COUNT(DISTINCT(t.`Account`)) *100 ),0) "% of Loosing
Accounts"
FROM
(
    SELECT tvd.`account` "Account", IF(SUM(tvd.`gross_pnl` +
tvd.`client_commission` + tvd.`interest`)>0, "Profit", "Loss") AS "NET P/L"
    FROM aaafx.`trading_valuation_daily` tvd
    WHERE TRUE
    AND tvd.`security_type` != 'BO'
    AND tvd.`date_time` >= 'DateTime'
    AND tvd.`date_time` <= 'DateTime'
    AND tvd.`account` > 1100
    GROUP BY tvd.`account`
)t;
```

Winners vs Losers SQL Script

```sql
SELECT
t.day,
ROUND((SUM(IF(t.`NET P/L` = "Profit", 1, 0)) / COUNT(DISTINCT(t.`Account`)) *100
),0) "% of Profitable Accounts",
ROUND((SUM(IF(t.`NET P/L` = "Loss", 1, 0)) / COUNT(DISTINCT(t.`Account`)) *100
),0) "% of Loosing Accounts"
FROM
(
    SELECT
     DATE(tvd.`date_time`) "day",
    tvd.`account` "Account", IF(SUM(tvd.`gross_pnl` + tvd.`client_commission` +
tvd.`interest`)>0, "Profit", "Loss") AS "NET P/L"
    FROM aaafx.`trading_valuation_daily` tvd
    WHERE TRUE
    AND tvd.`security_type` != 'BO'
    AND tvd.`date_time` >= '2020-01-01'
    AND tvd.`date_time` <= '2021-12-31'
    AND tvd.`account` > 1100
    GROUP BY tvd.`account`, DAY(tvd.`date_time`)
)t
GROUP BY t.day;
```

Figure 14Winners vs Losers SQL Script

```sql
-- Avg spread per symbol
SELECT t.symbol, ROUND(AVG(t.LP1_spread),2) "AVG LP1 Spread",
ROUND(AVG(t.LP2_spread),2) "AVG LP2 Spread"
FROM (
    SELECT
    cova.`symbol`,
    MIN(CASE WHEN cova.`broker_id` = 1 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END)
LP1_spread,
    MIN(CASE WHEN cova.`broker_id` = 188 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END) LP2_spread
    FROM aaafx_logging.`client_account_feed_rate` caf
    LEFT JOIN aaafx_logging.`coverage_account_feed_rate` cova ON caf.`id` =
cova.`client_account_feed_rate_id`
    JOIN aaafx_logging.`currency` cu ON REPLACE(cu.`name`, "/", "") =
cova.`symbol`
    WHERE TRUE
    AND caf.`id` = cova.`client_account_feed_rate_id`
    AND cova.`date_time` BETWEEN 'Month' AND 'Month'
    AND caf.`is_open`=1
    GROUP BY caf.`id`, caf.`client_ticket`
)t
GROUP BY t.`symbol`;
```

Average Spread per symbol SQL Script

```sql
select * from aaafx_logging_2020_001.`log_data_200` ld
WHERE ld.`id` BETWEEN 1520949847 AND 1523949847
AND ((ld.`message` LIKE '(2)[DealerRequestHandlerImpl]%')
OR (ld.`message` LIKE '(2)[closePosition] closePosition%')
OR (ld.`message` LIKE '(3) [handleBuySellCoverage]%')
OR (ld.`message` LIKE '(3)[handleBuySellCoverage]%')
OR (ld.`message` LIKE '(4)[signalBuySellCompleted]%')
OR (ld.`message` LIKE '(4)[signalCloseMarketCompleted]%')
OR (ld.`message` LIKE '[reject] executing reject command%')
OR (ld.`message` LIKE '[processReject] ProcessReject%')
OR (ld.`message` LIKE '[confirmTicket] Matched original ticket%'))
ORDER BY ld.`id` ASC
```

Execution Times SQL Script

```sql
-- LP1 vs LP2 vs OWN
SELECT
  caf.`client_ticket`,
  caf.`requested_price`,
  cova.`symbol`,
  IF(caf.`side`=0,"BUY","SELL") side,
  cova.date_time,
  MAX(CASE WHEN cova.`broker_ticket` IS NOT NULL THEN cova.`broker_name` END)
covered_in,
  MIN(CASE WHEN cova.`broker_id` = 1 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END)
LP1_spread,
  MIN(CASE WHEN cova.`broker_id` = 188 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END)
LP2_spread,
  MIN(CASE WHEN cova.`broker_id` = 190 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END)
OWN_spread,
  MIN(CASE WHEN cova.`broker_id` = 191 THEN (ROUND(cova.`ask_rate` -
cova.`bid_rate`,LENGTH(cu.`pipMultiplier`)) * cu.`pipMultiplier`) END) OWN_spread
FROM aaafx_logging.`client_account_feed_rate` caf
LEFT JOIN aaafx_logging.`coverage_account_feed_rate` cova ON caf.`id` =
cova.`client_account_feed_rate_id`
JOIN aaafx_logging.`currency` cu ON REPLACE(cu.`name`, "/", "") = cova.`symbol`
WHERE TRUE
AND caf.`id` = cova.`client_account_feed_rate_id`
AND cova.`date_time` BETWEEN '2021-02-28 22:00:00' AND '2021-03-31 21:00:00'
AND cova.`symbol` IN ('EURUSD','USDJPY','GBPUSD','USDCHF','EURCHF')
AND caf.`is_open`=1
GROUP BY caf.`id`, caf.`client_ticket`
HAVING `covered_in` IN ("LP1","LP2","OWN");
```

Best Execution Data SQL Script

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