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Fixing the Fix? Assessing the Effectiveness of the 4pm Fix

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1 Executive summary

Introduction

This study examines the most important benchmark in the foreign exchange (FX) market: the WM/R 4pm Closing Spot Rate, also known as 'the 4pm fix'. We study trading around the benchmark between 2012 and 2017 with a unique dataset that allows us to identify the actions of individual traders. These data provide new insights into how trading decisions affect the properties of the fix benchmark, and how the presence of the fix affects trading patterns. Two events are the particular focus of our analysis: the 2013 allegations that major banks had been colluding to rig the 4pm fix, and the 2015 reform of the benchmark methodology.

Benchmarks have played a significant role in markets for centuries. They are particularly important in markets, such as FX, that are fragmented and characterised by a significant amount of bilateral trading. In these markets, a benchmark reduces information asymmetries between dealers and their clients, increasing price transparency and reducing search costs (Duffie et al., 2017). Benchmarks are also hugely important for reference purposes, the WM/R rate is used as an input in MSCI and FTSE indices that funds totalling $6tn in net assets reference and track against (Mooney, 2016). Financial benchmarks are also widely used as reference rates to settle derivative contracts, and a broad range of participants rely on benchmarks as a fair and transparent price to execute, or for valuation purposes — to rebalance funds or portfolios.

The main contribution of this paper is to inform optimal benchmark design, through a characterisation of a benchmark's effectiveness and the liquidity in the market it references around two significant events: the dealer collusion revelations in 2013, and the change to the benchmark calculation methodology in 2015. We utilise a unique data set that includes participant identities — a crucial requirement to examine fix-trading behaviours. Very little research has been done on this before, as the earlier academic research on FX benchmark rates has been focused on examining price patterns around the fix window and related manipulative practices. We also make a significant contribution to the FX microstructure literature as the first study, in recent years, to provide liquidity metrics for a major inter-dealer venue that can only be derived from full orderbook data.

Firstly, we classify and measure the usefulness of the fix rate along three dimensions: how closely it represents rates throughout the day (representativeness); the extent that market participants can replicate the fix rate through their own trading (attainability) and how resilient it is to manipulation (robustness). This paper is among the first to propose benchmark-effectiveness measures. Duffie and Dworczak (2018), in a theoretical model, examines robustness and estimation efficiency — which is an abstraction similar to our representativeness measure. We find that the representativeness of the benchmark has increased after the lengthening of the benchmark window in 2015. We also find that, after this lengthening, the robustness of the benchmark increased, but at the cost of a reduction in attainability.

A benchmark is **representative** if it accurately represents prices of the underlying asset throughout the day. Representativeness is an important attribute of all financial benchmarks. Benchmark rates that often take on extreme values compared with rates at other times of the day are not very representative. Furthermore, price dynamics during and around the fix window should not exhibit clear signs of market inefficiencies such as short-term predictability and strong price reversals. We find that short-term price reversals in prices around the fix decrease steadily throughout our sample period, and disappear from 2015 onwards. This coincided with changes in trading behaviour of several types of market participants — dealer banks began doing relatively less trading *before* the fix and more *during* the fix, the total trading volume of dealers that were subsequently fined for rigging decreased by one fifth, and direct trading costs in the largest currencies in our sample decreased by 5 to 10% relative to other times of the day.

Attainability is a particular concern for trade-based benchmarks — benchmarks that are calculated by sampling trades on a reference market during a pre-defined window. Users of the benchmark may try to 'attain' the benchmark price by trading during this sampling window, but encounter tracking error when their trade prices vary from the benchmark price — due to factors such as the benchmark taking a median of a subset of trades. We find that the change to lengthen the reference window, which was recommended by the Financial Stability Board (FSB, 2014) and implemented by WM/R, reduced attainability (or tracking error) by a magnitude of between 2 and 5 times for the largest currencies in our sample. This significantly increases the tracking error of market participants, and thus trading costs, for those participants that use the benchmark for rebalancing purposes.

Robustness refers to the extent that a benchmark is susceptible to manipulation. We show that the changes implemented in 2015 to increase the fix window have increased robustness. We show that the introduction of outlier trades in a simulated price series, has half the impact with a 5-minute fix window in comparison to a 1-minute window. However, we also show that the impact in both settings is economically small, at less than 1 basis point. We suggest that this is because the existing benchmark design — its sampling method and use of medians — is highly robust to our method of simulating outlier (manipulative) trades.

Secondly, a well-functioning benchmark depends upon a **liquid reference market**. A useful and popular benchmark can also *cause* an agglomeration of liquidity (Duffie and Stein, 2015). Liquidity is, therefore, both a determinant of a benchmark's effectiveness and an outcome of it — for example, if a benchmark is more attainable, representative and robust, then it encourages more participation, which begets liquidity and enhances its effectiveness further. We examine how liquidity has evolved during our sample period. After the revelations of rigging in 2013, we find that trading costs during the fix have decreased, in the form of lower quoted spreads. After the lengthening of the fix window in 2015, quoted spreads and price impact rose, while orderbook depth decreased. These aggregate effects coincided with changes in the trading patterns of participants, particularly an increase in 'aggressive' or 'liquidity-taking' trading behaviour of high frequency traders (HFTs) around the fix window.

Thirdly, we document that, despite much controversy following the dealer collusion revelations in 2013, the benchmark is still very important. Both trading volume and the composition of participant types are broadly unchanged over our sample period. However, we do observe significant adjustments in trading patterns after key events in our sample: collusion revelations in 2013 and after changes to the benchmark calculation methodology in 2015.

Lastly, the changes made to the 4pm benchmark that we examine in this paper highlight the general trade-off that exists between attainability and robustness. For example, the benchmark calculation method ensures uncertainty about which trades are selected in its sample, which makes the benchmark harder to manipulate but also harder to attain. We discuss several incremental changes to the benchmark methodology that might increase its attainability without significantly reducing its robustness.

Section 1.2 describes the role of benchmarks and details of the 4pm fix, and discusses academic literature. Section 1.3 describes our data and measures, and provides descriptive statistics. Section 1.4 assesses how the benchmark's representativeness, attainability and robustness are affected by the 2013 media event, and the 2015 change in the window-calculation methodology. Section 1.5 assesses the change in liquidity of the underlying FX market around the fix. Section 1.6 relates our findings to the optimal design of benchmarks, and Section 1.7 concludes.

Background

Role of Benchmarks in Markets

Despite the importance of benchmarks to markets, only recently has academic research begun to examine them. Duffie and Stein (2015) characterise the benefits that benchmarks bring to markets, including lower search costs, higher market participation, better matching efficiency and lower moral hazard in delegated execution, and lower trading costs associated with higher liquidity at the benchmark. These benefits result in *agglomeration*, wherein participants choose to trade at the benchmark price, as the benefits of the benchmark outweigh their idiosyncratic reasons to trade without using it (to trade a time period away from it). Agglomeration then increases the benchmark's benefits, which then drives feedback effects. Duffie et al. (2017) propose a theory model in which the introduction of a benchmark in a bilateral OTC market improves liquidity by reducing market participant's search frictions. Aquilina et al. (2017) examine the reform of the ISDAFIX[1] interest rate swap benchmark in 2015, finding an improvement in liquidity, which they argue arises from increased transparency associated with a market-derived, rather than submission-based, benchmark.

There is comparatively more research on the manipulation of benchmarks, largely precipitated by the London Interbank Offered Rate (LIBOR) scandal, beginning with Abrantes-Metz et al. (2012), who examine the 1-month LIBOR rate. There have been some efforts to describe the characteristics, or optimal design, of effective benchmarks. Duffie and Stein (2015) argue that benchmarks should be derived from actual transactions, and Duffie and

[1] International Swaps and Derivatives Association Fix.

Dworczak (2018) demonstrate that benchmarks are more susceptible to manipulation if their reference market is more thinly traded. In their model, they characterise the choice benchmark administrators must make when designing their benchmark: they must trade off its robustness to manipulation against its efficiency[2] of estimating an asset's value. The International Organization of Securities Commissions (IOSCO) proposed a set of 'Principles of Effective Benchmarks'[3] in 2013, which include ensuring it is appropriate to the reference market's size, liquidity, and price dynamics; ensuring it is based on observable arm's length transactions; and that the methodology should be transparent.

The 4pm Fix and the FX market

This study examines the largest benchmark price in the spot foreign exchange markets: the WM/R Closing Spot Rate (known as 'the 4pm Fix')[4] and a market it sources prices from: Thomson Reuters Matching. The spot FX market is composed of inter-dealer and single-dealer venues. The dominant inter-dealer venues are Thomson Reuters Matching and EBS. In the determination of the 4pm Fix, rates are taken from these venues, as well as a third dealer-customer platform named Currenex for some currencies.

The 4pm Fix benchmark calculation methodology is published by Reuters (2017), but essentially consists of sourcing trades from the interdealer platforms during the fix window, as well as the quoted spread at the time of the trade. Median prices are then calculated separately for trades that execute at the bid (along with the opposing ask at the time), versus trades that execute at the ask/offer (along with the opposing bid at the time). The fix price is then taken as the mid-rate of these two medians. A bid and offer is also published, which is calculated as the higher of the median quoted spreads at the time of the trade, or a predefined minimum spread — this ensures the spread is always positive and economically significant. A single trade is captured each second from each of the reference platforms. Where there are insufficient trades, best bid and offer rates are instead captured.[5] Prior to 15 February 15 2015 this was a 1-minute window: 3:59:30 to 4:00:30. The fix window is now a 5-minute period from 3:57:30 to 4:02:30 London local time. We present a more detailed explanation of the methodology in Section .0.1.

The FX market is the most heavily traded market in the world, with \$1.7tn executed in spot FX per day in April 2016, down from \$2tn in April 2013, according to the Bank of International Settlements (2016). Around a third of total FX volume (\$5.1tn per day) is in spot, with the rest being swaps and other derivatives. The market is concentrated across certain currency pairs, in 2016 EURUSD accounted for 23% of all spot trading, USDJPY 17.7%, GBPUSD 9.2%, and AUDUSD 5.2%. The UK handles the majority of all FX market trading, with 37% of all volume in April 2016, down from 40.8% in 2013 (Bank of International Settlements, 2016).

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[2] Efficiency, in this model, is defined as the extent to which the benchmark estimates the asset's value without error within the calculation window. We refer to a similar concept as *representativeness* in our paper, meaning the extent that the benchmark price is an accurate reflection of prices throughout the day.

[3] Most of these principles relate to governance procedures of benchmark administrators and submitters, rather than the design of benchmarks.

[4] For brevity we refer to this as the 4pm Fix throughout this paper.

[5] In practice this occurs with less liquid currency pairs — see Reuters (2017) for a detailed description of this methodology.

Trading is concentrated on these venues by currency pairs: in the major currencies EBS has the majority of EURUSD,[6] USDJPY and USDCHF trading, while Reuters has GBPUSD and AUDUSD and several smaller currencies. These concentrations are difficult to verify, as the venues do not publish statistics, but they are perhaps reflected in the WM/R Closing Price methodology, which sources rates only from Reuters for GBPUSD and AUDUSD.[7]

Academic Literature

The 4pm Fix

Research that has focused on the 4pm fix in FX markets specifically is largely concerned with its manipulation. Osler et al. (2016) propose a model of dealers colluding, and Duffie and Dworczak (2018) and Saakvitne (2016) propose models where dealers do not collude. There have also been empirical examinations of the price dynamics around the fix by Evans (2017) and Ito and Yamada (2017), which find returns are consistent with collusive behaviour or individual manipulation or both.

Papers that examine the role and utility of the 4pm fix in markets begin with Melvin and Prins (2015), which examine its important role in FX hedging[8] by showing that equity market index movements predict end-of-month FX returns. Ito and Yamada (2017) find that trading volumes do not decrease after the extension to 5 minutes and that trading volume is more evenly distributed within the window. Marsh et al. (2017) examine the price discovery during the 4pm fix in the futures market versus the spot market in a recent sample. They find that inter-dealer trades have no price impact on average during the fix period. They explain this by demonstrating that order-flow is less directional in the fix than other intraday periods. Broker ITG examines the fix from an investor perspective by conducting transaction cost analyses of fix trades. They argue that the fix is one of the most volatile intraday periods to trade (ITG, 2014) with average returns of 10 to 25 basis points around the window, which they view as an economically significant implementation shortfall for asset managers. Chochrane (2015) argues that this is still a concern after the extension to 5 minutes in 2015.

FX Market Microstructure

We also provide the first taxonomy of trading participants in this market. This extends the work of Chaboud et al. (2014), the first to document the rise of the high-frequency traders in the FX market and their improvements to the efficiency of prices. The nature and existence of private information in FX markets has been a significant research interest, in contrast to equities markets, where its existence is considered uncontroversial. Peiers (1997) finds that Deutsche Bank was an informed trader in the Deutschemark and Ito et al. (1998) and Killeen et al. (2006) also provide evidence for the existence of FX market informed trading.

[6] Breedon and Vitale (2010) estimate EBS' share of EURUSD as at least 88%.

[7] AUDUSD, USDCAD, USDCZK, USDDKK, GBPUSD, USDHKD, EURHUF, USDILS, USDMXN, USDNOK, NZDUSD, USDPLN, USDRON, USDSEK, USDSGD, USDTRY and USDZAR are sourced only from Thomson Reuters Matching. USDCNH and USDRUB are sourced from both Thomson Reuters Matching and EBS. EURUSD, USDCHF and USDJPY are sourced from EBS, Currenex and Thomson Reuters Matching (Reuters, 2017).

[8] The predecessor to this paper is an unpublished working paper from 2010 called: 'London 4pm fix: The most important FX institution you have never heard of', demonstrating the lack of historical focus.

Academic research on the FX market may also help understand the context of the 4pm fix scandal. Menkhoff (1998) portrays a widespread view among FX dealers that fundamental information is unimportant. This view, alongside the established importance of order flows in driving returns, may have contributed to the collusive behaviours that were uncovered — wherein dealers shared order-flow information ahead of the fix.

Research on liquidity in FX markets has focused on its unique two-tiered structure (inter-dealer market and dealer markets) and the role of dealers. Melvin and Yin (2000) show a positive relationship between inter-dealer quoted spreads and volume and volatility, and Mende (2006) shows spreads widened on the day of the September 11th attacks. King et al. (2013) summarises unique behaviours of interdealer spreads in comparison to other markets. Dealers do not adjust their quotes to reflect changes in inventory (Bjonnes and Rime, 2005; Osler et al., 2011), and do not quote wider spreads to their informed customers (Osler et al., 2011) so that they can profit from their informed trades. Mancini et al. (2013) show FX liquidity has commonality across currencies with equity and bond markets.

Data Sources and Descriptive Statistics

Data Sources

We use proprietary order-book data from Thomson Reuters Matching (TRM) in our analysis, which contains all order-book events from the venue's matching engine (new orders, cancellations, executions — and subsets therein: hidden orders, non-resting orders, etc.).[9] These events are ordered sequentially and timestamped to the millisecond. The trades contain volume information and directional identifiers. The participant responsible for each event is also included, which map to 838 different legal entities in our sample. The participant identifier is a four character Terminal Controller Identifier (Dealing) Code (TCID). This reconciles to the legal entity name of the trading firm as well as the location of its trading desk. These entities are classified as large broker dealers, commercial banks, asset managers, independent trading firms including HFTs, hedge funds and other participants. Participants can trade directly on TRM as clients of a prime broker (prime broker clients — PBCs), on their own account — as direct participants, or indirectly through their broker — engaging them to trade as their principal or agent.[10] In our data, participants that trade through dealers as PBCs are separately identified. Trades that dealers perform on behalf of clients (whether principal or agency) are not separately identified from their own proprietary trades. The details of our classification methodology are presented in the Appendix, in Section .0.2.

Our sample period is approximately two and a half years from the 28 October 2010, to the 5 June 2015, and around 6 months from the 15 January 2017 to the 14 June 2017. This reflects the choice by the FCA for a sample period spanning the significant events for the fix, and a more recent period. This request excluded 2016 to reduce the collection burden

[9] This data was obtained directly by the FCA for market monitoring and research purposes.

[10] These relationships are analogous to those found in equity markets: Direct Market Access (DMA) through member firms, member firms and clients of member firms.

on firms. The currency pairs in our sample are AUDUSD, EURHUF, EURSEK, EURUSD and GBPUSD. Reuters is one of the most important inter-dealer platforms for FX, and is the only reference market for the calculation of the WM/R fix in all of the pairs in our sample except EURUSD.[11] Trades on the inter-dealer venue are purely wholesale in nature as the minimum trade size is one million of the respective base currency: GBP, EUR or AUD. We remove trading holidays and weekends from our sample, as these periods have very low trading and liquidity. We source historical 4pm fix prices from Datastream.

We also incorporate data from Thomson Reuters Tick History for our control variables that measure changes in volatility, carry and the TWI of USD. Volatility is taken from the one-week implied volatility of OTC options contracts, carry[12] is taken from the Deutsche Bank 'Balanced Currency Harvest USD' and the TWI[13] of USD is taken from the Deutsche Bank 'Short USD Currency Portfolio Index - Total Return ETF'.[14]

We obtain macro news announcements from 'FX Street', which provides a complete history of all currency-related macro news, including central-bank announcements, speeches, economic news releases and confidence indices. Each release is assigned a 'volatility rating' of 1 to 3.[15]

Market Structure and Composition over Time

Liquidity Measures

The unique nature of our data allows us to compute measures of trading behaviour on the level of individual market participants (TCIDs). Using the classification scheme described in Section .0.2 we aggregate these measures into category-wide variables.

We implement a range of market quality measures in this paper, which are discussed in more detail in Section 1.5. We detail two of these measures here, that we calculate on a participant category basis. We also compute a range of other variables: number of messages, number of aggressive and passive trades, average life of quotes, flow, VWAP and trade imbalance for each individual participant TCIDs. Some of these merit closer explanation, which we provide below.

The *effective spread* is computed as the difference between the trade price and the midpoint multiplied by two. This is, effectively, the quoted spread prevailing in the market at the time of a trade. We use the quoted spread prevailing before the market order that triggered the trade arrived (otherwise the effective spread would typically be nil). The effective spread

[11] EURUSD takes rates from the EBS and Currenex markets as well as TRM.

[12] Carry is the return obtained from holding an asset, which in an FX context refers to the a collection of assets that make up a 'carry trade'. This trade involves borrowing a currency with a low interest rate and buying a currency with a high interest rate.

[13] Trade Weighted Index: An index that aims to measure the effective value of an exchange rate by compiling a weighted average of exchange rates of home versus foreign currencies, with the weight for each foreign country equal to its share in trade.

[14] The RIC codes for the OTC options contracts are: GBPSWO=, AUDSWO=, EURUSWO=, EURSEKSWO=, EURHUFSWO=. Short USD Currency Portfolio Index — Total Return ETF: DBUSDXSI, Balanced Currency Harvest USD: DBHVBUSI.

[15] News rated 3 is the highest, and consists of official rates announcements, monetary policy meeting minutes, CPI releases, Bank Governor speeches, non-farm payrolls, etc.

is computed as:

$$\text{EffectiveSpread} = 2q\left(\frac{p_\tau - m_\tau}{m_\tau}\right)$$

where p_τ is the transaction price, m_τ is the midpoint of the best bid and offer (BBO) at the time of the trade, and q indicates the direction of the trade (+1 for buyer-initiated trades and -1 for seller initiated trades) which is taken from the initiator identifier in the orderbook data.

Price impact is computed for each individual trade, as the midpoint prevailing m seconds after a trade i, minus the midpoint at the time of a trade. We compute price impacts for 1 millisecond, 1 second, 5 seconds, 1 minute and 5 minutes. When aggregating over periods we use volume-weighted means. We only compute price impact from the perspective of the aggressive side of the trade. Price impact is computed as:

$$\text{PriceImpact}_{i,t} = q_{i,t}(m_{i,t+m} - m_{i,t})/m_{i,t}$$

Flow is the amount bought minus the amount sold by an individual TCID over a given time period. When aggregating flow over a given participant category, we sum the flow of the individual participants. Naturally, the flow summed across *all* TCIDs is always nil. We compute separate variables for aggressive and passive flow.

VWAP is the volume-weighted average transaction price attained by all TCIDs in a given category over a given time period.

Trade imbalance is the ratio of flow to volume, computed for each individual participant TCID. It is a measure of the one-sidedness of a participant's trading activity: if all trades are in the same direction, the trade imbalance is 1. If the participants buys and sells in equal amounts over a given time interval, the trade imbalance is 0. When aggregating trade imbalance over a participant category, we volume-weight the individual imbalances of the constituent TCIDs.

Market Structure

The WM/R 4pm fix is a benchmark price, which has two broad categories of users: firstly, those that use the fix as a valuation price for constructing indexes (for example, MSCI (2018)) that comprise bonds, equities or instruments in different currencies. This means that passive investment managers and ETFs will incur fund tracking errors unless they trade at this fix price. Melvin and Prins (2015) cite several surveys that show asset managers hedge most of their exchange-rate exposures.

Second, the benchmark is popular with investors and corporates who may not have FX trading capabilities, or a desire to manage intraday positions, such that a single transparent benchmark price is preferable. Such firms may issue a 'standing instruction' to the custodian of their investments to automatically execute FX positions at the benchmark (DuCharme, 2013) or to their brokers as 'trade at fix orders'.

Despite the 4pm fix's importance, there is no information available on which participants use it, how they access or trade with it, and what prices they receive. In this section we provide this information, for the first time, by currency pair, over time and by participant type.

Fix volumes: despite much controversy in recent years, and while volumes traded over our sample spanning 2012 to 2017 in the broader FX market have trended downward, fix volumes appear constant, as detailed in Figure 1.1. We also find that the composition of traders in the fix remains predominantly unchanged (Figure 1.3), though there does appear to be a reduction in share of trading by the major dealers ('Dealer-R'). Figure 1.2 and Table 1.3 shows the composition of participants in the fix window compared with the control window. The most striking difference is that HFTs have a much lower market share in the fix window than at other times of the day, at 14 and 30% respectively. Dealers, agency brokers and custodians, on the other hand, have a higher share of total volume in the fix window than in our control window.

Composition of fix traders: The most prominent trend in the market share of the different participant groups is the steady decline in the trading volume of the largest dealers (Figure 1.3). In particular, it is interesting to note a sharp decline in the trading volume of the dealers that were later fined for illegal trading practices, and a corresponding increase in the volume of other dealers, from the second quarter to the fourth quarter of 2013, around the time when the first news stories about rigging of the 4pm fix was published. It is not possible to determine if this decline is prompted from the dealers themselves reducing their fix-related trading or their clients switching dealers.

Figure 1.1: Total Volumes - Fix and Control Periods - 2012 to 2017 - GBPUSD and AUDUSD
This chart presents the total volume of trades each month, for GBPUSD and AUDUSD in the 12 to 2pm control period and the fix window period.

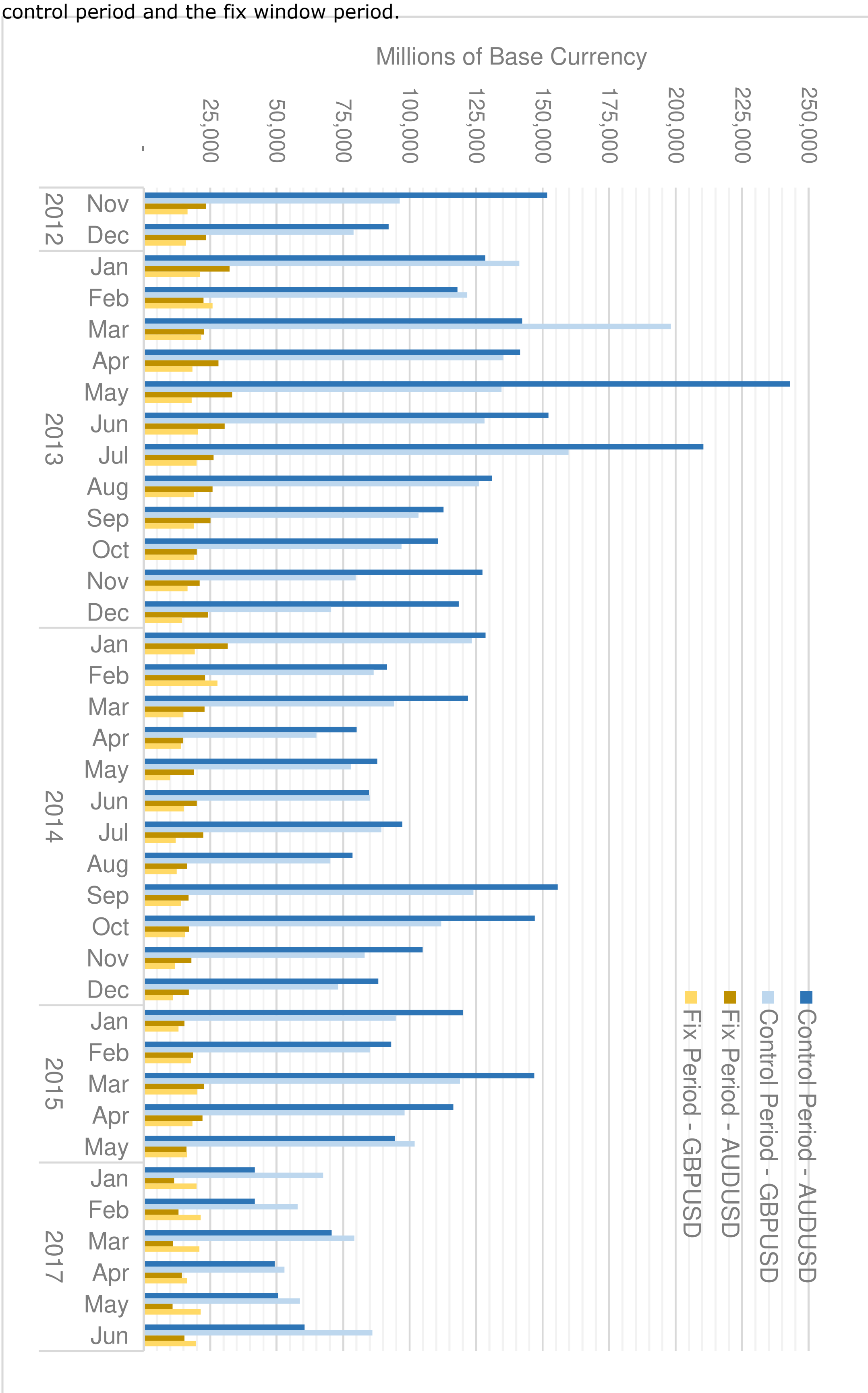


Figure 1.2: Trading Volume by Participant Categories - Fix and Non-Fix
This chart presents the proportion of total volume for each participant class, in the 12 to 2pm control period and the fix window period, calculated by the pooling GBPUSD and AUDSUSD in the entire 2012-2017 sample period.

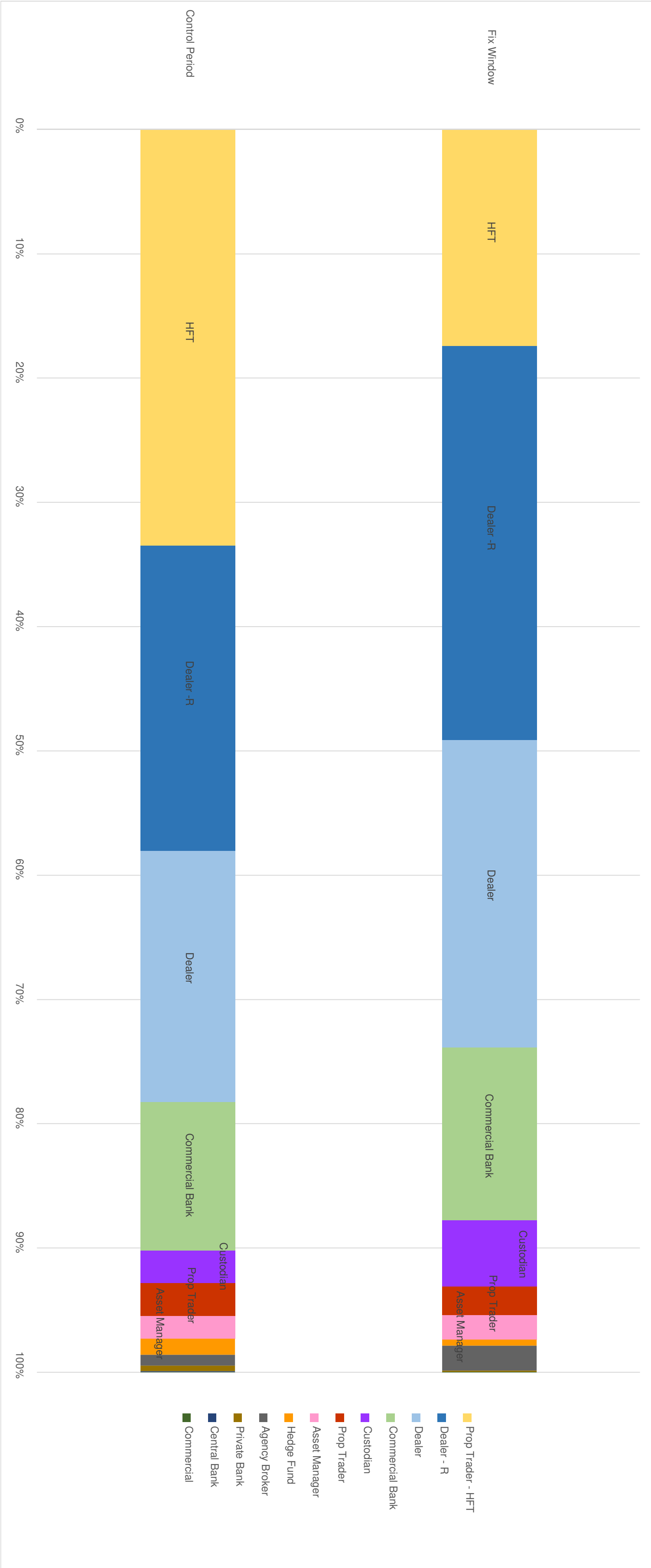


Figure 1.3: Trading Volume % by Participant Categories - by Month
This chart presents the proportion of total volume for each participant class in the fix window period, calculated by the pooling GBPUSD and AUDSUSD each month in the 2012 to 2017 sample period.

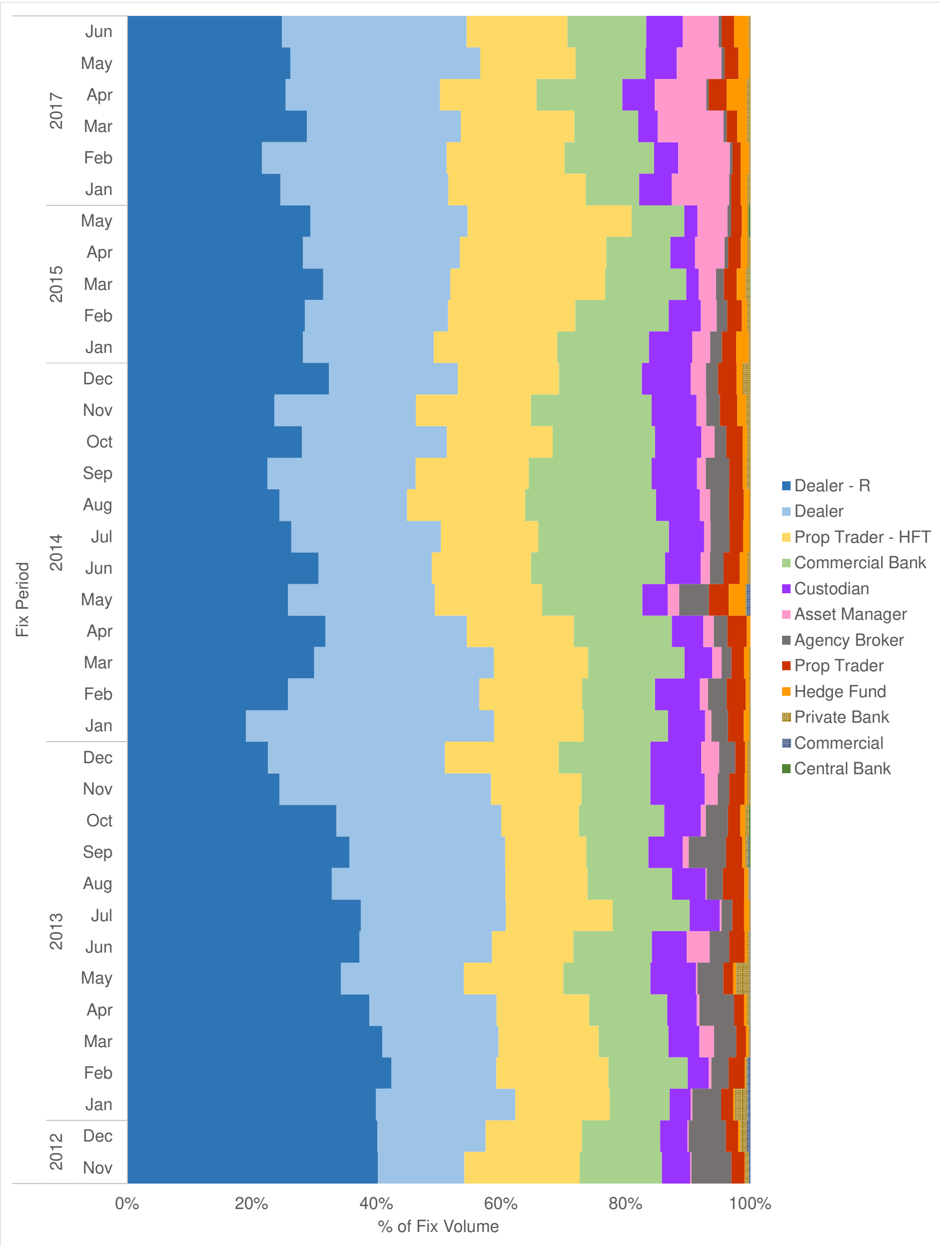


Table 1.1: Summary Statistics During the Fix by Currency-Year
Volume is total volume during the fix window. Depth is computed as the average of depth at bid and offer sides of the book (at the best bid and offer and the top 10 levels or all levels). Mean number of messages ('#msg'), quote life ('q.lif'), unique TCIDs ('#TCIDs'), number of trades ('#trades') and number of aggressor trades ('#agr.trades') are calculated across all currency-dates. #agr.trades is smaller than #trades because it doesn't include the component orders that make up a trade - of which there are least 2. Quoted spread ('Qtd.Sprd') is time-weighted, effective spreads ('Eff.Sprd.') and price impact (PI) is volume-weighted in basis points.

Pair	Year	# TCIDs	Volume	Depth best	Depth top	Depth total	#msg	q.life	# trades	#agr. trades	Qtd. sprd	Eff. sprd	PI 1ms	PI 1s	PI 5s
	2012	54.2	557.7	17.2	167	336.2	1623.4	93.43	251.7	97.8	1.1	1	0.58	0.62	0.65
	2013	51.4	604.5	14.6	122.9	288.8	1454.8	85.52	261.8	104.8	1.25	4	0.71	0.76	0.89
audusd	2014	45.6	463	13.5	117.5	298.9	1375.6	104.56	217.3	88.6	1.37	1.2	0.69	0.78	0.95
	2015	48.4	442.3	7	85.5	277.8	3454.6	69.27	314	136.7	1.93	1.5	0.96	1.2	1.38
	2017	43.2	298.1	7.4	92.3	319.5	3873.5	93.31	221.4	95.4	1.77	1.4	0.96	1.19	1.23
	2012	9.2	12.8	1.8	4.7	33.3	53.7	494.75	9.8	6.1	4.43	2.9	1.79	1.82	2.22
	2013	9.8	13.8	1.9	4.9	33.1	78.1	445.24	11	6.3	4.36	2.7	2.04	2.35	2.57
eurhuf	2014	10.5	13.5	2	4.9	31	93.7	282.61	11.1	6.2	4	2.4	1.91	1.96	1.89
	2015	15.9	27.3	2	4.6	28.5	315	193.59	24	12.3	6.09	4	2.19	2.39	2.37
	2017	16.1	26.7	2.2	8.4	39.1	789	139.75	24.1	12.9	3.76	2.6	1.16	1.23	1.4
	2012	28.1	153.2	3.2	6.4	52.3	471.1	43.92	93.3	42.5	1.76	1.4	0.99	0.92	0.97
	2013	27.3	139.9	3.1	6	52.9	573.8	23.56	85.2	39.1	1.94	1.5	1.11	1.12	1.34
eursek	2014	26.2	135.2	3.2	5.9	42.7	577.8	21.32	83.6	38.3	2.24	1.5	1.31	1.3	1.48
	2015	30.1	171.8	2.7	4.9	50	2330.6	12.91	128	60.4	3.22	2.2	1.31	1.47	1.76
	2017	31.2	137.7	3.2	15.6	104	1837.8	34.4	115.4	55.2	1.97	1.3	0.78	1.1	1.22
	2012	16.8	11.8	2.8	30.7	49	731.5	44.9	7.9	4.6	1.21	0.9	0.43	0.61	0.95
	2013	12.3	9	2.5	36.8	60	495	70.31	6.3	4.3	1.7	1.2	0.96	0.93	0.91
eurusd	2014	9.5	7.8	2.3	38.9	60	326.9	149.65	5.7	3.5	1.62	1.1	0.87	0.82	0.82
	2015	15.4	19.8	2	37.5	55	1659.8	23.85	14.3	7.6	2.26	1.4	1.14	1.3	1.21
	2017	16.5	29.9	1.4	15.8	54.2	2509.2	21.94	26.8	13	1.19	0.9	0.75	0.81	1
	2012	48.7	413.2	9.2	99.8	173.1	1602.7	45.54	213.1	87	0.85	0.8	0.58	0.58	0.63
	2013	49.3	449.5	8.7	85.9	188.1	1598.4	48.45	230.4	97.9	0.96	0.8	0.58	0.62	0.68
gbpusd	2014	44.1	345.1	8.7	76.9	174.6	1425.1	69.52	191.8	82.5	0.91	0.7	0.48	0.53	0.57
	2015	46.5	394.8	4.8	49.7	161.8	3578.6	37.71	299.9	135.8	1.33	0.9	0.64	0.8	0.92
	2017	48.7	463.5	4.6	58.3	299.3	5000.6	47.72	363.6	159.4	1.28	0.9	0.7	0.93	1

Table 1.2: Mean daily fix volume as share of control window volume. The mean trading volume in the fix is calculated for the currency-year and divided by the mean trading volume in the control window of 12 to 2pm.

year	audusd	eurhuf	eursek	eurusd	gbpusd
2012	0.20	0.06	0.20	0.02	0.20
2013	0.18	0.05	0.21	0.02	0.16
2014	0.19	0.05	0.26	0.02	0.16
2015	0.16	0.11	0.23	0.05	0.17
2017	0.23	0.18	0.31	0.12	0.29

Fix volume shares across time: most aspects of our data set feature large variation between currency pairs and across time. Table 1.1 shows that GBPUSD and AUDUSD are by far the most active currency pairs in our sample, with average daily volume at the fix of 480 and 400m units of base currency, respectively. EURSEK is at a third place with 140m in daily fix volume, while the trading volume of both EURHUF and EURUSD is much less, at 17 and 14m. EURUSD is of course the most active currency pair in the world in general, but trading is concentrated to other platforms. Of the currencies on our sample, EURSEK is the one that sees the largest relative increase in volume during the fix, with trading volume at the fix being 28% of volume during the control window on average. For AUDUSD and GBPUSD the share is 25 and 23% respectively, while it is only 10 and 6% for EURHUF and EURUSD. Table 1.2 shows the breakdown by year. Trading volume has been steadily declining for AUDUSD over time, while it has been standing still or growing for the other currency pairs.

Fix utilisation: Table 1.3 show the average trading imbalance, which is a measure of directionality of trading or what proportion of trades are in the same direction. This measure proxies for the extent a participant category utilises the fix as a benchmark, with high directionality implying greater utilisation. This measure is calculated for individual participants and averaged by category, and is higher during the fix window, with aggregate averages of 0.85 at the fix versus 0.58 during the control window. HFTs, prop traders and asset managers have lower directionality than participants from other categories, but their directionality is still higher during the fix. HFTs have a particularly low directionality, at 0.23 during the control and 0.63 during the fix. This demonstrates that the fix is (still) very much a mechanism for conducting large rebalancing flows, as described in e.g. Melvin and Prins (2015); Evans (2017). It also demonstrates that there are participants active in the fix that are not utilising it for benchmark purposes: HFTs, proprietary traders and asset managers. The trading pattern of HFTs is consistent with different trading strategies, such as market making, going after short-term profit opportunities or high-frequency arbitrage.

Informed order flow: dealers, HFTs and commercial banks have the highest 1- and 5-second price impact of any participants during the fix. Their price impact ranges between 1 to 1.2 basis points (Table 1.3). Hedge funds, commercials, agency brokers and custodians all have a lower price impact, ranging from 0.5 to 0.8 basis points at 1- and 5-seconds.

Correlated order flow: Table 1.4 shows how the flows (net position changes) of the participant groups are correlated. The flows of dealers and commercial banks are negatively correlated with the other participants, again consistent with these participants performing traditional market-making and liquidity provision during the fix. HFTs, hedge funds and

Table 1.3: Mean effective spreads, price impacts, volume shares and average imbalances by participant category for the fix and control window. All currencies pooled. Volume share is computed as the sum of traded quantity across all TCIDs in a participant category, divided by all trades in the control window (12 to 2pm) or in the fix window. Average trading imbalance ('Imbal.') is first calculated individually for all TCIDs in each category, and then reported as a mean for each category across all currency dates. Effective spread ('Eff.sprd') is: $2q\left(\frac{p_\tau - m_\tau}{m_\tau}\right)$ where p_τ is trade price, m_τ is the midpoint and q indicates the direction of the trade, expressed in basis points and weighted at the day-currency volume level and then meaned across all currency dates for the participant group. Price impact ('PI') is computed as the change in midpoint after x seconds, divided by the midpoint at the time of the trade in basis points. Price impact is volume-weighted and aggregated in the same manner as effective spread.

Category	Eff. Sprd.	PI 1ms	PI 1s	PI 5s	Volm. (ctrl)	Volm. (fix)	Imbal. (ctrl)	Imbal. (fix)
Agency Broker	1.9	0.51	0.61	0.72	0.0111	0.0361	0.78	0.93
Asset Manager	0.9	0.81	0.94	0.97	0.0366	0.0442	0.40	0.69
Central Bank					0.0040	0.0000	0.88	1.00
Commercial	0.8	0.32	0.54	0.47	0.0016	0.0040	0.79	0.93
Commcl. Bank	1.7	0.90	0.95	1.10	0.1448	0.1606	0.69	0.97
Custodian	1.5	0.58	0.67	0.70	0.0286	0.0683	0.68	0.92
Dealer - R	1.7	0.99	1.06	1.20	0.2379	0.2811	0.57	0.92
Dealer	1.7	0.87	0.97	1.05	0.1885	0.2169	0.58	0.91
Hedge Fund	1.1	0.62	0.76	0.80	0.0167	0.0120	0.70	0.93
Private Bank	1.1	0.33	0.42	0.33	0.0072	0.0080	0.77	0.97
Prop - HFT	1.3	0.88	1.08	1.15	0.2959	0.1446	0.23	0.63
Prop Trader	1.3	0.50	0.78	0.94	0.0270	0.0241	0.56	0.82

Table 1.4: Correlation of flows (net position change) during the fix, for GBPUSD and AUDUSD. Net position change is computed as the sum of signed trade volume across all TCIDs in each category, using trades in the fix window only.

	Broker	Ass.mngr	Cm.bank	Cstd	Dealer	Dealr-R	Hedge	Prop
Agency Broker								
Asset Manager	0.04							
Commercial Bank	-0.08	-0.24						
Custodian	0.03	-0.04	0.02					
Dealer	-0.04		-0.31	-0.27				
Dealer - R	-0.31	-0.23	-0.18	-0.12	-0.51			
Hedge Fund	0.08	0.37	-0.34	-0.11	0.06	-0.18		
Prop Trader	0.26	0.31	-0.24	-0.11	0.02	-0.42	0.41	
Prop Trader - HFT	0.26	0.35	-0.23	-0.07	-0.08	-0.46	0.41	0.69

prop traders have highly correlated flows, with correlation coefficients ranging between 0.4 to 0.7.

Table 1.5: Root mean square error (RMSE) between volume-weighted average price (VWAP) and the WM/R benchmark rate, by participant category. The daily RMSE is a comparison with the daily VWAP, the fix RMSE is a comparison with the fix-window VWAP. Currencies used are GBPUSD and AUDUSD. Units: basis points.

Participant	Daily RMSE	Fix RMSE
Asset Manager	22.78	1.24
Agency Broker	23.56	1.59
Hedge Fund	26.26	1.95
Commercial Bank	24.92	2.29
Dealer	20.65	3.16
Prop Trader	23.04	3.28
Prop Trader - HFT	21.90	3.31
Dealer - R	22.25	3.35
all	22.00	3.35
Custodian	20.07	3.67

Tracking error (fix attainability): in Table 1.5 we compare the volume-weighted average price (VWAP) attained by participants in each category with the daily WM/R 4pm fixing rate. The comparison is done by computing the root mean square difference (RMSE) between the VWAP and the fix rate. We compute VWAPs for all trades done during the day (daily VWAP), and for trades done during the fix window only (fix VWAP). The table shows only GBPUSD and AUDUSD, as these are the largest and most liquid currencies in our sample. Ranking participant groups by their RMSE against the fix rate indicates to what extent the participants are 'matching' the WM/R fix rate in their trading. Asset managers, agency brokers and hedge funds are all trading at relatively low RMSE's of 1.2 to 2.0 basis points. Prop traders, HFTs and dealers have a much higher RMSE of 3.3 to 3.4 basis points. Custodians have the highest fix-window RMSE of all participants.

Liquidity provision: we also observe significant differences in *how* participants trade, as shown in Table 1.1. Asset managers conduct 90% of their trading using marketable orders (labelled 'aggressive trades'), followed by proprietary traders and HFTs at 76 and 70%. This liquidity consumption by HFTs is high in comparison to equities markets, where they are considered important market-makers,[16] though this might be the case merely on the inter-dealer market in our sample. In comparison, dealers and commercial banks provide a large amount of liquidity, with 35 to 40% of their trading volume conducted using marketable orders. Custodians and agency brokers also conduct a large share of their trading using passive limit orders, at 65 to 60% of their total trading. Proprietary traders and HFTs have a significantly higher number of messages going to the trading platform relative to the number of trades they do, compared with most other participants.

Liquidity measures across time: quoted spreads are lowest for GBPUSD, AUDUSD and EURUSD at 1.0, 1.4 and 1.6 basis points, respectively (Table 1.1). Both quoted and effective spreads have increased from 2012 to 2015 for all currency pairs. Also 1 and 5-second price impact have on average increased from 2012 to 2015. These changes could be specific to

[16] Menkveld (2013) finds that around 80% of all HFT trading is passive and Baron et al. (2017) finds that 50% is, in a more recent sample.

the TRM trading platform, or they could be part of a wider trend.

Benchmark Quality

This study aims to track the evolution of the effectiveness of the fix over the last five years. The reform of the fix was a protracted and gradual process, with several events that we detail below. In this paper, we focus on two discrete events that have the most significant impact in our sample. Firstly, the initial revelations by Bloomberg on 12 June 2013 of dealer collusion and, secondly, the lengthening of the fix window on 15 February 2015. We refer to these events as the 'media' and 'window' events.

On 12 June 2013, Liam Vaughan and Choudhury (2013) published the first story that detailed a practice of collusion between major dealers to share client order information ahead of the fix. The shared information was used to infer the direction of buying and selling imbalances during the fix, allowing the colluding dealers to trade ahead of their clients. These revelations were unexpected, and prompted subsequent investigations by multiple securities regulators. Therefore, we expect the event to precipitate a change in participant behaviour in our data and refer to this as **'the media event'**. On 12 November 2014 the FCA fined five banks a total of £1.1 billion for 'failing to control business practices in their G10 spot foreign exchange (FX) trading operations'.[17]

In response to concerns about the benchmark, the Financial Stability Board (FSB) formed a working group that published a set of recommendations, on 30 September 2014 to improve the integrity of the benchmark, including widening the fix window from 1 minute to 5 minutes (FSB, 2014). These changes were implemented by WM/R on 15 February 2015.[18] The Fair and Efficient Markets Review, authored by the Bank of England, the FCA and HM Treasury (FEMR, 2015) said that the lengthening of the window would: 'Reduce the opportunity for manipulation' and 'increas[e] the range of FX trades captured during the fixing window, giving a more representative and resilient fix.' We examine this event as **'the window event'**.

On 1 April 2015 the FCA brought the WM/R 4pm fix into its regulatory regime[19] along with six other benchmarks, and following the regulation of the LIBOR in April 2013. In addition, the Market Abuse Regulation (MAR), introduced in July 2016, designated the manipulation of regulated benchmarks as a civil offence for the first time. We do not examine this event, as we view it as merely establishing into law the behavioural changes enacted through supervisory and enforcement actions. We will analyse the benchmark's effectiveness across three dimensions: analysing representativeness for each event, and its attainability and robustness for the window event.

[17] See: FCA fines five banks £1.1 billion for FX failings and announces industry-wide remediation programme The Commodity Futures Trading Commission (CFTC) also issued a $1.bn fine to the same banks. Barclays was later fined £284m by the FCA on the 20th of May, 2015.

[18] For the less liquid 'non-traded' currencies the change was from 2 minutes to 5 minutes.

[19] See: FCA PS 15/6: Bringing additional benchmarks into the regulatory and supervisory regime

Representativeness

The 4pm fix is perceived to be a daily ‘closing price’ for a market that does not actually close. It arises from the importance of daily closing prices in equities markets and the institutional infrastructure that surrounds it — funds calculate net asset values (NAV) using the closing price, and then calculate FX exposures using the 4pm fix. If the closing price is not representative of, or far away from, intraday prices, it does not represent an effective benchmark. Of course, differences will arise between the closing price and intraday prices as the value of assets change over time — the 4pm fix is the value *as at* 4pm. Users of the benchmark recognise that it is a *snapshot in time*, but they would like this snapshot not to be systemically at odds with intraday prices.

To be representative, the benchmark must accurately represent prices throughout the day, and the price dynamics around it should not have clear signs of market inefficiencies such as short-term predictability and price reversals. To operationalise this definition, we first take a daily volume-weighted average transaction price (daily VWAP) value, and investigate the deviation between this price and the 4pm benchmark rates. We then test how representativeness has changed around: the first revelations of rigging, and the lengthening of the reference window period to 5 minutes.

Any change in measured representativeness can, in principle, be divided into two components — a ‘mechanical’ effect arising purely from a change in the benchmarking methodology, and an ‘endogenous’ effect arising from changes to how market participants adapt to the new regime. We disentangle these two effects using two methods. We also investigate the price dynamics around the benchmark time for evidence of market inefficiencies.

Mechanical effect of increasing benchmark window length:

We attempt to isolate the possible mechanical effect that increasing the fix window from 1 to 5 minutes has, from any endogenous effects stemming from changes in the behaviour of participants. A mechanical effect may arise because the median of prices sampled over 5 minutes may be different to those sampled over 1 minute. To isolate such an effect, we study the statistic:

$$M_t = \sqrt{\frac{\sum_{n=1}^{N}(\tilde{b}_{t,n,5} - v_t)^2}{\sum_{n=1}^{N}(\tilde{b}_{t,n,1} - v_t)^2}}$$

Where we have employed the notation:
M_t : A measure of the mechanical effect of changing fix window from 1 to 5 minutes for day t
$\tilde{b}_{t,n,5}$: Synthetic 5-minute fix rate calculated for random time window n
$\tilde{b}_{t,n,1}$: Synthetic 1-minute fix rate calculated for random time window n
v_t : Volume-weighted average transaction price for day t
N : Number of random time windows per date

For a given t, the synthetic windows used for computing $\tilde{b}_{n,1}$ and $\tilde{b}_{n,5}$ have the same starting point — the first window extends 1 minute forward in time, while the second window extends 5 minutes forward. Moreover, no data from the actual fix window is used to compute

M. The reason is that price dynamics in the actual window are affected by the endogenous effects of participants adapting their behaviour to the new regime. We use the same control period of 12 to 2pm, which excludes the fix. We draw random 150 days from $2013-2015$, and compute $N = 1000$ random time windows for each day. The measure M_t is thus not a measure that depends on a before-after separation of the data.

After computing the measure M_t, we find that the mean of M_t is very close to one (0.99 ± 0.03). This means that the change in the benchmarking procedure, when examined by itself, would not have a material effect on the representativeness of the benchmark rates.[20]

Endogenous effect of increasing benchmark window length:

We now isolate any changes to representativeness driven purely by changes in the behaviour of market participants by controlling for time variation in volatility. We aim to measure the benchmark's representativeness as the variation between the fix rate and underlying market prices throughout the day.
We study the statistic $D_{t,p}$, defined as,

$$D_{t,p} = \sqrt{\frac{(b_{t,p} - v_{t,p})^2}{N^{-1} \sum_{n=1}^{N} (\tilde{b}_{t,p,n} - v_{t,p})^2}}$$

Where we have used the notation:
$D_{t,p}$: a measure of the behaviour-driven effect of changing the fix window
b_t : the actual benchmark rate for day t and currency-pair p
$\tilde{b}_{t,p,n}$: a synthetic benchmark rate calculated for random time window n, currency-pair p, on day t
$v_{t,p}$: Volume-weighted average transaction price for day t and currency-pair p
N : Number of random time windows in each day

The nominator measures the error of the benchmark rate as a proxy for the daily VWAP rate. The denominator is an adjustment for two things: i) the mechanical increase in the efficiency of the estimator from the window increasing from 1 to 5 minutes, and ii) time variation in price volatility unrelated to the fix methodology. The synthetic benchmarks are computed using data from between 12pm and 2pm, and in accordance with WM/R methodology.

We compute $D_{t,p}$ for all days in 2013 to 2015, using $N = 1000$ random windows for each day. The result is a time series spanning days both before and after the lengthening of the calculation window. When calculating the synthetic benchmark, we extend the length of the calculation window n after the 15 February 2015 in accordance with the actual change in methodology.

After computing representativeness on each date, to assess any statistically significant differences we estimate a regression model, with $D_{t,p}$ as our dependent variable. The control

[20] It is possible that our result may be biased due to the presence of any macroeconomics news, since the likelihood of the 5-minute period overlapping with macroeconomic news is higher than the 1-minute period. However, this would bias in favour of finding a difference in the measures, which we do not find.

variables are: $afterWindow$ takes the value of one after the window event date, $volatility$ is the implied FX options volatility for the currency pair at the time of the fix, $monthend$ takes the value of one if the pair-date is the last trading weekday, and $macro$ takes the value of one if there is a major macro news announcement from 2pm until the end of the fix. We also use currency and weekday fixed effects.

We estimate the three month period before and after the window event and find no change in representativeness after the event. We also find no change after the media event. We also estimate a similar model across all dates in the sample period from 2012 to 2015, with a timetrend variable $datecount$ that increments one for each date in our sample, with month-fixed effects. This points to no gradual increase in representativeness in the sample period. We do find the benchmark becomes significantly less representative on month-end dates, with the ratio increasing 137%, higher even than with macro news announcements at 46% (see Table 16). The results are reported in Section .0.4.

Price dynamics (market efficiency):

It has been documented in the existing literature that price dynamics around the 4pm fix have been different from other times of the day, and, in particular, that prices have exhibited short-term spikes and subsequent reversals (Evans, 2017).

We examine short-term reversals through a correlation analysis. Specifically, let v_1, v_2, v_3 denote the market-wide VWAPs in the 15 minutes before the fix, during the fix, and the 15 minutes after the fix, respectively. We compute the correlations in 'currency returns', meaning:

$$r = \text{cor}\left(\frac{v_2 - v_1}{v_1}, \frac{v_3 - v_2}{v_2}\right)$$

We pool together all currencies in the sample and compute r by quarter.
We find a negative and statistical significant correlation coefficient r for most quarters in the period 2012 to 2014. There is a visible change around the time the fix window was lengthened (the first quarter of 2015), and from 2015 onwards the correlations are generally insignificant. The correlation coefficients and corresponding p-values are shown in Figure 1.4.

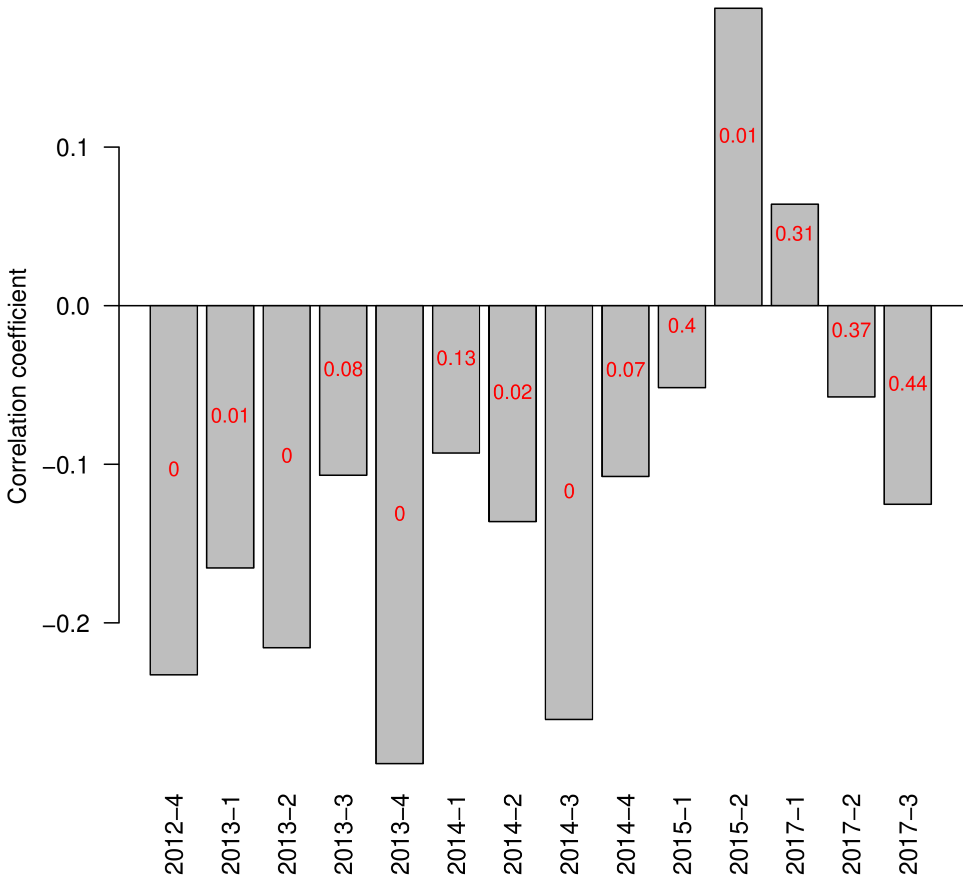
Significant serial dependence in price changes is not something one would expect to observe in an efficient market.[21] Therefore, market efficiency around the fix has improved significantly in our sample period. It is beyond the scope of this paper to provide any causal inferences for this improvement. While the disappearance of collusive behaviour is one potential cause, another is the lengthening of the fix providing for a longer period of time for liquidity shocks to dissipate.

Attainability

Attainability refers to the extent to which the benchmark price can be replicated by a market participant who implements a trading pattern that matches the benchmarking procedure. This dimension is only relevant for benchmarks that input prices from a reference market,

[21] A deeper analysis of these price patterns can be found in Evans (2017), including Sharpe ratios of possible trading strategies.

Figure 1.4: Price reversals around the fix — correlation and p-values in currency returns between the fix window and the 15 minutes after the fix period.
This Figure shows the correlation coefficient in currency returns, based on market-wide VWAPs. All currency returns are pooled together, giving 5 observations per date, and then grouped by quarter. The numbers show the p-value associated with the correlation coefficient, computed from a Fisher Z-transformation.



and for participants that wish to 'attain' or replicate the benchmark by trading on this reference market.[22]

The design of the WM/R, and indeed most benchmarks, is such that there is a degree of unpredictability in the selection of prices during the window. This is by intention and, as explored in Duffie and Dworczak (2018), this unpredictability is designed to make the benchmark less susceptible to manipulation (more robust), but it also makes it less attainable.[23] We examine the impact that key factors in the design of benchmark, such as the length of the window, have on attainability, and the impact of exogenous factors like volatility.

We empirically measure the attainability of 4pm fix rates by comparing the volume-weighted average price of all trades within the fix window ('within-window VWAP') with the fix rate. The difference between the within-window VWAP and the fix rate reflects the tracking error of the average market participant. We expect the average tracking error to be zero, but the variability of the tracking error is of interest, particularly how this variability changes when the calculation window is lengthened in 2015. We measure the attainability A of the fix rate as the root mean square error of the tracking error against the within-window VWAP:

$$A = \sqrt{K^{-1}\sum_{t=0}^{K}(f_t - w_t)^2}$$

Where K is a given number of trading days, and f_t and w_t are the fix rate and within-window VWAP at day t. We also calculate this by participant category to examine any heterogeneous effects on different participants.

The lengthening of the calculation window has a near-mechanical effect on the variability of the tracking error on a trading strategy that aims to replicate the fix rate. We illustrate this effect through a simulation exercise. The simulation works as follows: we generate a large number of simulated price paths, modelled as realisation of a Brownian motion process with volatility σ over the interval $[0, T]$, where T is the length of the fix window in seconds. We set $B(0) = 0$ for simplicity. For each price path we sample the simulated spot rate at the end of each second, and set the simulated fix rate f to be the median of this sample,

$$f = \text{median}\{B_1, B_2, .., B_T\}$$

To simulate a trading strategy of a hypothetical trader trying to replicate the fix rate, we also sample the spot rate at N equally spaced points in the interval $[0, T]$. These N points represent the trades of our hypothetical trader. We are interested in the average transaction price p of this trader,

$$p = N^{-1}\sum_{n\in\mathcal{N}} B_n$$

Where the set of time points $\mathcal{N}$ are equally spaced,

[22] A precondition for attainability is that the benchmarking procedure is sufficiently transparent for participants to know how to replicate it. For example, participants must know the time period that benchmark prices are drawn from so as to then trade in that period. There are other factors that determine attainability, which we explore in this paper.

[23] And practically impossible to attain in practice exactly.

$$\mathcal{N} = \left\{ \frac{T}{N+1}, \frac{2T}{N+2}, ..., \frac{NT}{N+1} \right\}$$

For each run u of the simulation we compute the 'tracking error' e_u,

$$e_u = f_u - p_u$$

We compute tracking errors for a large number U of simulations, $e_1, \ldots, e_U$, and examine their distribution. The theoretical error e has mean zero, and so we concentrate on the RMSE (standard deviation) of e.

This analysis assumes that each second within the fix window has a trade observation. In practice, during the 1-minute regime this was 44% of trades for GBPUSD in 2014, for example, and 27% in the 5-minute (see Table 35). We conduct an additional simulation which account for this, described in the Annex.

The results of the simulation exercise, presented in Figures 1.5 and 1.6, show that the lengthening of the window to 5 minutes increases tracking error by a factor of about 2.2 times for one replicating trade, and 2.17 for $N = 20$ replicating trades. A hypothetical participant that splits their order into multiple trades will greatly reduce their tracking error. Moving from 1 to 2 trades reduces tracking error by 36.2% in the 5-minute regime, and moving from 2 to 5 reduces it again by 37.3%. This effect diminishes with further splitting, with 5 to 10 reducing it by 6.6% and 10 to 20 by 1.2%. Most of the reduction occurs between 1 to 5 trades — a 60% reduction. This relationship is substantially the same for the 5-minute regime.

In our simulation, we hold constant parameters that are also important determinants of attainability: volatility and the spread. But when we examine actual tracking error around the window event, the window-length effect is large enough to dominate. The predicted relationship between tracking error and window length in our simulations is borne out in actual trading outcomes in our data. Figure 1.7 and Tables 1.6 and 1.7 show how the root mean square deviation between the within-window VWAP and daily WM/R benchmark rates increased after the fix window was lengthened in 2015. The variability of participants' tracking errors went up, and thus attainability decreased. The observed increase is larger than suggested by our simulation results — when pooling all currency pairs and all participant types we find that variability of the tracking error increased more than fivefold. One reason why empirical attainability decreased by much more than in our simulations is that spreads also increased in most currencies after the window change. All else being equal, when participants are trading at higher spreads, their tracking error against a midpoint fix rate also increases. This latter effect is endogenous, or behaviour-driven. The total change in observed attainability is thus a combination of an endogenous and a direct effect. Our empirical analysis of attainability is conducted on the ex-post decisions participants have made, in relation to trade timing and order splitting, which we examine earlier in our simulations.

The construction of the benchmarking procedure introduces a lower bound on the variability of the tracking error, as measured by the RMSE. The WM/R benchmarking procedure

Figure 1.5: Attainability Simulation — Varying n for 1-min and 5-min Fix Windows
This Figure reports the results of the simulation exercise which computes tracking error, reported on the y-axis in pips, for the 1 minute and 5 minute window lengths across a varying number of replicating trades (n), reported on the x-axis. Per-second volatility is calculated assuming a yearly volatility of 0.2.

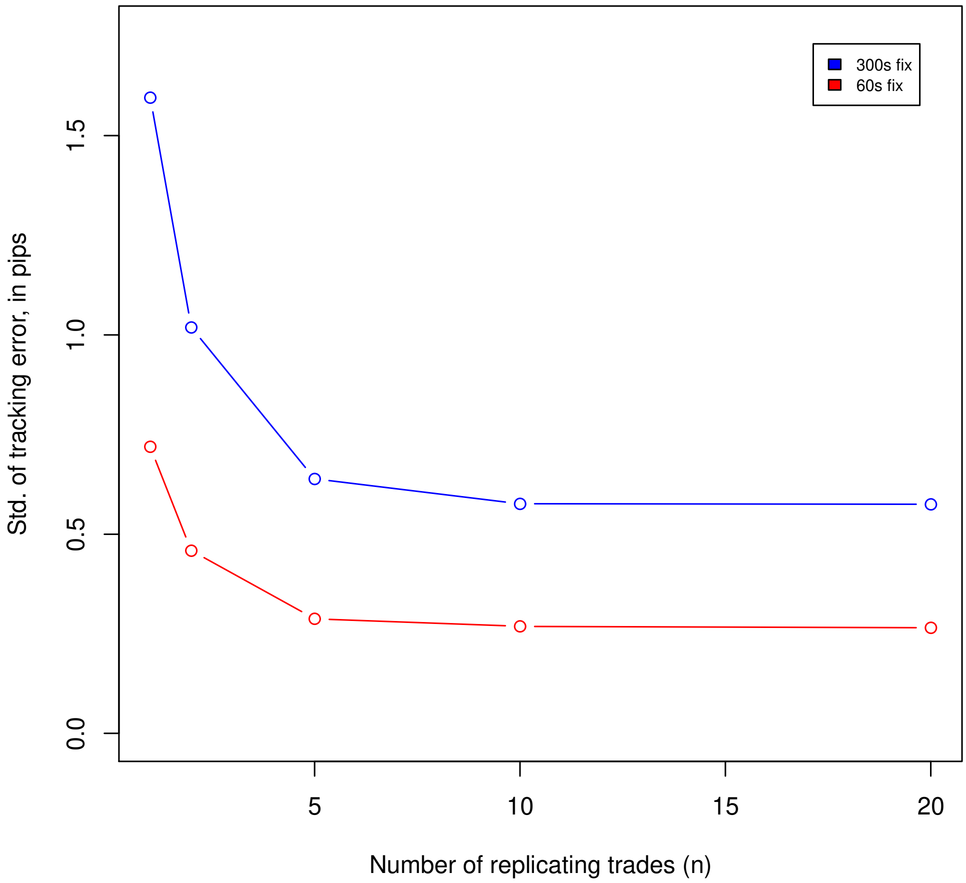
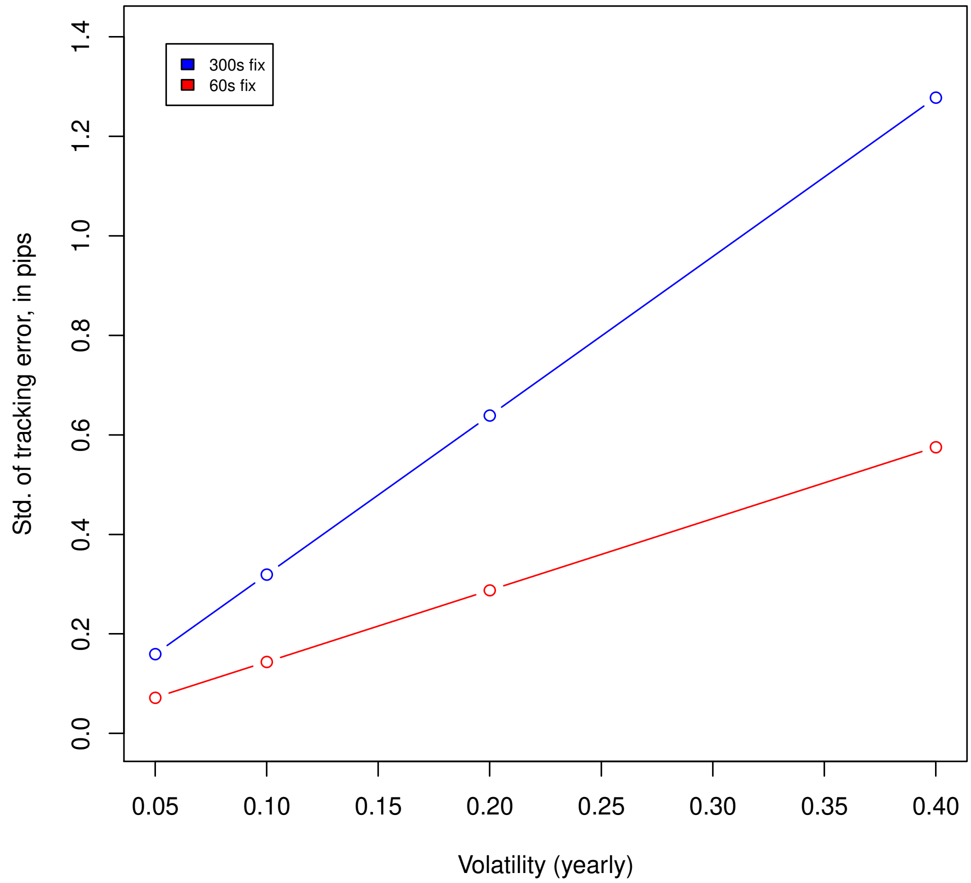


Figure 1.6: Attainability Simulation — Varying σ for 1-min and 5-min Fix Windows
This Figure reports the results of the simulation exercise which computes tracking error, reported on the y-axis in pips, for the 1 minute and 5 minute window lengths across a varying volatility parameter (σ), reported on the x-axis. σ refers to the yearly volatility, which is calculated per-second for the purposes of the simulation.



defines the fix rate as a median price, while the VWAP is an average price. The expected difference between an average and a median is zero for most reasonable models of spot exchange rate, but the expected square deviation is positive. We return to this design choice when we discuss robustness and possible improvements of the benchmarking methodology in Section 1.6.

Table 1.6: RMSE of normalised tracking error (deviation between fix-window VWAP and benchmark rate, divided by the benchmark rate), by participant type. The category-specific VWAP is computed as an volume-weighted average price of all trades done by a TCID within that category. Only participant types with 5 or more trades in fix window are included. Category 'all' is all types pooled, including types with less than 5 trades. Unit: basis points.

Participant type	Before	After
Asset Manager	1.35	2.08
Commercial Bank	1.37	6.40
Custodian	1.39	10.00
Dealer	1.43	7.58
Dealer - R	1.57	7.27
Prop Trader	1.50	8.32
Prop Trader - HFT	1.53	7.45
all	1.22	7.07

Table 1.7: RMSE of normalised tracking error (deviation between fix-window VWAP and benchmark rate, divided by the benchmark rate), by currency pair. Unit: basis points.

Pair	Before	After
audusd	1.06	11.57
eurhuf	2.24	2.71
eursek	2.47	1.65
eurusd	1.38	3.22
gbpusd	0.81	6.71

In this section we have demonstrated that participants can improve their tracking error by splitting their trades across more seconds in the window, but is this feasible in reality? We find that the mean trade size during the fix is 2.82 for AUDUSD and 2.92 for GBPUSD in 2015 (see Table 1.1). However, when we examine individual participant classes (see Table 1.8), smaller participants have average trade sizes of close to 1: (commercial bank: 1.22, private bank: 1.09, agency broker: 1.28) and even the smaller dealer category has a mean of 1.97. This implies that the smaller participant classes are unable to split their orders,[24] with even the largest participants in this market facing splitting constraints, and no categories able to split their orders up to the optimal levels of 5 or more. This constraint only exists because of the large minimum trade size of 1m USD on the inter-dealer platform, which appears to be too high to allow for optimal order splitting. It is possible that participants have total order sizes that exceed the constraint, but decide to execute a portion of this on other execution venues during the window, such that we overestimate their tracking error. It is also possible that they execute a portion before the window, but it is unclear what impact that would have on their tracking error.

[24]Available liquidity is not a determinant here as best bid or offer depth is typically much higher than average trade sizes (see Table 1.1).

Figure 1.7: Root mean square tracking error — variability of deviation between within-window VWAP and daily WM/R rate.
This Figure shows the root mean square deviation between within-window VWAP and daily WM/R rates, for all currency pairs pooled. Only participant categories averaging 5 or more trades in the fix window are shown, as well as the 'all' category which pools together all trades in the window. The 'before' sample ranges back to 3 months before the window change, the 'after' sample to 3 months after the change.

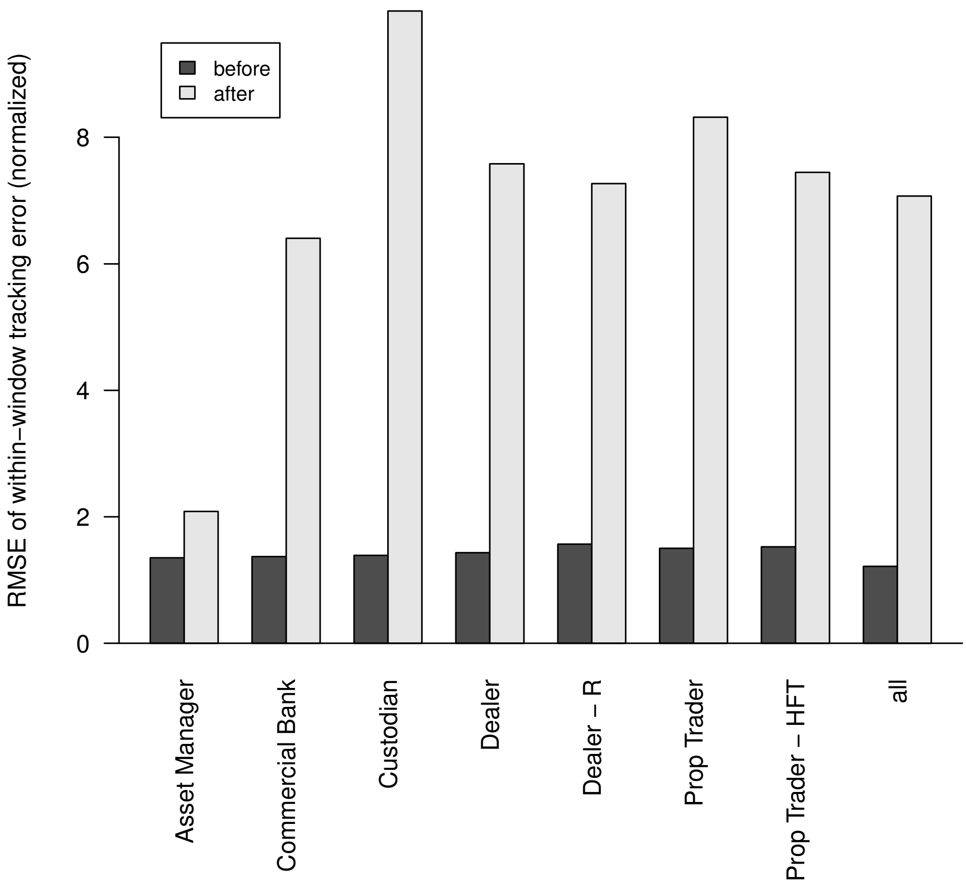


Table 1.8: Mean number of messages, quote life, unique TCIDs, number of trades and number of aggressor trades in the fix period, by participant category. Calculated as a mean across the total values for each measure (except q.life which is a mean) for each currency-date in our sample.

Category	#msg	q.life	#TCIDs	#trades	#agr.trades
Asset Manager	61.0	96.50	1.0	8.3	7.5
Commercial Bank	54.1	1556.38	6.7	23.1	8.2
Custodian	25.1	182.88	1.8	10.0	4.2
Dealer	172.4	150.41	6.0	32.7	11.8
Dealer - R	136.3	311.43	5.5	38.2	14.7
Hedge Fund	40.7	20.93	1.3	3.4	2.0
Private Bank	3.7	3974.92	1.1	2.4	1.2
Prop Trader	211.9	12.91	2.7	7.6	5.8
Prop Trader - HFT	749.1	60.86	7.0	34.4	24.2
Agency Broker	11.8	190.33	1.8	6.6	2.3
Central Bank	2.1	6954.92	1.0	1.0	
Commercial	76.0	155.50	1.0	1.9	1.4

Robustness

A benchmark is robust if it resistant to manipulation. We adopt a simulation-based methodology to assess the extent that the benchmark is resistant to a few 'outlier' trades. These outliers can be thought of as trades engineered with the purpose of affecting the fix rate. The method measures how much the benchmark deviates in the presence of such outliers, compared with when calculated on a dataset without outliers.

It is important to note that our method is limited in scope, and does not measure robustness against all possible forms of manipulation. Examples of other manipulation techniques include illegal sharing of customer information among liquidity providers, trading strategies based on exploiting short-term price impact and the spreading of false news. As such, our quantitative results on robustness are partial in nature.

Our simulation method is based on generating two price series: one 'clean' and one 'dirty'. The dirty series differ from the clean in that a certain number of outlier observations are inserted. We compare the fix rate computed on the dirty series, with the one computed on the clean series. The benchmarking procedure is considered robust when the deviation between the two simulated benchmarks is small.

We implement this methodology as follows. Let B_t be the clean price series, which we model as a random walk:

$$B_t = \sum_{n=1}^{t} z_n$$

$$z_n \sim N(0, \sigma_z) \text{ i.i.d.}$$

We assume that trades indexed $\mathcal{M} = \{t_1, t_2, \ldots, t_m\}$ have been manipulated, and model the dirty price series $\tilde{B}_t$ as,

$$\tilde{B}_t = \begin{cases} B_t & \text{if } t \notin \mathcal{M} \\ B_t + y_t & \text{if } t \in \mathcal{M} \end{cases}$$

where the 'manipulation term' y_t has ten times the variance of the clean trades,

$$y_n \sim N(0, 10\sigma_z) \text{ i.i.d.}$$

For a given calculation window of T seconds, we compute benchmark rates on the clean and dirty data sets, f and $\tilde{f}$, as the median prices in the interval $[0, T]$:

$$f = \text{median}(B_1, \ldots, B_T)$$
$$\tilde{f} = \text{median}(\tilde{B}_1, \ldots, \tilde{B}_T)$$

We compute these simulated benchmark rates $L = 1000$ times, and measure robustness R as the mean square error,

$$R = \sqrt{L^{-1} \sum_{l=1}^{L} \left(f - \tilde{f}\right)^2}$$

We use $m = 5$ outlier price observations and recompute benchmark rates for $L = 1000$ simulation runs, with a length $T = 60$, or 1 minute.

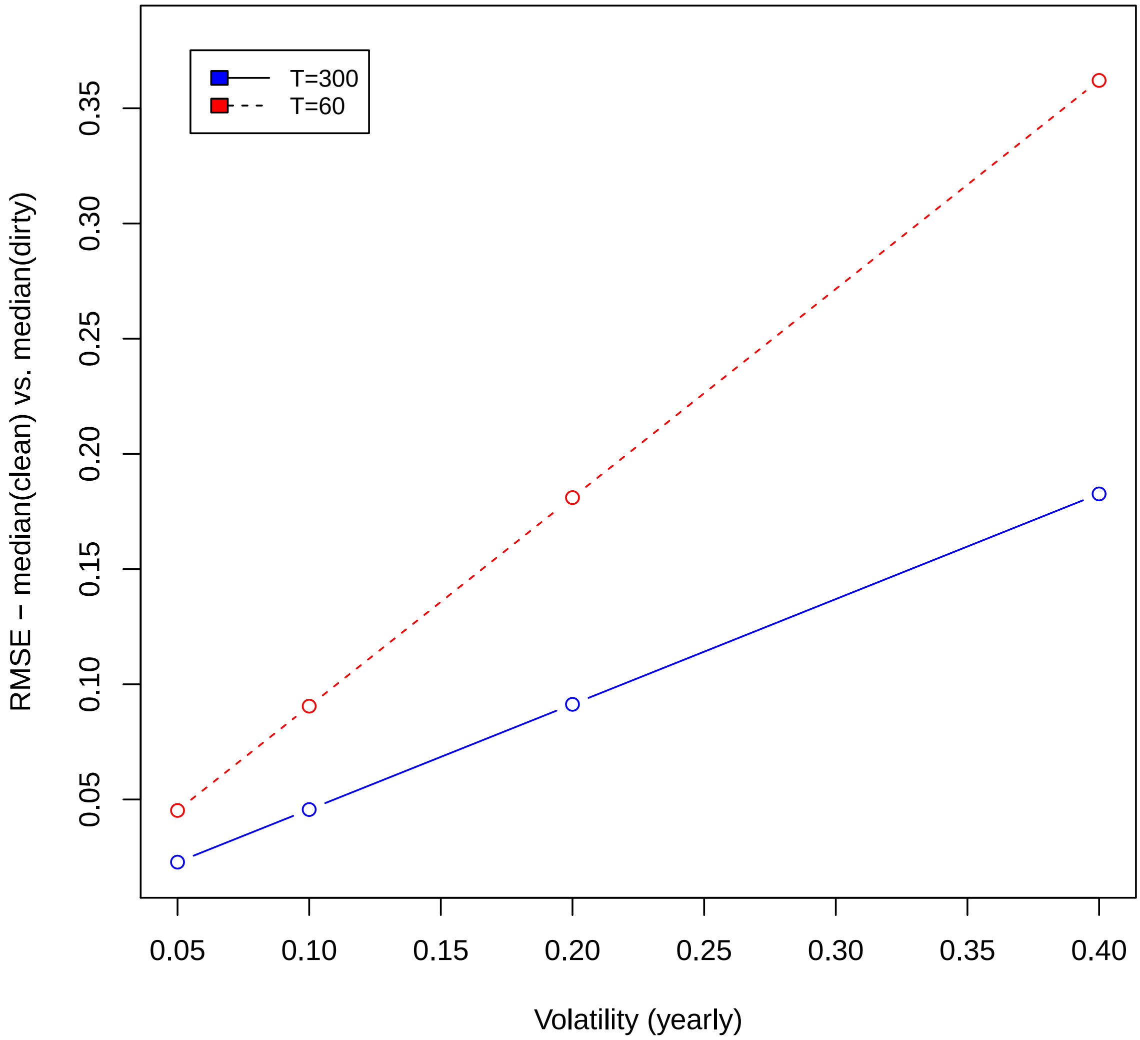
First, Figure 1.8 shows that the benchmark computed on 'dirty' data, meaning a data set with outliers, deviates very little from the one computed on 'clean' data. The root mean square deviation between the two benchmarks, denoted by R, ranges from 0.05 pips to 0.35 pips for yearly volatilities ranging from 5 to 40%. 'Pips' refer to the minimum allowable price increment in our (and most FX) markets, which is the price quoted to 4 decimal places. For a currency pair that is traded at a price of \$1, 1 pip represents a 0.01% (or 1 basis point) change in prices.

The small effect that we find likely relates to the general property of medians — it takes a large number of observations to significantly affect the median. In statistical robustness theory, this is referred to as the *breakdown point* — the proportion of 'incorrect' observations an estimator (such as the median) can handle before affecting the result. The median has the highest possible breakdown point of any location estimator, while the mean has the lowest possible breakdown point. In this respect, the median and mean represent two extreme choices in benchmark design.

Second, Figure 1.8 shows that the improvement in robustness from lengthening the fix window (moving from the red to the blue line) is highly dependent on the volatility of the price-generating process, but also that the overall improvement in robustness is small.

Our analysis makes several assumptions, the most important of which is that of non-permanent price impact. While we find the price impact to be lower in the fix period than the control period, we still find it to be non-zero (See Table 1.3). The introduction of price impact would decrease the benchmark's robustness under both the 1-minute and the 5-minute window, as 'dirty trades' would affect subsequent trades. But the effect that incorporating price impact would have on the move to 5-minute window is unclear. If we assume the level of price impact is exogenous to the change to 5 minutes, introducing price impact would decrease robustness more for the 1-minute period than the 5-minute period, as the longer window allows more time for price impact to dissipate.

Figure 1.8: Robustness and price volatility.
This Figure shows robustness measure R plotted against yearly volatilities of 5 to 40 %. Unit: pips.



Reference Market Liquidity

In Section 1.4 we examined the quality — or the effectiveness — of the benchmark itself. In this chapter, we examine the liquidity of the underlying FX market during, and around, the fix calculation period. Because the underlying FX market is an input to the fix calculation, its liquidity is endogenously related to the benchmark's effectiveness — it is both a determinant of and an outcome of it. For example, a decrease in the representativeness of the benchmark may prompt market participants to stop using it, reducing trading volumes and liquidity. The reduction in trading volumes will then further reduce the benchmark's representativeness. A reduction in the attainability of the benchmark may also prompt participants to avoid using it, or to decide to trade outside of the reference window. Therefore, we expect liquidity to change in the reference market due to endogenous feedback effects from the changes in the benchmark we characterise in Section 1.4, i.e. the media event and the window event.

Methodology

To assess the liquidity of the reference market, we compute a range of market liquidity measures using tick-by-tick orderbook data and then compute volume and time-weighted means for each currency-date. We compute these over two time periods: the fix window, and a control window.

We then estimate these market liquidity measures using a regression model. To control for changes in liquidity exogenous to the fix itself, we express fix liquidity as a log ratio of the control observation.

$$\ln y_t = \alpha + \beta(\text{after})_t + \Gamma^T C_t + w_t$$

y_t is the fix-to-control ratio of a given liquidity measure, meaning the fix observation divided by the control observation. C_t is a vector of control variables and *after* is an indicator variable taking the value one after the relevant event. We use subscript t to index time, and assume (w_t) to be a white-noise sequence. We estimate this model separately for each currency pair.

The reason for expressing the dependent variable as a ratio of the fix observation to the control window observation is the autocorrelation and seasonality effects present in the untransformed levels.[25]

[25] In general we find very little to no evidence for autocorrelation in these ratio-measures. In the levels there is significant serial dependence. We have also modelled the level of each liquidity measure using ARMA time-series models with seasonal effects and exogenous controls (SARMAX models). The SARMAX models give the same conclusions as the regression models reported in this paper.

Market Liquidity Measures

Volume is recorded separately for both the passive and active sides of each trade. This means that when one unit is traded, the daily trade volume will increase by two. Total volume is computed by summing all trade volume for TCIDs in a given category and a given time period. Volume forms a dependent variable in our regressions as log ratio of the total volume in the fix to total volume in the control period (12 to 2pm) for a given currency date.

The *quoted spread* is calculated with respect to each event in our orderbook data: such as limit order placements, cancellations, trades and order amendments. We then calculate a time-weighted average quoted spread, weighted according to the time interval a spread is active. The spreads reported in this paper are relative, meaning that we compute the difference between best buy and sell price,[26] and divide by the midpoint. Quoted spread forms a dependent variable in our regressions as log ratio of the time-weighted average quoted spread in the fix to the time-weighted average quoted spread in the control period for a given currency date.

Depth of the orderbook is also measured for each order book message. This is computed as a time-weighted mean of the sum of the buy and sell sides of the orderbook. We compute three depth measures: depth at the best bid and offer level, depth at the top ten levels, and depth at all levels. Depth forms a dependent variable in our regressions as the log ratio of the time-weighted average quoted depth in the fix to time-weighted average quoted depth in the control period for a given currency date.

The *effective spread* is computed as the quoted spread prevailing in the market at the time of a trade, and *price impact* is computed for each individual trade, as described in more detail in Section 1.3.2. Effective spread and price impact form dependent variables in our regressions as log ratios of the same measures in their respective control periods for a given currency date.

Control variables

$volatility$ measures changes in volatility and is calculated as a log ratio (or the log return) of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. We also include a $vollevel$ control, which is the time-weighted average of the options midpoint price.

We include $carry$ and $shortUSD$ calculated as the log ratio (or the log return) of the time weighted average of the index values in the control period, versus the fix window. The index prices are updated every 10 seconds. The Carry index is a proxy for changes in global carry strategies which may impact underlying liquidity in the currency pairs. The Short USD is a TWI index designed to proxy for the value of the USD against all other currency pairs (as opposed to as a cross rate), which may also impact underlying liquidity in individual crosses.

To control for outsized trading that occurs on month-end dates for valuation purposes (Melvin and Prins, 2015), we calculate $monthend$, which takes the value of one on the last

[26]The 'best bid' is the highest buy price on the orderbook at a given time, and the 'best ask' is the lowest sell price.

trading weekday of the month, factoring in trading holidays.

To control for macroeconomic news announcements, we construct $macro$, which is an indicator variable that takes a value of one for macro news events with the highest volatility rating of three that occur in the period 9am to 4pm UK local time.

We scale all of our measures by a 'control window', which is a time period selected to be reflective of broader market liquidity, but is also exogenous to any changes in the fix. We select 12pm-2pm to avoid any pre-fix trading, as well as the US open and major macroeconomic news announcements that occur around it. We also use a control window of 9am to 11am to ensure our results are robust to control period selection.

Liquidity improves after dealer collusion revelations

Regression results are reported in Table 1.9 in a consolidated format that reports only the estimates for the $AfterDummy$ variable for each dependent liquidity variable. Control variable estimates are omitted, with the full regression estimates reported in the Annex in Tables 17 to 32. Table 1.9 first reports the results of regressions of market liquidity over the three months before and after the 12 June 2013, which is the first time dealer collusion behaviour was published in the media (the 'media event').

For the two major currencies in our sample, AUDUSD and GBPUSD, we find a statistically and economically significant decrease in quoted and effective spreads relative to the control window of 10 and 11%, respectively. This could be explained from a decrease in collusion related adverse selection costs for liquidity providers, assuming the collusive behaviour ceased following its disclosure. The lack of findings on currencies other than AUDUSD and GBPUSD could be explained by EURSEK traders placing more importance on the ECB fix in comparison to WM/R. EURHUF could be explained by the comparatively small amount of funds and indexes holding HUF and thus the relative unimportance of the fix for HUF.

We examine the trading behaviours of participants in and around the fix to explain our liquidity findings. We measure no significant changes to trading patterns *within* the fix (Table 34), but the allocation of trading volume between the pre-fix, fix and post-fix periods did change significantly for some of the participant categories (Table 1.10). Dealers did less of their trading *before* the fix and more of their trading *during* the fix after the media event, with the smaller dealers reducing their pre-fix aggressor trading by a third. The total volume of the largest dealers decreased by 19%, which we can speculate reflected a reduction in customer orders. Also, HFTs increased relative amount of trading done during the fix window after the media event, but not by as much as the dealers.

Liquidity worsens after fix window lengthening

The fix window was lengthened from 1 to 5 minutes on 15 February 2015. We find evidence of a significant worsening of market liquidity conditions in the 3 months after this date in comparison to the 3 months before,[27] in the form of wider quoted spreads and lower depth. This coincided with sharp changes in the trading behaviour of HFTs and dealers.

[27] Our findings are robust to the choice of a 1.5 month window.

Table 1.9: Regressions of Liquidity Variables - Media and Window Events
This table reports coefficient estimates for the window and media event studies using the specification in Formula 1.5.1 for the regressions in each currency pair. For each dependent variable in the first column, only the estimates for the $AfterDummy$ variable are reported. The control variable estimates are omitted, with the full regression estimates reported in the Annex. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after the 12 June 2013 for 'the media event' and after the 15 February 2015 for the 'the window event' regressions. $Volume$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $Quotedspread$ is the log ratio of the time-weighted quoted spread in the fix, versus the control period, for a given a currency-date. $Depthatbest$ is the log ratio of the time-weighted depth at the best bid and offer in the fix, versus the control period, for a given a currency-date. $DepthatTop10$ is the log ratio of the time-weighted depth at the best 10 bid and offer price levels in the fix, versus the control period, for a given a currency-date. $Effectivespread$ is the log ratio of the volume-weighted spread at the time a trade occurs , versus the control period, for a given a currency-date. The dependent variable, $Priceimpact(1sec)$ is the log ratio of the volume-weighted price impact of a trade over a 1-second period, versus the control period, for a given a currency-date. Robust t-statistics are reported in parentheses.

Media Event	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
Volume	0.08	0.35*	0.1	0.18	0.16
	0.65	1.81	0.55	0.83	1.2
Quoted Spread	-0.10***	-0.01	0.1	0.09**	-0.11***
	-3.85	-0.16	1.39	1.97	-4.48
Depth at Best	-0.1	-0.003	0.06	-0.02	0.13
	-1.03	-0.04	0.48	-0.39	1.43
Depth at Top 10	-0.01	-0.21**	-0.03	0.01	0.11*
	-0.23	-2.39	-0.31	0.67	1.89
Effective Spread	-0.12***	-0.05	0.18**	0.01	-0.10***
	-3.72	-0.41	2.48	0.09	-4.07
Price Impact (1 Second)	-0.09	0.23	0.1	-0.39*	-0.05
	-1.08	1	0.83	-1.92	-0.6

Window Event	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
Volume	0.08	0.34*	0.19	0.61***	0.26**
	0.6	1.76	1.18	3.1	2.01
Quoted Spreads	0.07***	0.33***	-0.02	0.11***	0.06*
	2.77	4.49	-0.42	5.03	1.91
Depth at Best	-0.25***	-0.04	-0.22**	-0.0002	-0.26***
	-4.02	-0.51	-2.46	-0.004	-3.09
Depth at Top 10	-0.20***	0.15	-0.15*	0.06***	-0.07
	-4.08	1.63	-1.79	2.6	-1.31
Effective Spread	0.02	0.36***	-0.20***	-0.12*	-0.10***
	0.83	3.94	-3	-1.8	-3.28
Price Impact (1 Second)	0.22***	-0.07	0.02	0.29	0.22***
	3.63	-0.44	0.23	0.73	3.25

*p<0.1; **p<0.05; ***p<0.01

Table 1.10: Media event: Mean volume of aggressor and passive trades, by pre-fix-post windows, before and after (*) the event, for GBPUSD and AUDUSD. Volume is first summed across all TCIDs in each participant group, for each currency-date-fix quarter combination, and then averaged across currency pairs and dates. Absolute value (‘Tot’) in million of base currency, others as share of total. P-values of two-sample t-test for difference in means for the ratios pre/total and fix/total.

Participant		Before				After				
Aggr. Trades:	Tot	Pre	Fix	Post	Tot*	Pre*	Fix*	Post*	p pre	p fix
Agency Broker	22.8	0.21	0.50	0.29	18.3	0.15	0.56	0.30	0.10	0.29
Asset Manager	8.8	0.27	0.51	0.23	21.2	0.19	0.74	0.07		
Commercial Bank	67.1	0.25	0.54	0.21	51.7	0.22	0.56	0.22	0.81	0.55
Custodian	30.3	0.23	0.53	0.24	28.8	0.22	0.56	0.22	0.48	0.53
Dealer	101.8	0.27	0.53	0.19	101.3	0.18	0.59	0.22	0.00	0.00
Dealer - R	196.7	0.24	0.55	0.21	158.9	0.21	0.60	0.19	0.10	0.01
Hedge Fund	9.6	0.21	0.42	0.38	10.5	0.26	0.44	0.29	0.67	0.99
Private Bank	17.0	0.26	0.54	0.20	9.9	0.20	0.20	0.60		
Prop Trader	17.8	0.30	0.47	0.22	24.6	0.26	0.50	0.24	0.07	0.43
Prop Trader - HFT	163.5	0.35	0.33	0.31	158.0	0.33	0.36	0.31	0.02	0.02
Passive Trades:										
Agency Broker	42.7	0.14	0.66	0.20	28.0	0.19	0.56	0.25	0.37	0.08
Asset Manager	12.6	0.32	0.52	0.16	8.8	0.54	0.25	0.21	0.95	
Commercial Bank	85.0	0.31	0.44	0.25	85.4	0.27	0.49	0.24	0.52	0.14
Custodian	38.5	0.20	0.57	0.23	29.7	0.21	0.50	0.29	0.80	0.04
Dealer	124.3	0.29	0.47	0.24	140.1	0.22	0.53	0.24	0.00	0.01
Dealer - R	187.7	0.23	0.56	0.21	180.2	0.22	0.59	0.19	0.57	0.19
Hedge Fund	8.6	0.35	0.28	0.37	8.8	0.24	0.40	0.35	0.74	0.37
Private Bank	14.7	0.29	0.45	0.26	7.0	0.33	0.28	0.38	0.65	0.06
Prop Trader	10.5	0.29	0.40	0.31	9.8	0.21	0.47	0.32	0.86	0.00
Prop Trader - HFT	106.6	0.39	0.31	0.30	65.8	0.34	0.34	0.32	0.01	0.22

Market liquidity results

Table 1.9 shows that total traded volume increased for GBPUSD, EURUSD and EURHUF after the change. It might be tempting to explain this increase in volume with the extension of the fix volume from one to five minutes, but fix volumes should be driven by benchmark-related execution requirements that should be exogenous to the window length — the need to rebalance FX exposures to avoid tracking error in a passive index fund, for example. An increase in volume could instead be explained by trader decisions to reallocate fix volumes from before or around the fix, to during the fix after the window change. Volume is significantly higher at month-ends for all currencies, in line with findings of the previous literature (Melvin and Prins, 2015; Evans, 2017; Marsh et al., 2017). The macro dummy is negative where significant, meaning that fix volume relative to the control window tends to be lower on days with important macro announcements. Table 26 shows that quoted spreads at the fix relative to the control window are significantly higher in all currencies except EURSEK after the change. The depth of the orderbook tends to be lower after the change, both at the best level and the top ten levels. This applies to all currencies except EURHUF, for which depth is not affected, and EURUSD, where depth at top ten levels actually increase slightly at the fix relative to the control.

The rise in quoted spreads and decline in depth does not, however, result in higher *explicit* trading costs, measured at the time of trade (effective spreads), for the *average* market participant. We see an increase in the proportion of liquidity-taking trades by HFTs following the event, which could explain the increase in quoted spreads.

Interestingly, effective spreads move in the opposite direction of the quoted spread in EURSEK, EURUSD and GBPUSD, with effective spreads in AUDUSD being unaffected. The effective spread measure is a function of trade timing decisions by participants, if participants are able to execute comparatively more of their trades when the quoted spread is lower, effective spreads may decrease. Price impact is higher after the change in both the major currencies of our sample (AUDUSD and GBPUSD), as shown in Table 1.9. These tables also show that price impact tends to be higher on month-end dates.

Attainability, as discussed in Section 1.4.2, is affected by liquidity. The WM/R benchmark is reported and utilised as a median price. However, participants that want to replicate it are not able to obtain a median price, but must execute at the best bid and ask prices. Therefore, the tracking error for a fix with no price changes is at least the half-spread. The effect of the spread is not included in our simulation exercise, where we do not model the bid-ask spread for simplicity. Increases in quoted spreads will increase on the tracking error faced by participants, unless they are able to alter their trading strategies to obtain liquidity when the spread is comparatively lower. These timing effects will be reflected in the effective spread (the spread on actual trades). For the window event, we find an increase in quoted spreads across all currencies, but this does not impact effective spreads. Effective spreads for GBPUSD and EURSEK actually decline by 10 and 20% respectively. This may explain why empirical attainability decreases for GBPUSD less than AUDUSD (8 times versus 11 times) and EURSEK attainability increases (See Table 1.7). Though this reconciliation is incomplete without consideration to changes in volatility.

Changes in trading of individual participants

There was significant discussion in the FSB's 2015 post-implementation report about changes to the behaviour of participants in response to the window lengthening. In this section, we examine these changes to corroborate these discussions and explain our market liquidity results.

Table 1.11 shows volume for each of the four quarters of the fix, broken down by participant category. Each quarter is 15 seconds in duration in the before period, and 75 seconds in duration in the after period. Before the change, there was a tendency for volume to be concentrated in the first part of the fix, as evident in Table 1.11. Large dealers typically did 50% more aggressor volume in the first quarter of the fix than the last, with an even larger difference for passive trades (Table 1.11). Volume is more evenly distributed over the fix window in the new regime, although it does still tend to tail off somewhat during the final quarter, and this effect is statistically significant across most categories.[28]

Changes in price impact of individual participants is of interest to test whether the lengthening of the fix window results in more obvious trading signals — measured as increased price impact. The first-quarter aggressor trading of major dealers had the largest price impact during the fix in the old regime, with an average of 1.3 basis points. The price impact of the large dealers falls during the remainder of the fix. Prop traders have the opposite pattern in price impact — it started low, at 0.3 basis points on average, and increased to 1.2 basis points by the end of the fix. In the new regime, price impact for the major dealers (Dealer - R) still falls slightly, from 1.0 to 0.8 basis points, while for other dealers the price impact is constant at 1.0. HFTs have the largest price impact under the new regime, of 1.3 to 1.4 basis points.

The p-value in Table 1.12 refers to a two-sample t-test of whether the mean price impact during the fix is different before and after the fix window was lengthened. The categories with changes in price impact that are significant at the 5% level are: dealers, prop traders and HFTs. The average price impact of dealers *across the fix* has risen from 0.79 to 1.01 basis points, possibly due to the shift in the distribution of volume within the fix. The average price impact for prop traders has risen from 0.76 to 1.12 basis points, while for HFTs it has risen from 1.05 to 1.33 basis points.

We next examine the proportion of trading that happens before and after the fix. This is of interest as it is possibly a measure of the extent to which participants choose to avoid trading at the fix, by trading before it. Participants may trade ahead of the fix to avoid fix-related price volatility. The FSB's 2015 post-implementation report says that fix trades by dealers have become significantly more automated through the use of agency execution algorithms — shifting fix trading flows from voice trading desks to automated trading desks. This appears to be in response to increased scrutiny of fix trades by front-office manage-

[28]The p-values in Table 1.11 refer to a two-sample t-test of difference in means of the ratio (trading volume in first half of the fix)/(trading volume in second half of the fix). Given the data, it can be read as a statistical test of whether trading volume is more evenly spread out in the after period.

ment and compliance staff (FSB, 2015). Our results do indicate that trading volume is more evenly distributed across the fix window now than before, and we find evidence of a change in the trade execution strategies of these participants. These results are detailed in Table 1.11, with other research by Ito and Yamada (2017) finding a similar distributional change. The switch to algorithms may also explain our observed reduction in effective spreads. An increase in timing ability, stemming from an algorithm being more capable to trade when the spread is comparatively narrower, would result in a reduction in effective spreads.

However, this change in behaviour by dealers has prompted some to suggest that other participants, namely HFTs, are more able to detect and trade on the order flow imbalance signal of these dealers, such as Ito and Yamada (2017) and Pragma (2015). We find some evidence to support this claim, with increased price impact during the fix window and a larger proportion of HFT volumes. Table 1.13 shows volume for the different participant categories, for the period 5 minutes before the fix, during the fix, and 5 minutes after the fix. These tables show a striking change in how much some important participants are trading right before relative to *at* the fix. Dealers used to do around 25% of their total volume in this time window during the pre-fix period. After the change, major and other dealers do 13% of their aggressor volume during the pre-period, and 17% of their passive volume. HFTs display a similar change — they have gone from doing on average 37 to 62% of their total aggressor volume during this period at the fix. Moreover, whilst the major dealers (Dealer -R) have reduced the absolute amount of aggressor trading done during time period, from 81.6 to 75.3m, HFTs have increased from 123.5 to 142.5m. If we sum up all trading volume, aggressor and passive, HFTs, smaller dealers and asset managers have increased their trading volume in this time window by 8, 10 and 24% respectively. Larger dealers have reduced their volume by 5%, and agency brokers, commercial banks, custodians and hedge funds have reduced their volume even more (from 25 to 40% reductions).

Implications for Benchmark Design

The findings in this study have several implications for the design of the 4PM Spot Closing Rate, and for benchmarks more generally. These are in respect to appropriate window length, minimum trade sizes, and sampling and weighting decisions.

We find that an increase in the size of the window of inputs used to calculate a benchmark results in increased tracking error (or reduced attainability) for participants trying to replicate a benchmark price. Therefore, benchmark administrators and regulators should be mindful that efforts to increase robustness must be weighed against attainability costs. We find that participants can significantly reduce their tracking error by splitting their fix orders over the reference window, but they may be unable to do so due to the large minimum trade size requirement of the reference market. As discussed in Section 1.4.2, the average trade size in the fix is between 1m and 2m, for participants that utilise it. This means that participants are already splitting orders as much as the minimum trade size of 1m USD allows them to. The large minimum trade size also means that smaller trading participants experience larger tracking error than larger participants.

Table 1.11: Window event: Mean volume of aggressor and passive trades, by fix quarter, before and after (*) the event, for GBPUSD and AUDUSD. Volume is first summed across all TCIDs in each participant group, for each currency-date-fix quarter combination, and then averaged across currency pairs and dates. Absolute value ('Tot') in million of base currency, quarterly volume ('Q') as share of total. P-value of two-sample t-test for difference in mean of the ratio (first half)/(second half).

Participant			Before					After			
Aggr. Trades:	Tot	Q1	Q2	Q3	Q4	Tot*	Q1*	Q2*	Q3*	Q4*	p-value
Agency Broker	13.7	0.21	0.17	0.30	0.32	10.1	0.19	0.21	0.35	0.25	0.60
Asset Manager	14.7	0.27	0.27	0.25	0.22	23.5	0.23	0.25	0.28	0.23	0.02
Commercial Bank	36.2	0.37	0.23	0.22	0.18	24.6	0.28	0.23	0.30	0.18	0.01
Custodian	27.4	0.31	0.34	0.24	0.11	21.5	0.23	0.25	0.24	0.28	0.00
Dealer	42.4	0.26	0.31	0.23	0.20	46.6	0.20	0.25	0.28	0.26	0.00
Dealer - R	48.3	0.31	0.25	0.23	0.21	55.4	0.28	0.25	0.26	0.21	0.02
Hedge Fund	10.1	0.20	0.40	0.10	0.30	6.0	0.24	0.24	0.29	0.23	0.94
Private Bank	3.5		0.43	0.29	0.29	6.8	0.32	0.18	0.15	0.35	
Prop Trader	12.2	0.31	0.27	0.23	0.19	12.1	0.25	0.24	0.24	0.26	0.06
Prop Trader - HFT	48.0	0.28	0.28	0.26	0.18	89.1	0.25	0.26	0.26	0.22	0.00
Passive Trades:											
Agency Broker	12.3	0.26	0.26	0.28	0.21	12.0	0.25	0.27	0.23	0.25	0.02
Asset Manager	6.0		0.67	0.17	0.17	15.0	0.07	0.33	0.40	0.20	
Commercial Bank	40.3	0.31	0.28	0.22	0.19	39.9	0.22	0.23	0.30	0.25	0.05
Custodian	26.6	0.28	0.26	0.26	0.20	19.1	0.21	0.25	0.24	0.30	0.20
Dealer	41.3	0.28	0.27	0.24	0.20	69.0	0.26	0.26	0.27	0.22	0.00
Dealer - R	65.2	0.30	0.30	0.23	0.16	85.4	0.25	0.28	0.26	0.21	0.00
Hedge Fund	10.9	0.25	0.25	0.23	0.26	12.0	0.23	0.25	0.31	0.22	0.25
Private Bank	10.5	0.10	0.10	0.48	0.33	8.1	0.24	0.29	0.22	0.25	
Prop Trader	8.9	0.29	0.29	0.20	0.22	7.9	0.29	0.21	0.21	0.29	0.28
Prop Trader - HFT	27.7	0.36	0.20	0.23	0.21	29.4	0.29	0.22	0.25	0.24	0.01

Table 1.12: Window event: Mean price impact (5sec), by fix quarter, before and after (*), for GBPUSD and AUDUSD. Volume is first summed across all TCIDs in each participant group, for each currency-date-fix quarter combination, and then averaged across currency pairs and dates. Basis points. P-value for two-sample t-test of difference in mean price impact across the entire fix.

		Before				After			
Participant	Q1	Q2	Q3	Q4	Q1*	Q2*	Q3*	Q4*	p-value
Agency Broker	-0.6	0.1	0.2	-0.0	1.5	0.8	0.7	0.7	0.72
Asset Manager	0.4	1.0	1.2	1.0	1.5	1.1	1.1	1.2	0.70
Commercial Bank	0.8	0.8	0.8	0.9	0.5	0.7	0.6	0.4	0.84
Custodian	0.4	0.8	0.5	0.6	0.8	0.7	0.3	0.9	0.23
Dealer	0.7	1.0	0.8	1.0	0.9	1.0	0.7	1.0	0.02
Dealer - R	1.3	1.0	0.8	0.9	0.9	0.9	0.8	0.8	0.54
Hedge Fund	-0.4	0.2	-0.3	0.8	-0.4	0.2	0.8	1.1	0.24
Private Bank		1.0	-1.3	-0.2	1.3	-0.2	1.6	1.2	
Prop Trader	0.3	1.3	0.8	1.1	0.8	0.9	1.2	1.2	0.02
Prop Trader - HFT	1.0	1.3	1.1	1.3	1.1	1.4	1.1	1.3	0.00

Table 1.13: Window event: Mean volume of aggressor and passive trades, by pre-fix-post windows, before and after (*) the event, for GBPUSD and AUDUSD. Volume is first summed across all TCIDs in each participant group, for each currency-date-fix quarter combination, and then averaged across currency pairs and dates. Absolute value ('Tot') in million of base currency, others as share of total. P-values of two-sample t-test for difference in means for the ratios pre/total and fix/total.

Participant		Before				After				
Aggr. Trades:	Tot	Pre	Fix	Post	Tot*	Pre*	Fix*	Post*	p pre	p fix
Agency Broker	12.8	0.20	0.45	0.34	9.7	0.22	0.41	0.37	0.75	0.02
Asset Manager	23.0	0.29	0.41	0.31	32.5	0.20	0.57	0.22	0.00	0.00
Commercial Bank	46.3	0.24	0.56	0.20	28.4	0.18	0.62	0.20	0.39	0.01
Custodian	32.4	0.33	0.52	0.15	18.5	0.21	0.52	0.27	0.15	0.00
Dealer	73.2	0.24	0.52	0.24	68.0	0.17	0.65	0.18	0.00	0.00
Dealer - R	81.6	0.23	0.54	0.23	75.3	0.13	0.69	0.17	0.00	0.00
Hedge Fund	9.9	0.28	0.35	0.37	6.4	0.35	0.37	0.29	0.66	0.19
Private Bank	4.9	0.33	0.24	0.43	6.2	0.28	0.30	0.42		
Prop Trader	15.5	0.26	0.46	0.28	15.1	0.22	0.54	0.24	0.01	0.00
Prop Trader - HFT	123.5	0.32	0.37	0.31	142.5	0.18	0.62	0.19	0.00	0.00
Passive Trades:										
Agency Broker	14.9	0.25	0.38	0.37	10.2	0.28	0.50	0.22	0.35	0.00
Asset Manager	10.2	0.27	0.59	0.14	8.8	0.11	0.55	0.34		
Commercial Bank	67.5	0.26	0.52	0.23	57.1	0.20	0.62	0.17	0.06	0.00
Custodian	31.7	0.26	0.54	0.20	20.8	0.19	0.56	0.25	0.84	0.00
Dealer	87.0	0.28	0.45	0.27	108.0	0.17	0.63	0.20	0.00	0.00
Dealer - R	120.6	0.25	0.52	0.23	117.8	0.14	0.72	0.15	0.00	0.00
Hedge Fund	16.0	0.26	0.36	0.38	12.1	0.23	0.51	0.25	0.74	0.00
Private Bank	7.0	0.23	0.39	0.38	8.2	0.36	0.44	0.20		
Prop Trader	10.7	0.27	0.41	0.32	8.0	0.26	0.47	0.27	0.28	0.00
Prop Trader - HFT	55.2	0.33	0.39	0.28	50.5	0.24	0.52	0.25	0.00	0.00

Our simulation results for attainability and robustness highlight the tension that exists between these properties. We have shown that a lengthening of the calculation window decreases attainability substantially, but only improves our robustness measure by a small amount. Several of our results stem from the use of a median in the WM/R benchmarking methodology, and it is therefore natural to ask whether the trade off between attainability and robustness can improved upon by using another location estimator in the benchmarking procedure. To quantify the choice we can use the simulation methodology developed in Section 1.4.3, but instead of studying the deviation between the 'clean' and 'dirty' benchmarks f and $\tilde{f}$ using medians as the benchmarking procedure, we consider different benchmarking procedures and study the deviation between the dirty benchmark $\tilde{f}$ and the mean clean price in the fix window, $\bar{B} = T^{-1} \sum_{t=1}^{T} B_t$. In statistical terms, we examine the *(statistical) efficiency* of various location estimators.

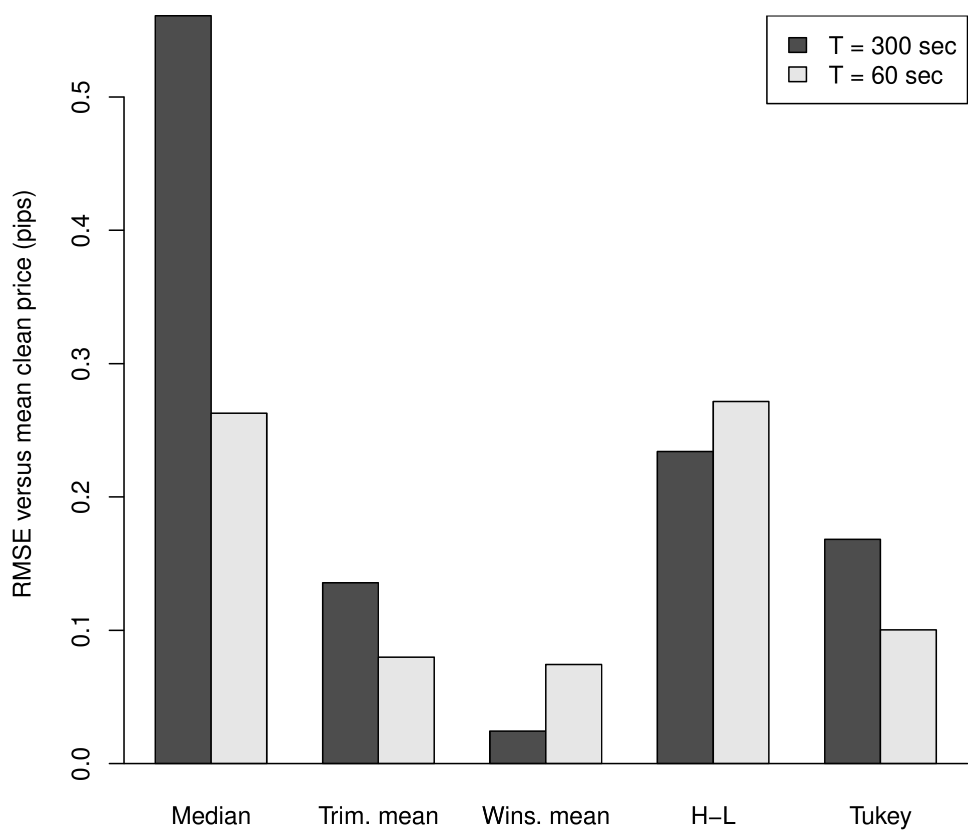
Figure 1.9 shows the deviation between mean clean price and various benchmarking procedures, for calculation windows of 60 and 300 seconds. It is clear that the median does not perform very well in comparison to the other estimators. In statistical terms, the median suffers from low efficiency. The large increase in the RMSE of the median when lengthening the window from 60 to 300 seconds further underlines the poor efficiency properties of the median. In comparison, both the trimmed and the winsorised mean perform much better, also compared with the more complicated Hodges-Lehman and Tukey biweight estimators. The winsorised mean performs especially well under the longer fix window, taking on the lowest variability of the benchmarking procedures under consideration. These results highlight that the median is, in a sense, an extreme choice of benchmarking methodology — it has good robustness properties but very poor efficiency, and that alternatives exists with almost equally good robustness but much better efficiency.

The choice of sampling only one trade per second for the benchmark is also a choice that improves the robustness of the benchmark, as a would-be manipulator's trades cannot guarantee their trades are selected, but this choice also diminishes attainability. However, we think that increasing the number of trades sampled within a second would not improve attainability significantly, as the intra-second volatility is small relative to the inter-second volatility, and trades that consume multiple levels of liquidity are rare. The same is true of the choice to not use volume weighting in the benchmark, though we argue that the large number of single share executions means that this does not impact attainability significantly.

Duffie and Dworczak (2018) explore the trade-off between efficient estimation and the robustness to manipulative strategies in a theoretical setting. In their model they argue that the optimal transaction-based methodology is a capped volume weighted mean price, which weights transactions linearly up to an optimal size, after which weightings are constant.
Reductions in attainability are important, as they may lead to participants deciding not to trade at the benchmark, which then result in negative liquidity agglomeration effects that then diminish the benchmark's representativeness. There is already evidence of this in the case of the popularity of NEX market's 'eFIX' pre-fix netting product[29] — an 'independent netting and execution facility' (FSB, 2015) that arranges matches between counterparties ahead of and at the yet-to-be-determined fix price. This means that flow that would have been executed within the fix window is instead executed outside of it. The netting facility

[29] www.nexmarkets.com/~media/Files/E/EBSBrokertec/info-sheets/NEXMARKETS_eFix_Matching_v1.pdf

Figure 1.9: Efficiency of different benchmarking procedures.
This Figure shows the root mean square deviation between the mean 'clean' price over the fix window, B_T, and various statistical location estimators ('benchmarking procedures'). The estimators used are the median, the mean with 5% of the data trimmed away on either side, the mean with 5% of the data winsorised on either side, the Hodges-Lehman estimator and Tukey's biweighted robust mean estimator. Unit: pips.



relies on, but does not contribute to, fix price discovery. This is a similar case to dark pool venues in equity markets that reference the lit market price to match orders.

Conclusion

In this paper we have examined the effectiveness of the 4pm fix, the largest benchmark in FX markets. We proposed three dimensions along which the effectiveness of the benchmark can be evaluated: how closely the benchmark rate represents rates throughout the day (representativeness), the extent that market participants can replicate the fix rate through their own trading (attainability) and how resilient it is to manipulation (robustness). We also examine the liquidity conditions in the reference market, as liquidity is both a determinant and an outcome of benchmark effectiveness. Our unique dataset, consisting of event-by-event orderbook data identifying individual participants, allows us to connect these aggregate effects with changes in the trading patterns of different market participants around the benchmark.

Our first finding on representativeness is that price reversals after the fix mostly or wholly disappeared when the fix window was lengthened in 2015. It is not clear what would cause such a price pattern in the first place. Strong short-term predictability in prices is not something one would expect to see in a well-functioning financial market, although we are not the first to document it in the context of the 4pm fix, see Evans (2017) and Ito and Yamada (2017). We do conclude that the disappearance of price reversals indicate an improved functioning of the reference market during the fix window. This constitutes an improvement in the representativeness of the fix. This evidence is consistent with a curtailing of certain disruptive trading practices (see e.g. Osler et al. (2016) and Saakvitne (2016) for examples of such trading practices), which would have the effect of lowering the prevalence of extreme price movements around the fix, which in turn improves the benchmark's representativeness.

Our second finding on representativeness relates to the impact of the window lengthening in 2015, and the media reports of rigging allegations in 2013. The deviation between fix rates and daily volume-weighted average rates does not decrease for these events, after controlling for variables such as macroeconomic news and month-end dates. We do not find an effect on representativeness, despite the changes we observe in participant behaviour: a 20% reduction in the fix trading volume of the dealers that were involved in the scandal, as well as a change in the relative share of trading volume that dealers executed before, during and after the fix.

Our findings on attainability and robustness highlight the general trade-off that exists in benchmark design; the efforts to improve robustness, by lengthening the fix window to 5 minutes, came at the cost of as much as a fivefold increase in tracking error for users of the benchmark. We believe the increase in tracking error had two causes: a near-mechanical effect, which we illustrate and quantify through simulations; and a behaviour-driven effect, in the form of higher explicit trading costs (spreads). We do not take a stance on whether the overall effect amounts to an improvement or not, but it seems likely that there are reasonable benchmark designs that perform better than the current fix methodology on at least one of these two dimensions, without performing notably worse on the other.

The question of optimal benchmark design is one that the literature has only recently begun to examine — particularly how trade-based benchmarks should be designed. The history of the 4pm fix shows that robustness is an important consideration for trade-based benchmarks. It also brings to the forefront the issue of attainability, which is a unique concern for trade-based benchmarks. Overall, the 4pm fix's methodology of sampling transaction prices over a very short and predetermined time interval does facilitate attainability more than alternative designs, such as closing auctions in equity markets with randomised clearing times and other mechanisms known only to participants ex-post.

Our findings also underline the importance of market liquidity as both a determinant of and an outcome of the effectiveness of a benchmark. For example, explicit trading costs (spreads) directly impact the attainability of a benchmark through the tracking error it impose on participants trying to replicate the benchmark rate, and changes to the benchmark design that feed back into market liquidity will therefore indirectly affect the benchmark's attainability, as in the case of lengthening the fix window. Similarly, both the robustness and representativeness of the benchmarking procedure relies on having a liquid reference market, and so these aspects of benchmark effectiveness can also be inadvertently affected by changes to benchmark design through endogenous feedback effects. Therefore, a proposed change to a benchmark should not be examined in isolation, without taking into account the likely adaptations by market participants.

Annex

Methodology for Calculating the Fix

If the number of trades in the 1- or 5-minute window exceeds currency's threshold[30] proceed with **trade methodology** below, otherwise proceed with the **order methodology** in the next section:

Trade methodology:

1. For each second in the window, sample[31] a single trade and record:
   (a) the trade price
   (b) whether it is a bid/offer trade (buy/sell)
   (c) the opposing side best bid or offer price[32]
2. At the end of the window, pool together all:
   (a) bid trade prices with opposing bid prices
   (b) offer trade prices with opposing offer prices
3. Calculate a median of each of the bid and offer pools
4. Calculate the midpoint of these two medians
5. This is the WM/R 4pm fix Rate

If the number of trades is less than the currency's threshold, proceed with order methodology:

Order methodology:

1. For each second in the window, sample[33] the best bid and offer orders.
2. At the end of the window, pool together all:
   (a) bid orders
   (b) offer orders
3. Calculate a median of each of the bid and offer pools
4. Calculate the midpoint of these two medians
5. This is the WM/R 4pm fix Rate

[30] This threshold is predefined by WM/R and is not published.
[31] Trades are selected using a confidential sampling process. If the trade sampled is not a 'valid' trade (if it is outside of the BBO at the time of the trade) then the second is discarded.
[32] For example, if the trade sampled is an offer trade (a buy trade) obtain the best bid at the time of the trade. If the bid and offer are crossed at this point in time, the second is discarded.
[33] Trades are selected using a confidential sampling process. If the order sampled are not 'valid' orders (if they are crossed) then the second is discarded.

Participant Categorisation Details

All order and trade events are identified by a four character Terminal Controller Identifier (Dealing) Code (TCID). This reconciles to the legal entity name of the trading firm as well as the location of its trading desk. A major dealer in our sample will have several TCIDs, but these are not separated by desk (e.g. treasury vs forwards), nor by flow (agency vs proprietary). There are 838 unique active TCIDs in our sample period and we assigned them to 11 different categories of participants. We did this by first sourcing additional information about the participants from Orbis' Bureau van Dijk database of private and public companies. We then examined the websites of the companies to understand the nature of their business. Where information was scarce, as was the case for e.g. proprietary trading firms, we examined alternative sources, like the LinkedIn pages of their executives. This enabled us to discern if the business was principally focused in e.g. asset management, agency broking or proprietary trading.

'Dealers' consist of the investment banking firms that are dominant in the FX market as dealers. They number 14 in total, and must have an average rank in 2012 to 2017 Euromoney surveys in the top 18[34] in three or more of the flow categories: Non-Financials, Real Money, Leveraged Funds and (non-dealing) Banks. We also identify a separate category of dealers, being the 7 that were fined for abuses within the WM/R 4pm fix, and this consists of almost all the top 5 dealers in practice. The FX market is highly concentrated, with Euromoney's 2017 survey estimating that the top 5 banks account for 41.05% and 44.79% of trading in 2017 and 2016 respectively.[35] In applying our categories, we apply the same category to all global entities: if a bank is a major dealer with 20 TCIDs in different global offices, we apply the same category to all. In practice over 95% of the trading of the major dealers is done in London, New York, Tokyo and Singapore. For the 4pm benchmark, this will consist of London and New York.

Custodians are firms that list the provision of custodian and fund administration as their core functions. While they might also provide fund management and other services, the vast majority of their funds under management are as custodian or administrator. While firms like J.P. Morgan and Citi have large custodian businesses, which, unfortunately, are not separately identified from their dealer businesses, we aim to classify firms according to their most dominant economic functions. Commercial banks are banks that are not Dealers, and typically self-described as 'Commercial Banks'; these form the vast majority of TCIDs in our sample by number.

We have exercised judgement in the application of the categories so that they are as informative as possible. 'Private Bank' is differentiated from 'Commercial Bank' where the firm describes itself as such, or lists 'Wealth Management' as its primary function. 'Hedge Fund' is differentiated from Asset Management where the firm describes itself as such, or references 'global macro strategies', 'FICC[36] trading' or 'quantitative analysis' as a primary focus. In contrast, asset managers make reference to managing pension or mutual funds without a FICC focus. We have vastly more hedge funds in our sample than asset managers.

[34]Most satisfy this requirement if the threshold is also set at 10.
[35]See: Euromoney Survey Release 2017.
[36]Fixed Income Currency & Commodities

'Agency Broker' is differentiated from 'Commercial Bank' where the firm is primarily focused on agency execution services and describes itself foremost as a broker and does not provide commercial banking services. This category includes firms which provide FX spot and derivatives execution services to retail clients.

'Prop Trading' firms are those which manage trade using their own capital. 'Prop Trader — HFT' are a subset of this category, which employ strategies that are high frequency in nature. Many of these firms are self-described HFTs, but we also apply an objective criteria that the 1% left tail of the distribution of all order resting times in the sample for a TCID is below 200 milliseconds. We apply this as a secondary identification procedure for firms that are not self-described as HFTs.

Lastly, the 'Commercial' category consists of firms of an entirely non-financial nature — there are just a handful of these TCIDs in our sample. 'Central Bank' consists of central bank trading.

Of course, while we have categorised the nature of these businesses, we are unable to disaggregate their own flows from their clients, and to disaggregate their client flows. Most of the firms in our sample are dealers or banks. The asset managers that we see trading on their own account are a small subset of the total number of asset managers that are engaging their dealers to trade on their behalf.

Chaboud et al. (2014) utilises a dataset from EBS that contains identifiers for human and non-human automated trades, tracking the rise in computerised trading in FX markets from 2003 to 2007. They find that the percentage of trades with at least one automated counterparty rises almost linearly from 0% to between 60 and 80%. We do not have an identifier for algorithmic trades in our data, but we suspect the use of algorithms to submit orders (whether as programmed by a human or by an automated algorithm)[37] to be highly pervasive in our sample from 2012 to 17, with Schaumburg (2014) and Arnold and Schaefer (2014) finding evidence this trend persists. Chaboud et al. (2014) are not able to distinguish HFT trades, as we are able to in our data.

Extended Attainability Simulation

The attainability simulation conducted in the paper assumes that every second in the benchmark window has a valid trade observation. The WM/R methodology excludes seconds that do not have trades, and in practice it is common for a significant number of seconds to have zero trades.

In this simulation we extend the first by accounting for the fact that the WM/R benchmark rate typically is not computed upon 60 trades, but a much smaller number.

We model the total number of trades in the fix window m as the state of the Poisson process $M(T)$, and the trade times $t_1, \ldots, t_m$ as the associated arrival times. This is a natural generalization of the previous model, as it implies that the trade times $t_1, \ldots, t_m$ are uniformly

[37] For example, much trading is now handled by humans programming smart order routers that provide order splitting functionality across multiple trading venues.

scattered across the interval $[0, T]$.

The intensity of the Poisson process $M(t)$ can be estimated from the data, as the mean number of trades in the fix window. Clearly it is appropriate to use a different intensity when the fix window is $T = 300$ seconds long from when it is $T = 60$ seconds.

Now for each trade time t_i we sample the price process, $B(t_i)$, and compute the benchmark rate f as the median:

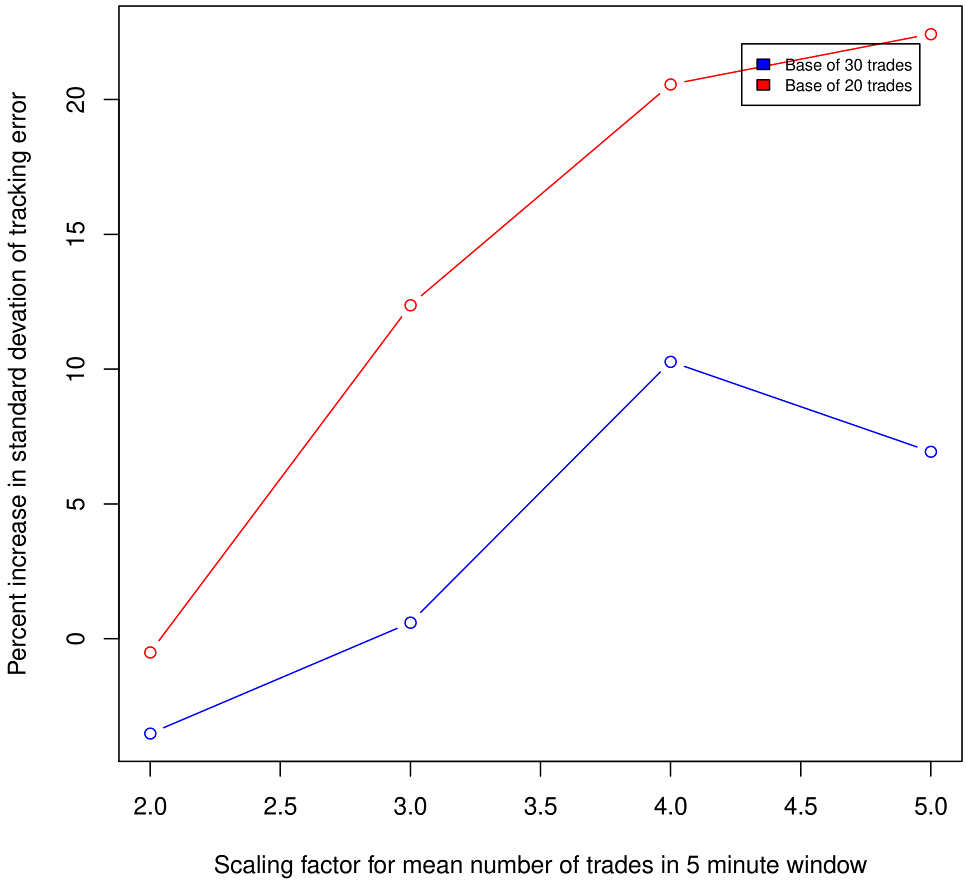
$$f = \text{median}\{B_1, B_2, \dots, B_m\}$$

The average price attained by the hypothetical trader trying to replicate the spot rate is computed in the same manner as Simulation 1, and correspondingly we study the 'tracking errors' $e_1, \dots, e_K$ from a large number K of simulations, for $T = 1$ and $T = 5$.

Results of Simulation

The results of this simulation are reported in Figure 10. The red line shows the percentage increase in in RMSE a hypothetical participant that wishes to attain the benchmark experiences under a 60-second window regime to a 300-second window. The mean number of trades in the old regime is 20, and the mean number of trades in the new regime is 20*(the number on the x-axis). The blue line is similar, but now the mean number of trades in the old regime is 30.

Figure 10: Simulation of Benchmark Windows with Varying Seconds With Trades
This Figure reports the results of the simulation exercise, which computes tracking error, reported on the y-axis in pips, for the 1-minute and 5-minute window lengths across a varying number of seconds with trades (m), reported on the x-axis. Per-second volatility is calculated assuming a yearly volatility of 0.2.



Full Regression Tables

Table 14: Regression of Representativeness Measure $D_{t,p}$ — Media Event
This table reports coefficient estimates for the window event study for a pooled regression of currency-pair dates. The dependent variable, $D_{t,p}$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $AfterMedia$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 12 June 2013. $eurhuf$, $eursek$, $eurusd$ and $gbpusd$ are dummy variables for each currency pair, representing currency fixed effects. $Vol(level)$ is the time-weighted average of the options midpoint price for fix window. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 2pm to the end of the fix.

	Representativeness: $D_{t,p}$
after media	-0.21
	-0.97
eurhuf	0.02
	0.05
eursek	0.19
	0.50
eurusd	0.16
	0.43
gbpusd	-0.04
	-0.12
vol (level)	0.01
	0.09
monthend	2.80^{***}
	4.64
macro	1.37^{***}
	3.68
Weekday Dummy?	Yes
Month Dummy?	Yes
Constant	3.17^{***}
	8.51
Observations	1,035
R^2	0.04
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 15: Regression of Representativeness Measure $D_{t,p}$ — Window Event
This table reports coefficient estimates for the window event study for a pooled regression of currency-pair dates. The dependent variable, $D_{t,p}$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $AfterWindow$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $eurhuf$, $eursek$, $eurusd$ and $gbpusd$ are dummy variables for each currency pair, representing currency fixed effects. $Vol(level)$ is the time-weighted average of the options midpoint price for fix window. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 2pm to the end of the fix.

	Representativeness: $D_{t,p}$
after window	-0.06
	-0.22
eurhuf	0.73
	1.47
eursek	0.41
	0.90
eurusd	0.26
	0.64
gbpusd	0.07
	0.16
vol (level)	0.12
	0.81
monthend	-0.65
	-0.79
macro	0.08
	0.20
Weekday Dummy?	Yes
Month Dummy?	Yes
Constant	3.09^{***}
	6.50
Observations	763
R^2	0.01
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 16: Regression of Representativeness Measure $D_{t,p}$ — Full Sample Time Trend
This table reports coefficient estimates for a pooled regression of currency-pair dates. The dependent variable, $D_{t,p}$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $datecount$ is a time trend variable, which increments one for each date in our sample. $eurhuf$, $eursek$, $eurusd$ and $gbpusd$ are dummy variables for each currency pair, representing currency fixed effects. $Vol(level)$ is the time-weighted average of the options midpoint price for fix window. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 2pm to the end of the fix.

	Representativeness: $D_{t,p}$
datecount	-0.0001
	-0.27
eurhuf	0.22
	1.16
eursek	0.36^{*}
	1.86
eurusd	0.14
	0.73
gbpusd	-0.13
	-0.68
vol (level)	0.02
	0.30
monthend	1.37^{***}
	4.10
macro	0.43^{**}
	2.21
Weekday Dummy?	Yes
Month Dummy?	Yes
Constant	2.81^{***}
	10.12
Observations	3,207
R^2	0.02
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 17: Regression of Log Ratio of Volume (Fix/Non-Fix) — Media Event
This table reports coefficient estimates for media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Volume$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Volume				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.08	0.35*	0.10	0.18	0.16
	0.65	1.81	0.55	0.83	1.20
Volatility	0.06	0.003	−0.04	0.14	0.14**
	0.92	0.03	−0.47	1.28	2.30
Vol. (level)	−0.03	−0.04	−0.08	0.09	−0.02
	−0.43	−0.57	−1.14	0.75	−0.28
Carry (ratio)	−0.02	−0.16*	0.03	−0.12	−0.01
	−0.39	−1.84	0.42	−1.02	−0.26
Short USD (ratio)	0.02	−0.08	−0.05	−0.06	0.05
	0.37	−0.86	−0.89	−0.56	0.96
Month-end	1.19***	0.92*	0.96***	0.78*	1.22***
	2.82	1.93	4.21	1.93	8.27
Macro	−0.12	0.24	0.03	0.09	−0.10
	−0.98	1.23	0.21	0.37	−0.83
Constant	−1.86***	−3.31***	−1.75***	−4.52***	−1.90***
	−12.91	−12.94	−7.44	−20.80	−13.60
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	124	112	127	94	126
R^2	0.17	0.13	0.08	0.17	0.23

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 18: Regression of Log Ratio of Quoted spread (Fix/Non-Fix) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Quotedspread$ is the log ratio of the time-weighted quoted spread in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Quoted spread				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.10^{***}	-0.01	0.10	0.09^{**}	-0.11^{***}
	-3.85	-0.16	1.39	1.97	-4.48
Volatility	0.01	-0.02	0.04^{*}	0.02	-0.01
	1.24	-0.43	1.80	0.92	-0.48
Vol. (level)	-0.03^{**}	0.03	-0.04	0.09^{***}	-0.02
	-2.45	0.57	-1.45	2.86	-1.60
Carry (ratio)	0.01	-0.02	-0.04	-0.003	0.003
	1.07	-0.38	-1.25	-0.09	0.21
Short USD (ratio)	-0.01	-0.02	0.01	-0.01	0.01
	-1.42	-0.40	0.47	-0.48	0.76
Month-end	0.02	0.22	0.07	-0.07	-0.01
	0.22	0.65	0.68	-0.63	-0.23
Macro	0.02	-0.06	-0.005	0.02	0.01
	0.98	-0.57	-0.08	0.43	0.51
Constant	-0.29^{***}	-0.29^{**}	-0.56^{***}	0.24^{***}	-0.33^{***}
	-12.25	-2.42	-8.61	5.36	-13.09
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	130	127	127	126
R^2	0.40	0.03	0.10	0.16	0.22
Note:	*p<0.1; **p<0.05; ***p<0.01				
	Volatility, Carry and Short USD are standardized ratios (fix/nonfix).				

Table 19: Regression of Log Ratio of Depth at best (Fix/Non-Fix) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Depthatbest$ is the log ratio of the time-weighted depth at the best bid and offer in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Depth at best				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	−0.10	−0.003	0.06	−0.02	0.13
	−1.03	−0.04	0.48	−0.39	1.43
Volatility	0.01	0.07	0.02	0.01	−0.04
	0.15	1.58	0.29	0.50	−0.90
Vol. (level)	0.22***	−0.01	−0.06	0.07**	−0.03
	4.59	−0.25	−1.18	2.53	−0.58
Carry (ratio)	0.004	−0.04	0.01	−0.002	−0.02
	0.10	−1.04	0.13	−0.08	−0.46
Short USD (ratio)	0.01	0.04	−0.05	0.03	−0.03
	0.28	0.99	−0.91	1.18	−0.74
Month-end	0.28*	0.02	0.30*	0.08	0.49**
	1.94	0.14	1.85	0.44	2.42
Macro	0.18**	0.06	0.12	0.03	0.15*
	2.08	0.76	1.25	0.64	1.80
Constant	0.84***	−0.32***	0.39***	0.06	0.58***
	8.28	−3.98	3.48	0.88	6.33
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	124	130	127	127	126
R^2	0.25	0.10	0.06	0.11	0.12

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 20: Regression of Log Ratio of Depth at Top 10 (Fix/Non-Fix) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $DepthatTop10$ is the log ratio of the time-weighted depth at the best 10 bid and offer price levels in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Depth at top 10				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.01	-0.21^{**}	-0.03	0.01	0.11^{*}
	-0.23	-2.39	-0.31	0.67	1.89
Volatility	0.003	0.07	0.03	-0.004	-0.02
	0.13	1.47	0.54	-0.35	-0.96
Vol. (level)	0.10^{***}	-0.04	-0.08	0.003	-0.01
	3.27	-0.89	-1.59	0.19	-0.25
Carry (ratio)	-0.01	0.02	0.01	-0.01	-0.04
	-0.32	0.43	0.33	-0.92	-1.60
Short USD (ratio)	0.02	0.05	-0.05	0.01	0.02
	0.73	1.38	-1.15	0.94	0.77
Month-end	0.26^{*}	0.05	0.23	0.07	0.32^{***}
	1.77	0.24	1.30	0.96	3.26
Macro	0.10^{**}	0.07	0.14^{*}	-0.02	0.06
	2.14	0.92	1.75	-0.70	1.19
Constant	0.31^{***}	-0.17	0.28^{***}	0.08^{***}	0.19^{***}
	3.72	-1.22	2.84	3.11	3.52
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	124	130	127	127	126
R^2	0.24	0.13	0.10	0.07	0.17

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 21: Regression of Log Ratio of Effective Spread (Fix/Non-Fix) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Effectivespread$ is the log ratio of the volume-weighted spread at the time a trade occurs , versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Effective spread				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.12^{***}	-0.05	0.18^{**}	0.01	-0.10^{***}
	-3.72	-0.41	2.48	0.09	-4.07
Volatility	0.01	0.06	0.01	0.10^{**}	0.02
	1.17	1.05	0.56	2.03	1.29
Vol. (level)	0.01	0.12^{**}	-0.11^{***}	0.01	-0.01
	0.88	2.14	-3.24	0.14	-0.88
Carry (ratio)	-0.01	-0.02	-0.04	-0.07^{*}	-0.01
	-0.39	-0.36	-1.53	-1.65	-0.96
Short USD (ratio)	-0.003	0.05	0.002	-0.03	0.02
	-0.30	0.65	0.08	-0.69	1.40
Month-end	0.12^{***}	0.25	0.30^{***}	0.11	0.15^{***}
	2.81	0.80	3.57	0.47	2.70
Macro	-0.03	-0.09	0.05	-0.03	0.03
	-1.40	-0.65	0.83	-0.36	1.20
Constant	-0.03	-0.40^{**}	-0.42^{***}	0.27^{**}	-0.09^{***}
	-0.91	-2.46	-5.54	2.23	-3.46
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	124	112	127	94	126
R^2	0.25	0.07	0.13	0.18	0.21

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 22: Regression of Log Ratio of Price impact (1ms) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(1ms)$ is the log ratio of the volume-weighted price impact of a trade over a 1 millisecond period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (1ms)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.04	-0.03	0.11	0.08	-0.12^{*}
	-0.47	-0.18	0.94	0.52	-1.83
Volatility	0.04	-0.01	0.02	0.32^{***}	0.03
	1.19	-0.06	0.44	3.64	0.94
Vol. (level)	-0.01	0.10	-0.07	0.06	-0.03
	-0.22	1.21	-1.20	0.61	-0.71
Carry (ratio)	-0.02	-0.04	0.004	-0.01	0.03
	-0.58	-0.47	0.08	-0.12	1.01
Short USD (ratio)	0.01	-0.04	0.06	0.03	0.02
	0.46	-0.43	1.26	0.25	0.61
Month-end	0.26	-0.43	0.21	-0.87^{**}	0.16
	1.03	-0.90	0.84	-2.04	0.57
Macro	-0.06	0.12	-0.07	-0.11	-0.02
	-0.80	0.70	-0.71	-0.61	-0.29
Constant	-0.43^{***}	-0.40^{*}	-0.58^{***}	0.61^{***}	-0.34^{***}
	-4.74	-1.71	-4.97	4.68	-4.40
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	123	106	127	88	126
R^2	0.07	0.07	0.06	0.24	0.09

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 23: Regression of Log Ratio of Price impact (1 Second) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(1sec)$ is the log ratio of the volume-weighted price impact of a trade over a 1 second period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (1sec)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.09	0.23	0.10	-0.39^{*}	-0.05
	-1.08	1.00	0.83	-1.92	-0.60
Volatility	0.02	-0.05	0.02	0.30^{***}	0.03
	0.49	-0.41	0.43	2.89	0.59
Vol. (level)	-0.04	0.04	-0.03	-0.07	-0.06
	-0.95	0.47	-0.55	-0.78	-1.26
Carry (ratio)	0.01	0.04	-0.01	0.01	0.04
	0.35	0.40	-0.22	0.08	1.02
Short USD (ratio)	-0.02	-0.06	0.04	-0.02	0.01
	-0.45	-0.57	0.77	-0.24	0.29
Month-end	0.16	-0.60^{*}	0.05	-0.59	0.12
	0.74	-1.75	0.22	-1.08	0.53
Macro	-0.08	0.14	-0.11	-0.15	-0.04
	-1.15	0.72	-1.07	-0.88	-0.48
Constant	-0.64^{***}	-0.40	-0.49^{***}	0.19	-0.47^{***}
	-5.83	-1.45	-4.50	1.01	-4.28
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	123	106	127	82	126
R^2	0.11	0.06	0.04	0.29	0.05

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 24: Regression of Log Ratio of Price impact (5 Sec) — Media Event
This table reports coefficient estimates for the media event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(5sec)$ is the log ratio of the volume-weighted price impact of a trade over a 5 second period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the media event' on the 12 June 2013. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (5sec)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	−0.10	0.07	−0.11	0.60	0.04
	−0.88	0.31	−0.54	1.31	0.44
Volatility	−0.03	−0.08	0.06	0.04	0.05
	−0.72	−0.61	1.32	0.18	1.03
Vol. (level)	−0.03	0.11	−0.01	0.30	−0.10**
	−0.52	1.40	−0.12	1.18	−2.14
Carry (ratio)	−0.01	0.04	−0.08	0.005	0.05
	−0.18	0.31	−1.31	0.02	1.23
Short USD (ratio)	−0.02	−0.05	0.01	−0.17	−0.02
	−0.35	−0.50	0.21	−0.74	−0.45
Month-end	0.17	−0.18	0.21	0.25	0.11
	0.68	−0.33	0.93	0.37	0.44
Macro	−0.03	0.05	−0.09	−0.16	−0.04
	−0.31	0.25	−0.59	−0.28	−0.44
Constant	−0.56***	−0.18	−0.30**	0.15	−0.39***
	−3.35	−0.70	−2.01	0.60	−3.55
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	123	101	127	72	124
R^2	0.11	0.05	0.07	0.09	0.09

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 25: Regression of Log Ratio of Volume (Fix/Non-Fix) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Volume$ is the log ratio of the total volume traded in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Volume				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.08	0.34*	0.19	0.61***	0.26**
	0.60	1.76	1.18	3.10	2.01
Volatility	−0.03	−0.15	0.13	0.25***	−0.12**
	−0.30	−1.27	1.58	3.18	−1.97
Vol. (level)	−0.09	−0.03	0.02	−0.15	−0.01
	−1.47	−0.24	0.17	−1.47	−0.27
Carry (ratio)	−0.002	−0.13	0.08	−0.20**	−0.04
	−0.02	−1.46	1.09	−2.27	−0.79
Short USD (ratio)	0.10	0.14	0.03	0.15	0.03
	1.45	1.50	0.39	1.62	0.51
Month-end	2.13***	1.30***	1.19***	0.96**	1.36***
	8.55	2.67	4.01	2.37	13.59
Macro	−0.25*	−0.39*	0.06	−0.16	−0.24**
	−1.72	−1.77	0.36	−0.78	−2.01
Constant	−1.59***	−2.47***	−1.70***	−3.58***	−1.82***
	−8.61	−8.92	−9.36	−15.82	−10.92
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	114	120	108	121
R^2	0.34	0.23	0.28	0.23	0.25

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 26: Regression of Log Ratio of Quoted spread (Fix/Non-Fix) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Quotedspread$ is the log ratio of the time-weighted quoted spread in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Quoted spread				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.07***	0.33***	−0.02	0.11***	0.06*
	2.77	4.49	−0.42	5.03	1.91
Volatility	0.02	0.03	0.02	0.02	0.03*
	1.35	0.85	0.59	1.37	1.71
Vol. (level)	−0.01	−0.02	−0.02	0.01	0.01
	−1.09	−0.56	−0.83	0.93	0.78
Carry (ratio)	0.01	0.07**	−0.001	0.01	0.02
	0.74	2.25	−0.03	1.34	1.12
Short USD (ratio)	0.02*	0.002	0.04	0.02	0.01
	1.66	0.07	1.22	1.36	0.84
Month-end	−0.04	0.19	0.003	0.01	−0.06
	−0.72	0.61	0.03	0.17	−0.96
Macro	0.005	−0.01	−0.0002	0.04*	0.03
	0.17	−0.16	−0.003	1.72	0.73
Constant	−0.37***	−0.24***	−0.20***	0.01	−0.37***
	−10.77	−3.20	−3.38	0.29	−9.87
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	122	120	121	121
R^2	0.16	0.25	0.07	0.32	0.15

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 27: Regression of Log Ratio of Depth at best (Fix/Non-Fix) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Depthatbest$ is the log ratio of the time-weighted depth at the best bid and offer in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month - end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Depth at best				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.25^{***}	-0.04	-0.22^{**}	-0.0002	-0.26^{***}
	-4.02	-0.51	-2.46	-0.004	-3.09
Volatility	-0.02	-0.06^{*}	0.06	-0.01	-0.06^{**}
	-0.55	-1.72	0.96	-0.40	-2.00
Vol. (level)	0.004	-0.09^{*}	0.04	0.01	0.02
	0.13	-1.77	0.72	0.47	0.56
Carry (ratio)	-0.04	0.02	0.04	-0.03^{**}	-0.05
	-1.21	0.44	0.74	-2.01	-1.24
Short USD (ratio)	0.10^{**}	-0.05	-0.02	-0.03	0.02
	2.43	-1.18	-0.52	-1.25	0.73
Month-end	0.35^{***}	-0.05	0.30^{*}	0.05	0.29^{***}
	3.08	-0.18	1.95	1.08	3.12
Macro	-0.01	-0.14	0.03	-0.07^{*}	-0.09
	-0.14	-1.45	0.31	-1.78	-1.03
Constant	0.35^{***}	0.002	0.31^{**}	-0.16^{***}	0.51^{***}
	5.56	0.02	2.50	-4.86	5.52
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	122	120	121	121
R^2	0.25	0.12	0.18	0.10	0.19

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 28: Regression of Log Ratio of Depth at Top 10 (Fix/Non-Fix) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $DepthatTop10$ is the log ratio of the time-weighted depth at the best 10 bid and offer price levels in the fix, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Depth at top 10				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	-0.20^{***}	0.15	-0.15^{*}	0.06^{***}	-0.07
	-4.08	1.63	-1.79	2.60	-1.31
Volatility	-0.02	-0.05	-0.01	-0.02	-0.05^{*}
	-1.27	-1.50	-0.13	-1.35	-1.67
Vol. (level)	-0.003	-0.06	0.04	-0.01	-0.02
	-0.13	-1.23	0.77	-0.53	-0.66
Carry (ratio)	-0.01	-0.01	0.03	-0.01	-0.001
	-0.75	-0.24	0.66	-1.25	-0.02
Short USD (ratio)	0.05^{*}	-0.10^{*}	-0.01	-0.01	0.03
	1.87	-1.92	-0.24	-1.06	1.08
Month-end	0.27^{***}	-0.20	0.03	-0.03	0.25^{**}
	3.19	-0.78	0.24	-1.14	2.41
Macro	0.01	-0.15	0.10	-0.04^{*}	-0.05
	0.16	-1.46	1.02	-1.87	-0.84
Constant	0.29^{***}	-0.08	0.10	-0.05^{**}	0.20^{***}
	4.03	-0.93	0.81	-2.31	2.64
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	122	120	121	121
R^2	0.24	0.10	0.11	0.17	0.11

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 29: Regression of Log Ratio of Effective Spread (Fix/Non-Fix) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Effectivespread$ is the log ratio of the volume-weighted spread at the time a trade occurs , versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm..

	Effective spread				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.02	0.36^{***}	-0.20^{***}	-0.12^{*}	-0.10^{***}
	0.83	3.94	-3.00	-1.80	-3.28
Volatility	0.002	0.03	0.05	0.01	0.03
	0.15	0.71	1.34	0.22	1.59
Vol. (level)	0.01	0.02	-0.03	0.01	0.001
	0.62	0.30	-0.95	0.32	0.08
Carry (ratio)	0.01	0.07^{*}	0.04	-0.04	0.02
	1.12	1.77	1.28	-1.23	0.98
Short USD (ratio)	0.01	-0.07	0.01	-0.01	0.02
	1.48	-1.38	0.27	-0.16	1.33
Month-end	0.15^{***}	0.10	-0.09	0.20	0.07^{**}
	3.34	0.53	-0.79	1.32	2.10
Macro	-0.03	-0.02	0.001	-0.05	0.02
	-1.08	-0.19	0.01	-0.75	0.50
Constant	-0.10^{***}	-0.25^{*}	0.12^{*}	0.03	-0.11^{***}
	-4.05	-1.76	1.84	0.33	-3.43
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	114	120	108	121
R^2	0.15	0.23	0.12	0.09	0.17

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 30: Regression of Log Ratio of Price impact (1ms) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(1ms)$ is the log ratio of the volume-weighted price impact of a trade over a 1 millisecond period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (1ms)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.13^{*}	-0.12	-0.03	0.25^{*}	0.18^{**}
	1.93	-0.74	-0.32	1.94	2.50
Volatility	-0.04	-0.02	0.22^{*}	0.02	0.09^{***}
	-0.84	-0.32	1.81	0.33	2.71
Vol. (level)	0.07^{*}	0.04	-0.02	0.02	-0.01
	1.72	0.43	-0.30	0.26	-0.43
Carry (ratio)	0.02	0.11	-0.12	0.04	0.06^{*}
	0.69	1.50	-1.17	0.66	1.75
Short USD (ratio)	-0.001	0.06	0.18	0.03	0.03
	-0.04	0.71	1.54	0.48	0.94
Month-end	0.34	0.17	0.20	0.03	0.09
	1.12	0.36	1.17	0.16	0.79
Macro	-0.06	-0.07	-0.08	-0.06	0.11
	-0.70	-0.38	-0.58	-0.54	1.61
Constant	-0.52^{***}	-0.16	-0.16	-0.30^{**}	-0.42^{***}
	-5.31	-0.80	-1.27	-2.30	-6.28
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	110	120	104	121
R^2	0.14	0.05	0.25	0.10	0.18

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 31: Regression of Log Ratio of Price impact (1 Second) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(1sec)$ is the log ratio of the volume-weighted price impact of a trade over a 1 second period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time- weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (1sec)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.22^{***}	-0.07	0.02	0.29	0.22^{***}
	3.63	-0.44	0.23	0.73	3.25
Volatility	-0.02	0.04	0.07	-0.31^{*}	0.11^{***}
	-0.41	0.51	1.54	-1.85	3.56
Vol. (level)	0.08^{**}	0.09	0.03	-0.13	0.03
	2.44	1.12	0.83	-0.56	1.02
Carry (ratio)	0.004	0.12^{*}	-0.02	-0.04	0.07^{**}
	0.16	1.80	-0.49	-0.29	2.39
Short USD (ratio)	-0.02	0.02	0.02	-0.05	0.08^{**}
	-0.72	0.20	0.42	-0.31	2.30
Month-end	0.32^{*}	-0.01	0.13	0.50	0.15^{**}
	1.73	-0.01	0.68	1.15	2.14
Macro	-0.12^{*}	0.01	-0.03	-0.13	0.13^{**}
	-1.79	0.06	-0.38	-0.39	1.98
Constant	-0.38^{***}	-0.18	-0.16	-0.57^{**}	-0.48^{***}
	-4.36	-0.91	-1.53	-2.44	-5.72
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	110	119	101	121
R^2	0.23	0.06	0.05	0.17	0.30

Note: *p<0.1; **p<0.05; ***p<0.01
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Table 32: Regression of Log Ratio of Price impact (5 Sec) — Window Event
This table reports coefficient estimates for the window event study using the specification in Formula 1.5.1 for regressions in each currency pair. The dependent variable, $Priceimpact(5sec)$ is the log ratio of the volume-weighted price impact of a trade over a 5 second period, versus the control period, for a given a currency-date. $AfterDummy$ is a dummy variable, which takes the value of one for the time period after 'the window event' on the 15 February 2015. $Volatility$ is the log ratio of the time-weighted average of the 1-week options midpoint price for the respective currency in the control period, versus the fix window. $Vol(level)$ is the time-weighted average of the options midpoint price for the fix window. $Carry(ratio)$ and $ShortUSD(ratio)$ is the log ratio (or the log return) of the time-weighted average of these index values in the control period, versus the fix window. Carry is an ETF that employs carry strategies and Short USD is a basket index designed to replicate a TWI of short USD. $Month-end$ is a dummy variable that takes the value of one for the last trading day of the month in the respective currency. $macro$ is a dummy variable that takes the value of one for macro news events of the highest volatility rating that occur in the period from 9am to 4pm.

	Price impact (5sec)				
	AUDUSD	EURHUF	EURSEK	EURUSD	GBPUSD
	(1)	(2)	(3)	(4)	(5)
After dummy	0.20^{**}	-0.17	0.12	0.08	0.26^{**}
	2.52	-1.00	1.24	0.28	2.37
Volatility	0.05	0.19^{**}	0.21^{**}	-0.06	0.07^{*}
	1.14	2.04	2.49	-0.47	1.67
Vol. (level)	0.09^{**}	0.09	-0.03	0.15	0.01
	2.27	1.00	-0.73	0.64	0.28
Carry (ratio)	0.02	0.11	-0.10	-0.03	0.01
	0.63	1.46	-1.35	-0.20	0.30
Short USD (ratio)	0.01	-0.01	0.14^{*}	-0.09	0.12^{**}
	0.42	-0.12	1.74	-0.56	2.56
Month-end	0.38^{***}	-0.35	0.08	0.38	0.40^{***}
	3.07	-0.78	0.36	1.08	3.10
Macro	-0.11	0.01	-0.03	-0.34	0.14
	-1.18	0.05	-0.29	-1.20	1.26
Constant	-0.25^{***}	-0.51^{**}	-0.26^{**}	-0.11	-0.36^{***}
	-2.65	-1.97	-2.40	-0.52	-4.05
Weekday dummy?	Yes	Yes	Yes	Yes	Yes
Observations	121	106	117	86	121
R^2	0.20	0.13	0.26	0.07	0.18

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Volatility, Carry and Short USD are standardized ratios (fix/nonfix).

Miscellaneous Figures and Tables

Figure 11: Mean Trading Volume — every 15 Seconds — 3 Months Pre-Post Window Change — GBPUSD
This Figure reports mean trading volume in GBPUSD for 15-second time intervals from 15:55 to 16:05, with means calculated across all time intervals in a 3-month period before and after the window event. Volume is in millions of USD and Time is reported in decimal format.

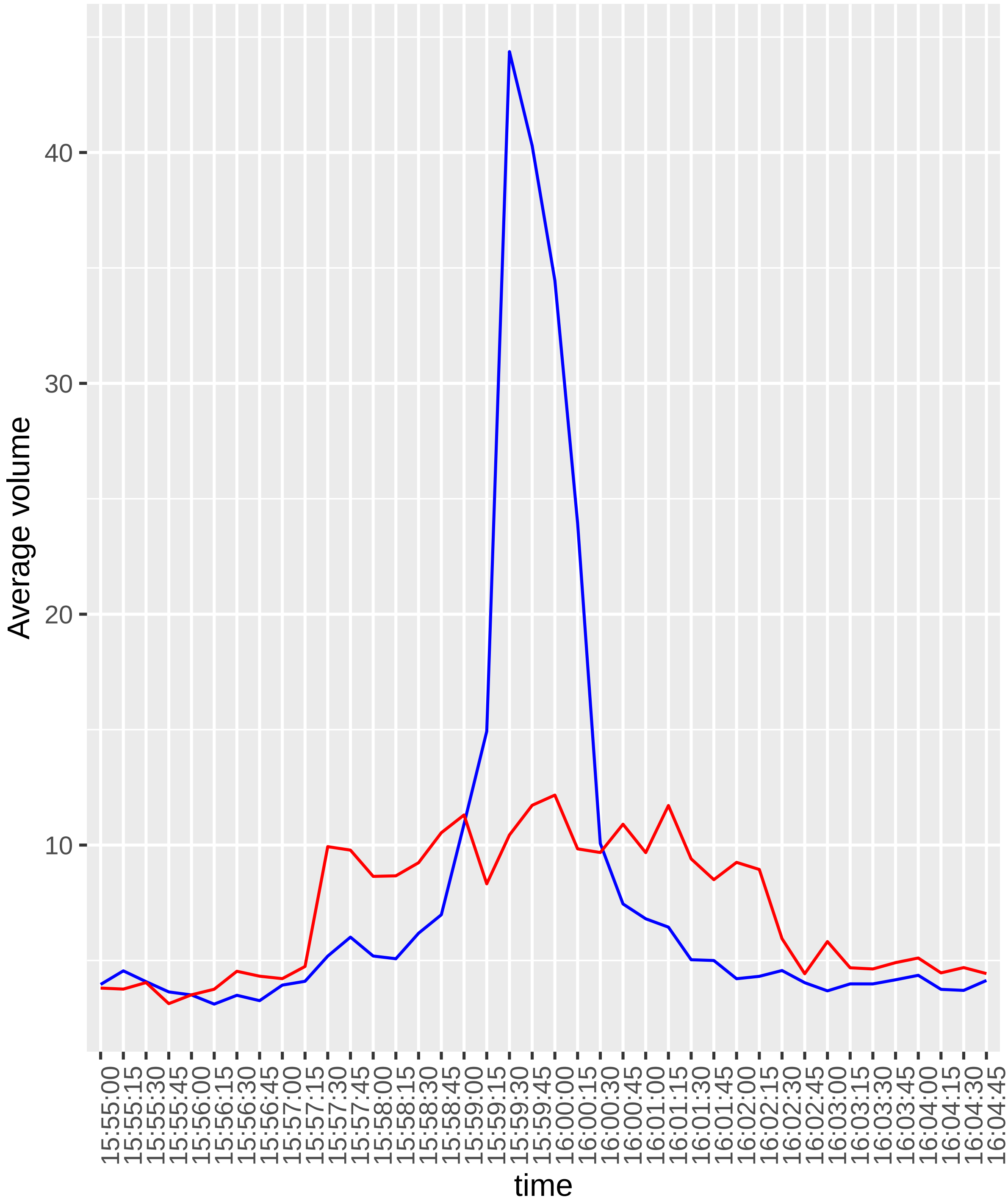


Figure 12: Mean Trading Volume — every 15 Seconds — 3 Months Pre-Post Window Change — AUDUSD
This Figure reports mean trading volume in AUDUSD for 15-second time intervals from 15:55 to 16:05, with means calculated across all time intervals in a 3-month period before and after the window event. Volume is in millions of USD and Time is reported in decimal format.

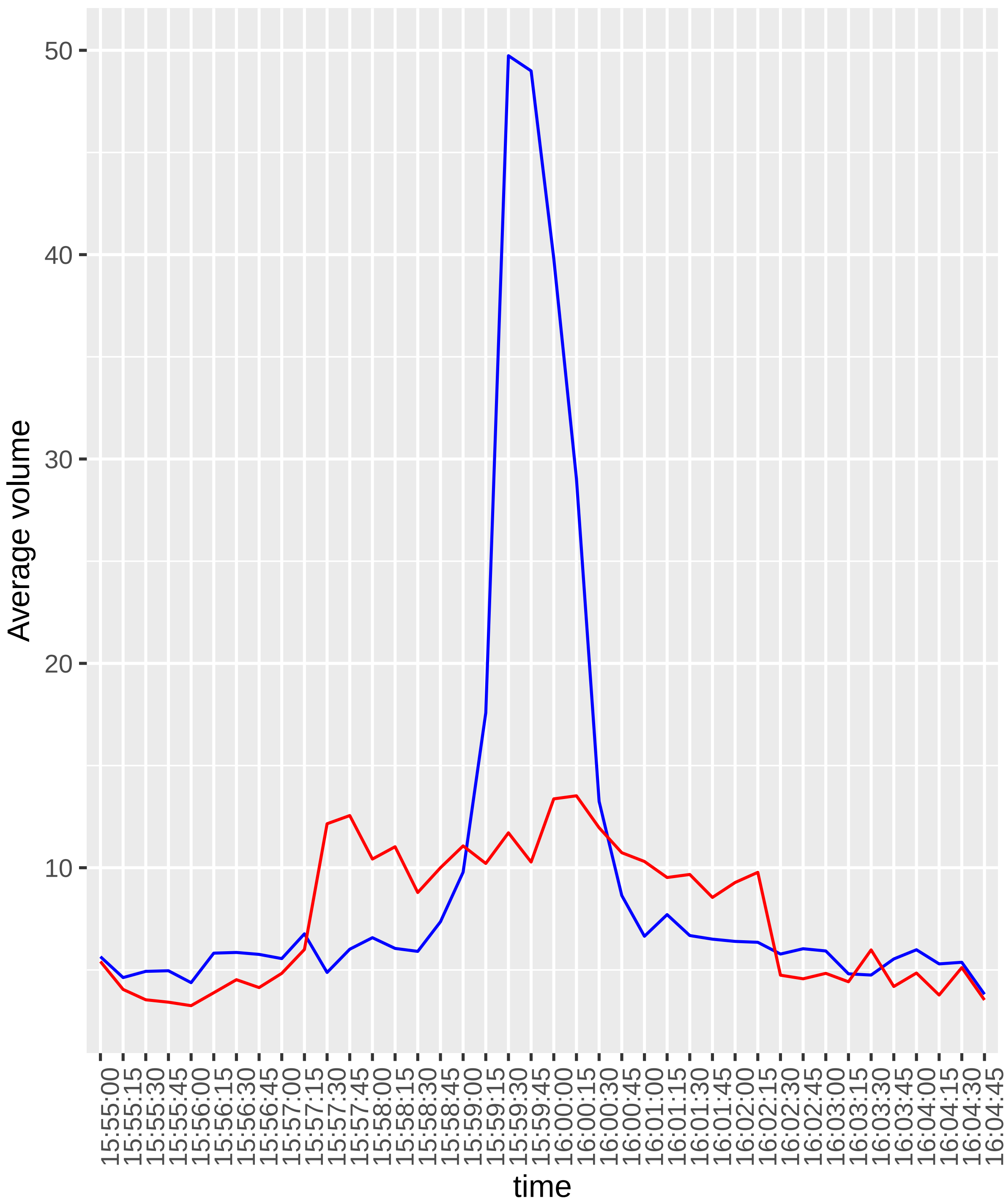


Figure 13: Mean Time-Weighted Quoted Spreads — every 15 Seconds — 3 Months Pre-Post Window Change — GBPUSD
This Figure reports mean time-weighted quoted spreads in GBPUSD for 15-second time intervals from 15:55 to 16:05, with means calculated across all time intervals in a 3-month period before and after the window event. The spread is in absolute values and Time is reported in decimal format.

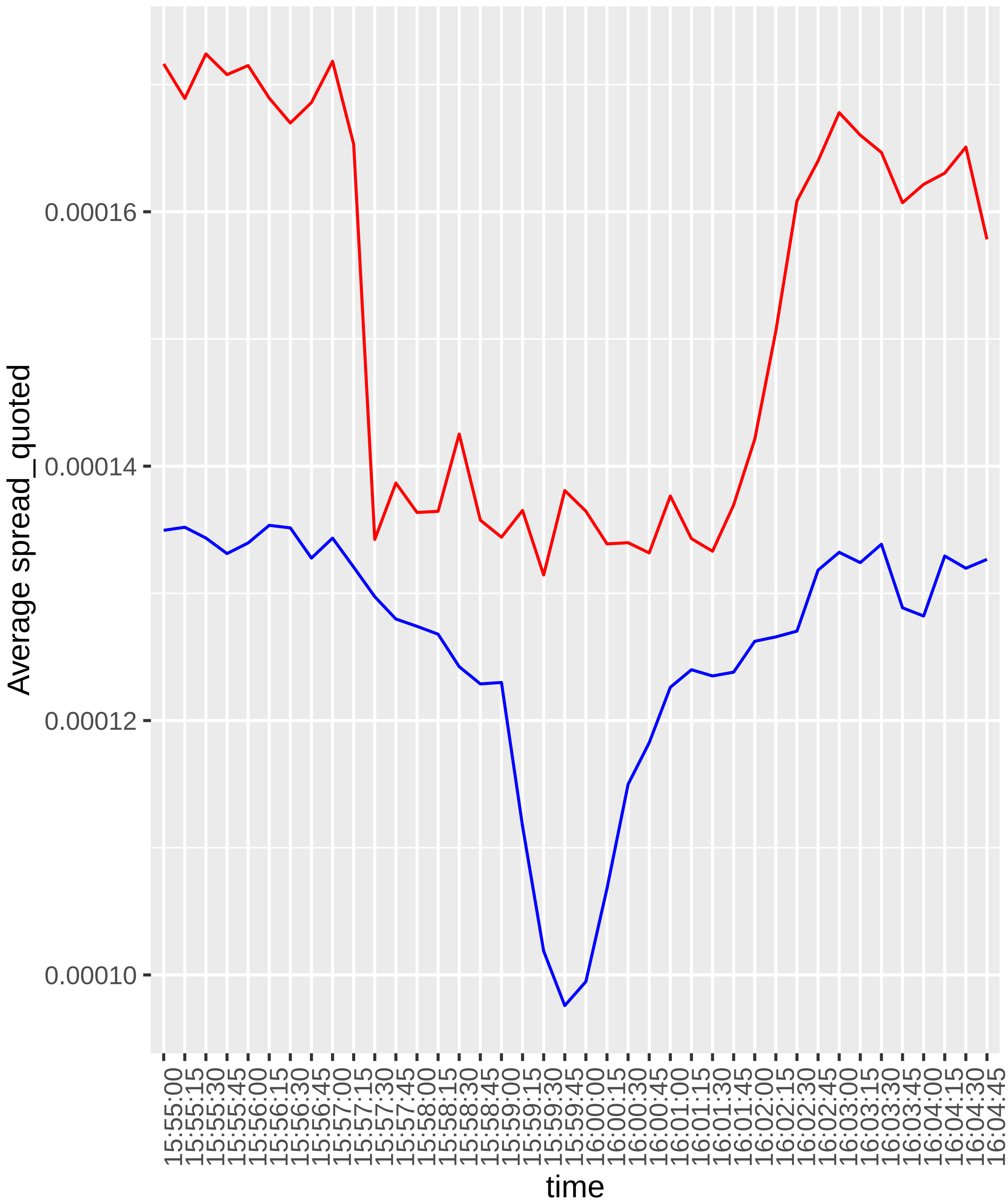


Figure 14: Mean Time-Weighted Quoted Spreads — every 15 Seconds — 3 Months Pre-Post Window Change — AUDUSD
This Figure reports mean time-weighted quoted spreads in AUDUSD for 15-second time intervals from 15:55 to 16:05, with means calculated across all time intervals in a 3-month period before and after the window event. The spread is in absolute values and Time is reported in decimal format.

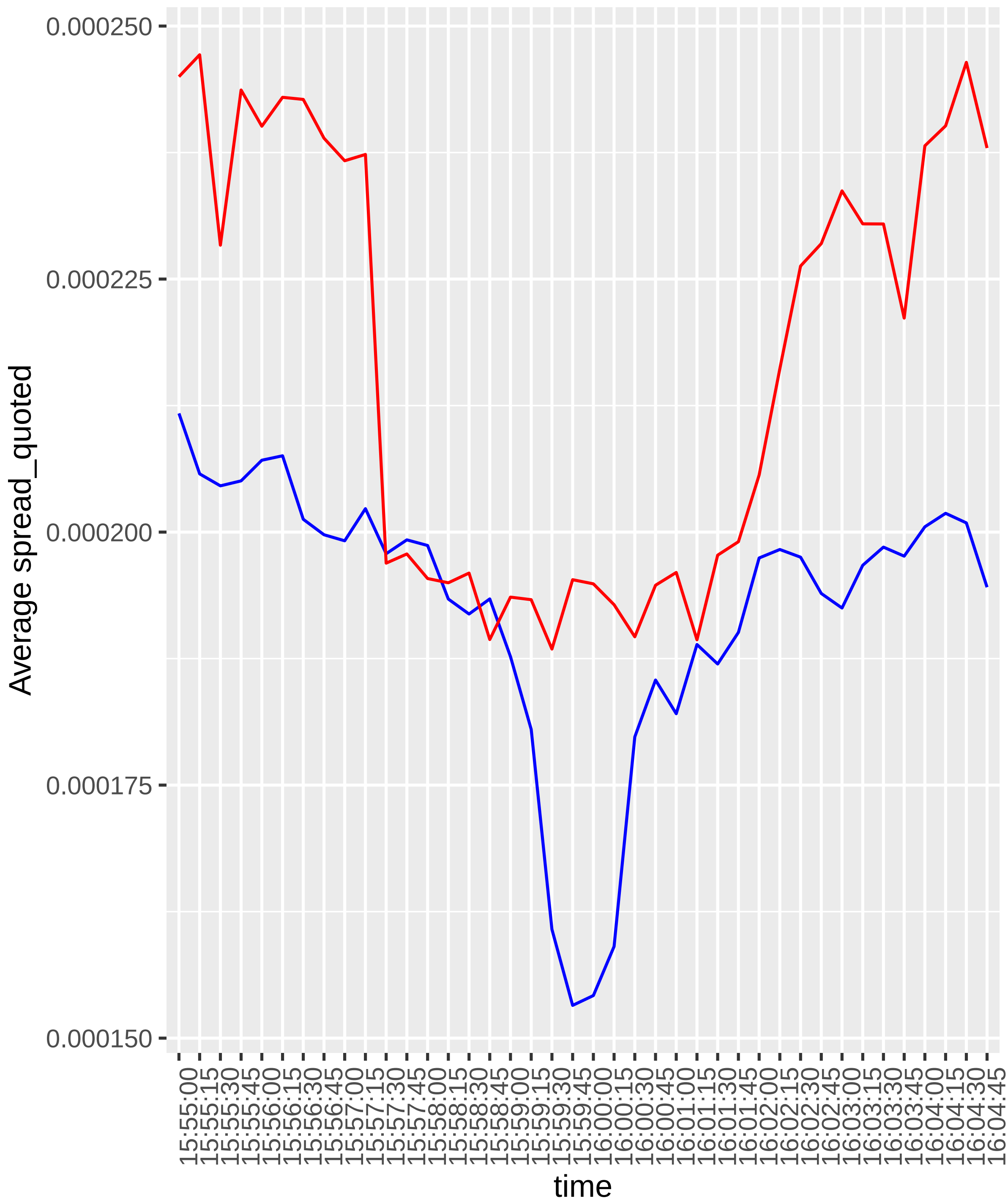


Figure 15: Mean Total Volume — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports mean volume in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample.

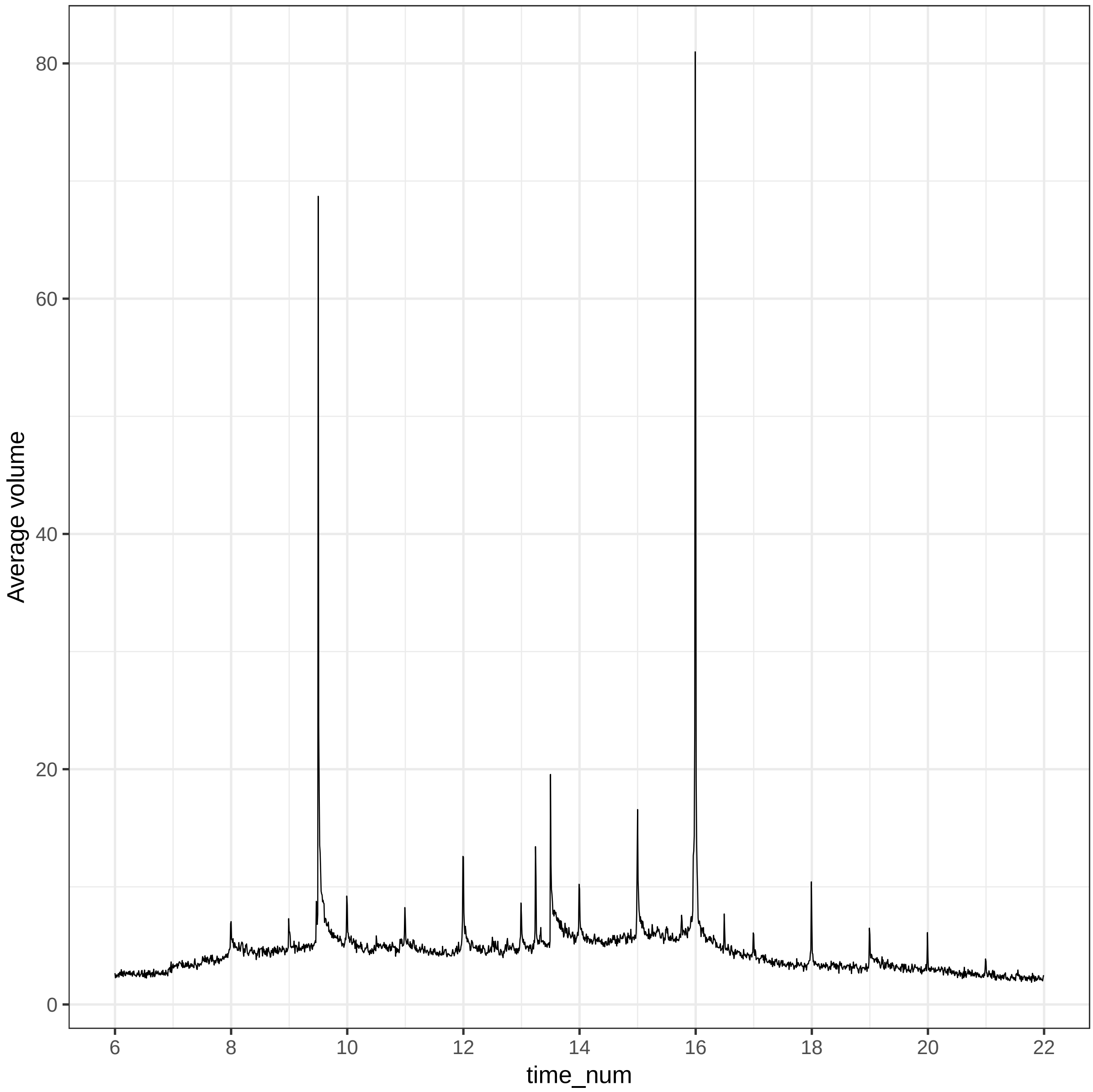


Figure 16: Mean Total Volume — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean volume in AUDUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample.

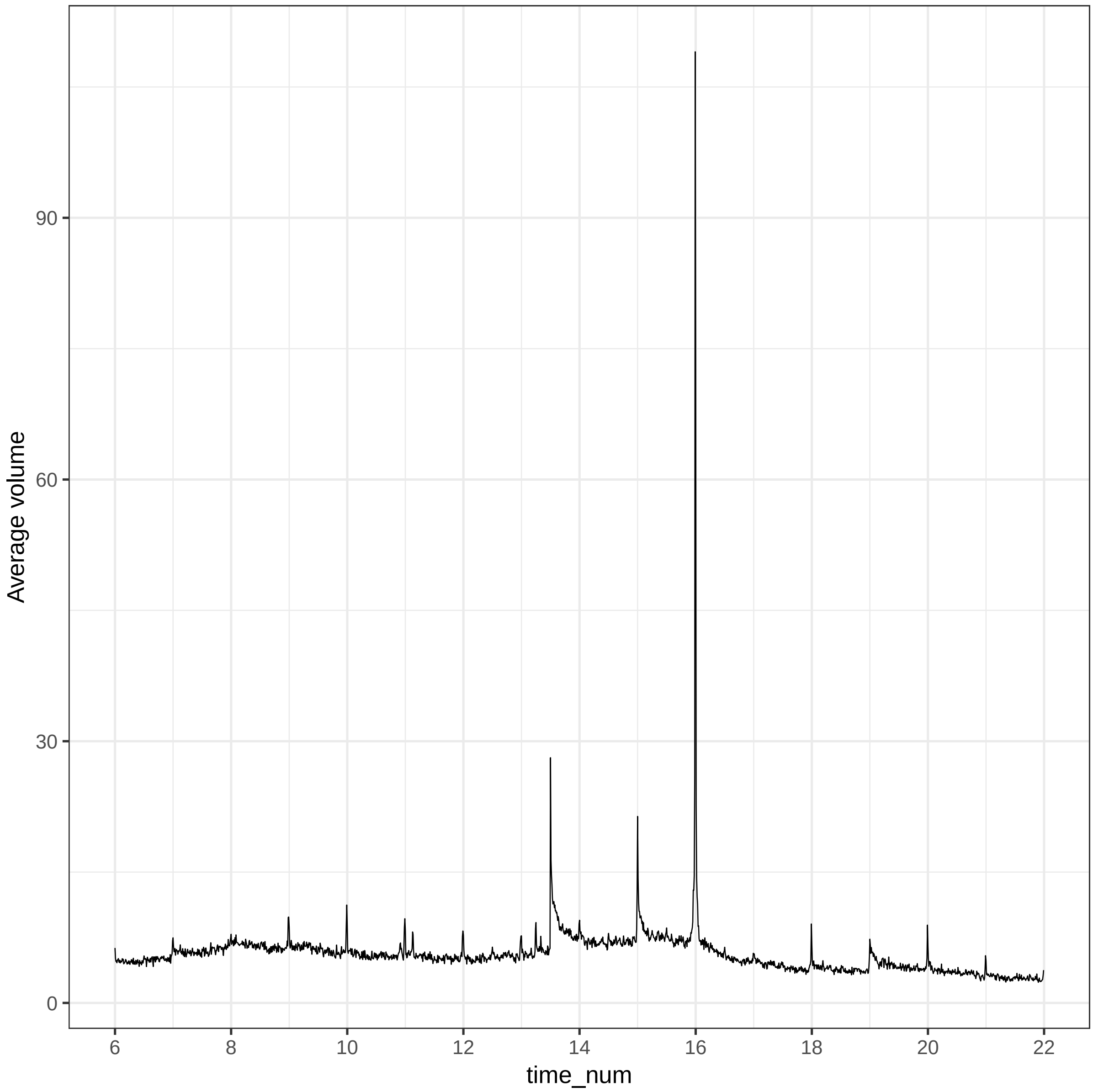


Figure 17: Mean Time-Weighted Quoted Spreads — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports time-weighted quoted spreads in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The spread is in absolute values.

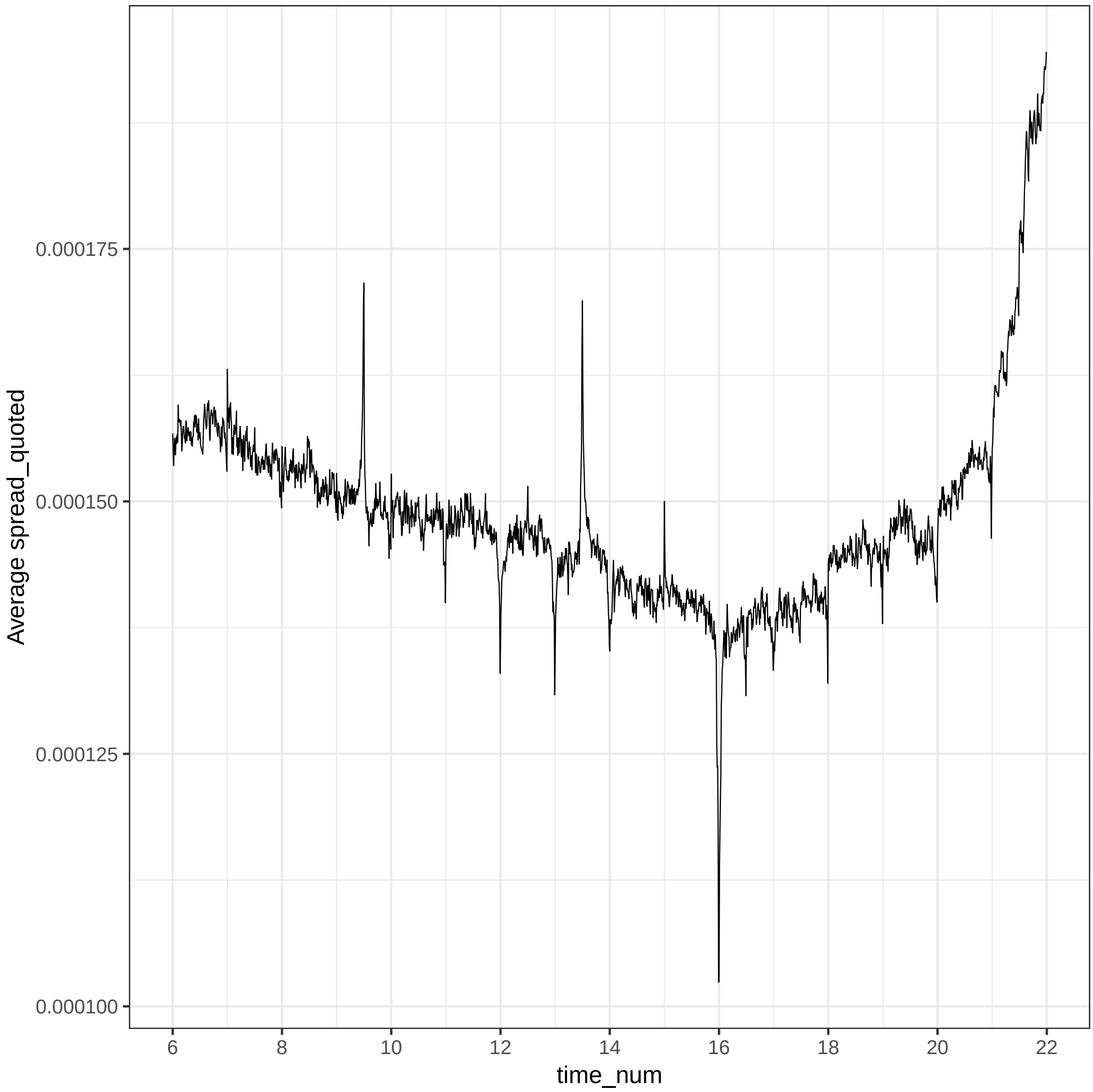


Figure 18: Mean Time-Weighted Quoted Spreads — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean time-weighted quoted spreads in AUDUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The spread is in absolute values.

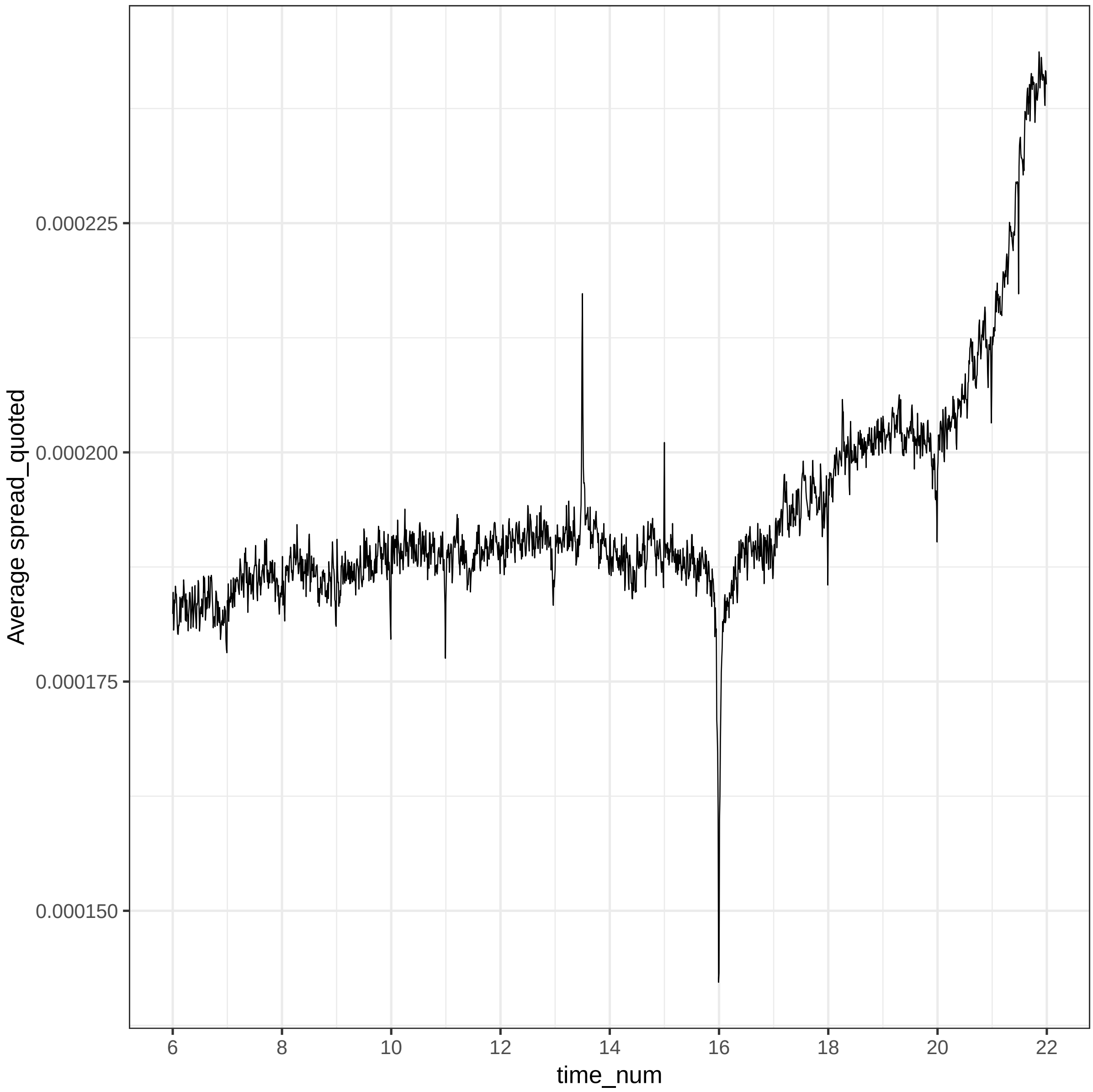


Figure 19: Mean Volume-Weighted Effective Spreads — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports mean volume-weighted effective spreads in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The spread is in absolute values.

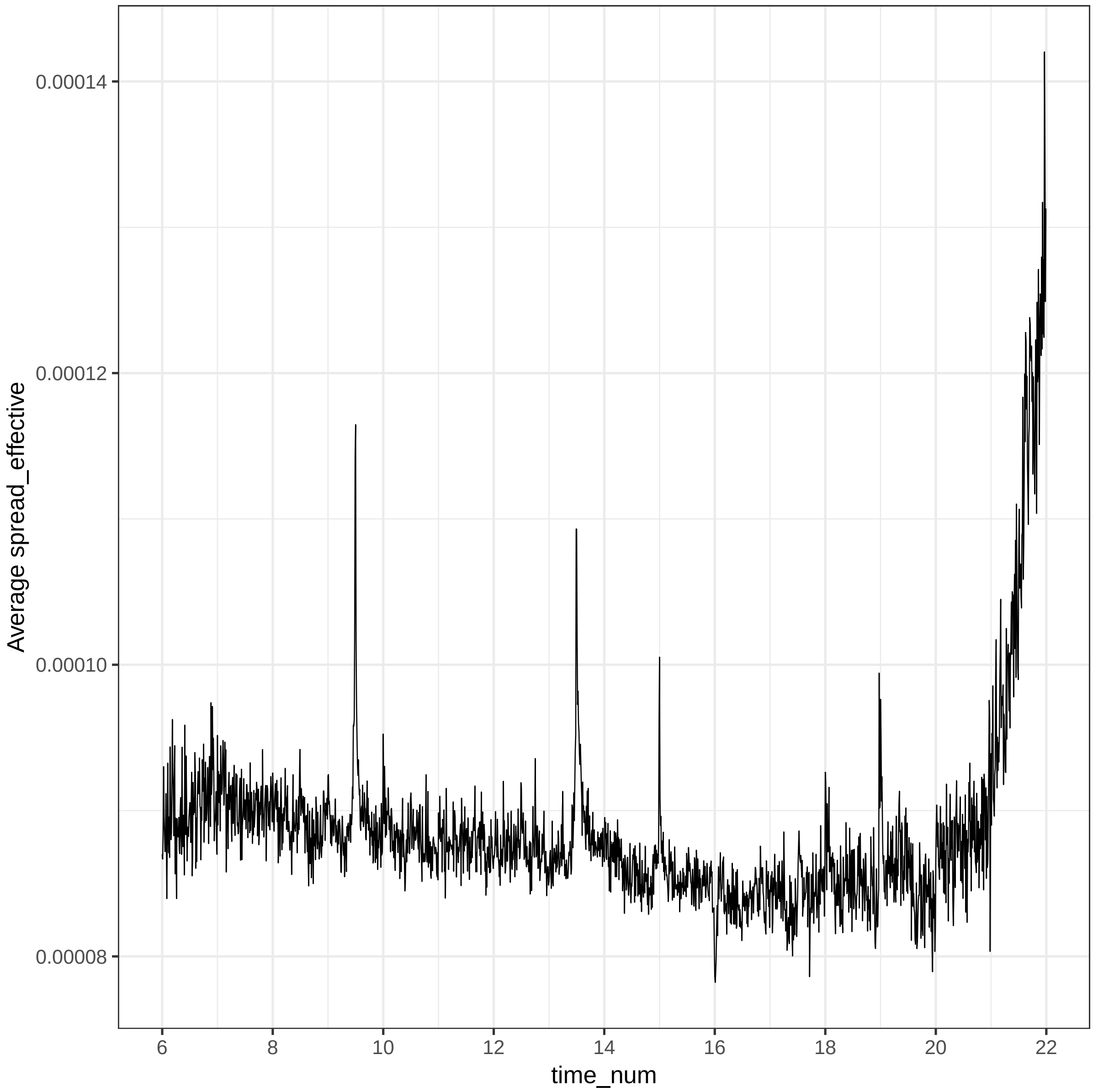


Figure 20: Mean Volume-Weighted Effective Spreads — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean volume-weighted effective spreads in AUDUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The spread is in absolute values.

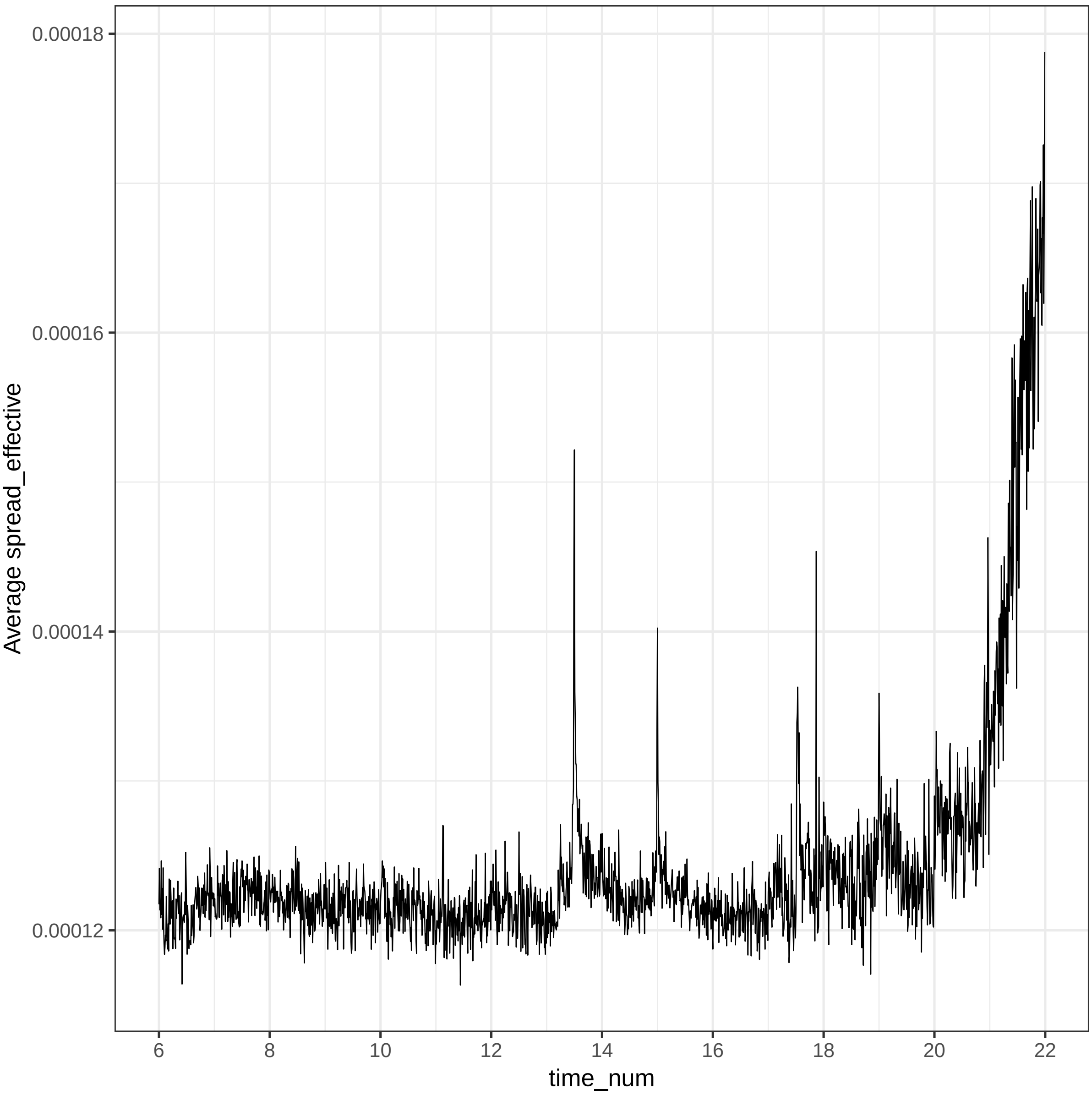


Figure 21: Mean Volume-Weighted 1-Second Price Impact — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports mean volume-weighted price impacts in GBPUSD, calculated over 1 second, for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The price impact is in absolute values.

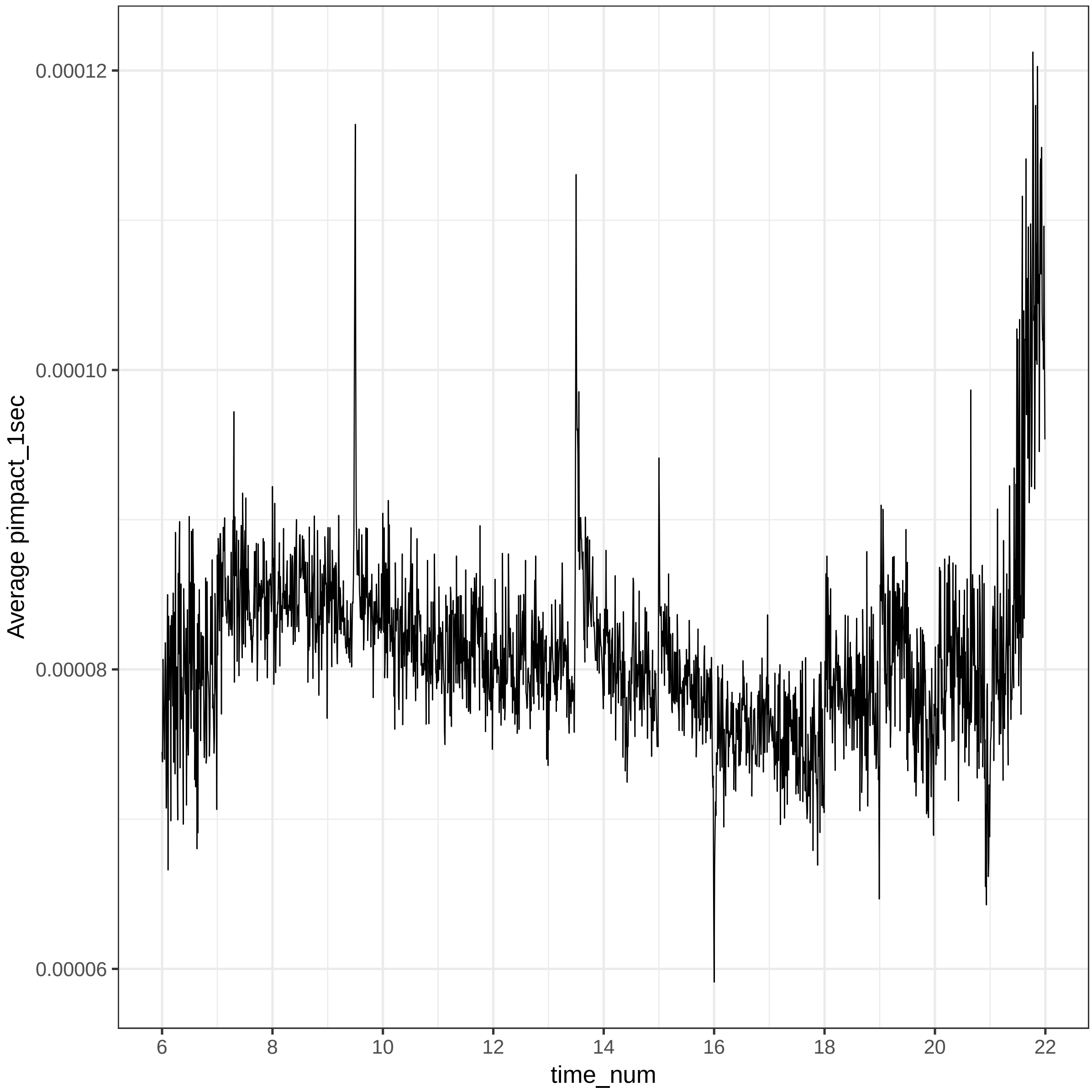


Figure 22: Mean Volume-Weighted 1-Second Price Impact — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean volume-weighted price impacts in AUDUSD, calculated over 1 second, for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. The price impact is in absolute values.

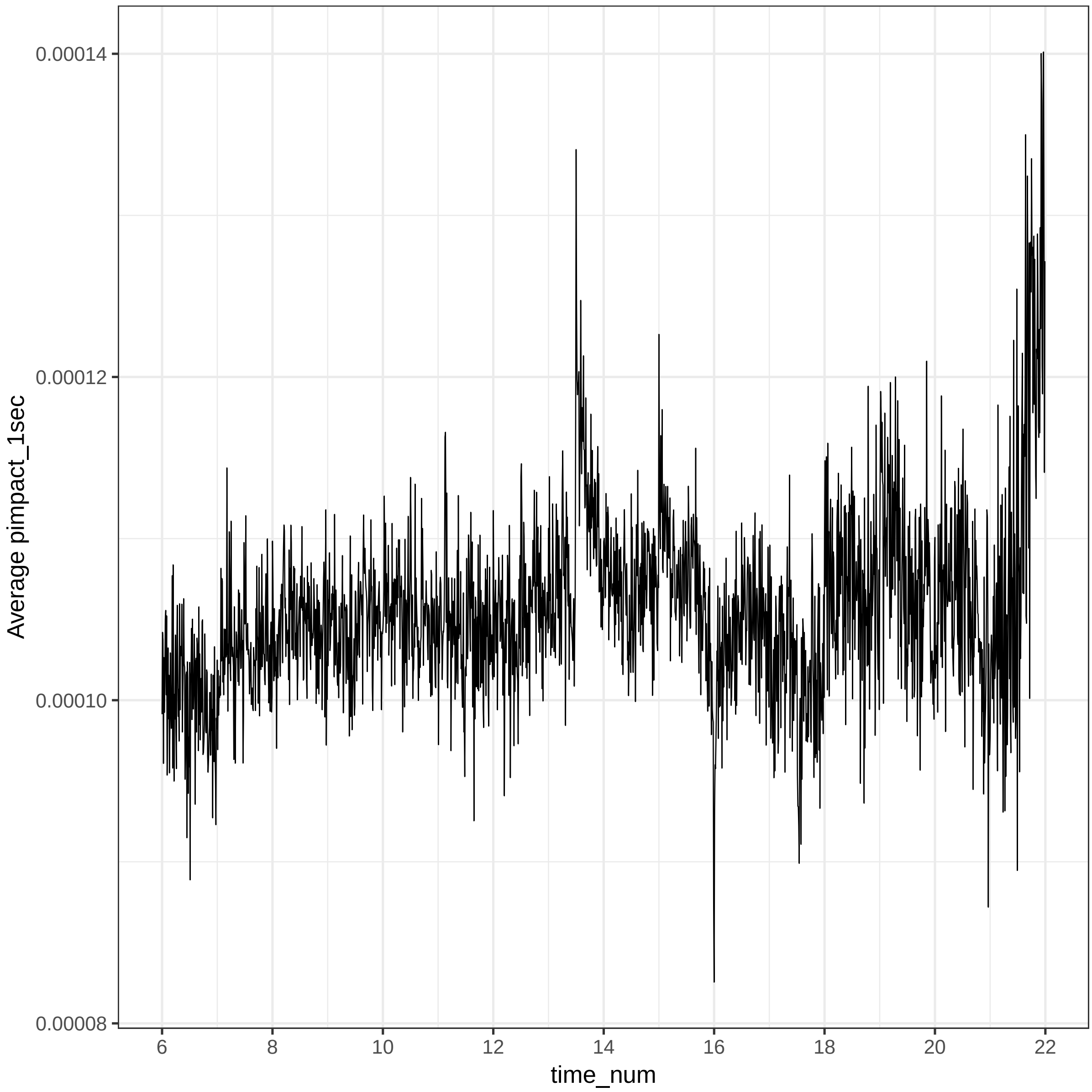


Figure 23: Mean Time-Weighted Average Depth at the Best Bid or Offer — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports time-weighted average depths in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. Depth is reported with millions of USD.

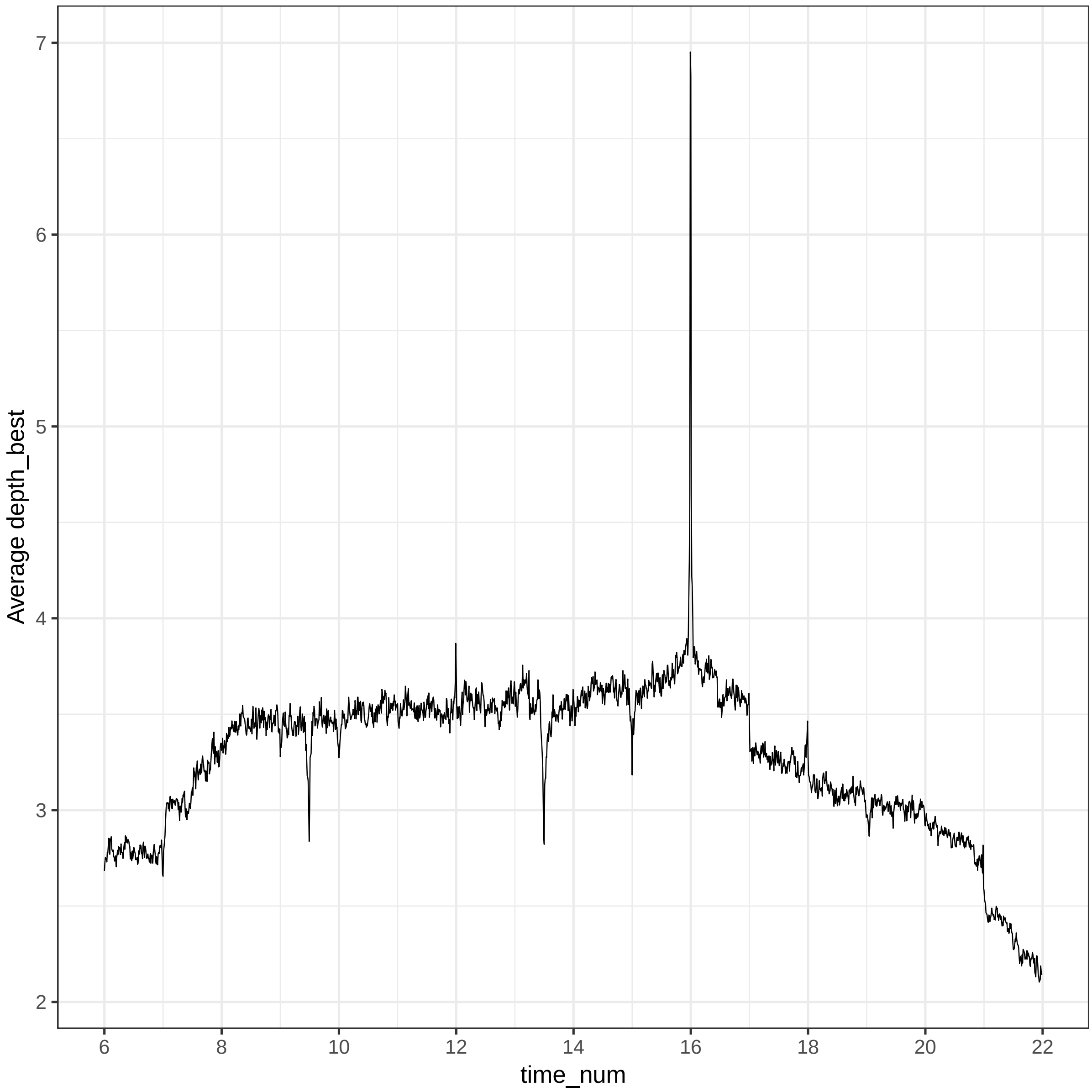


Figure 24: Mean Time-Weighted Average Depth at the Best Bid or Offer — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean time-weighted average depths in AUDUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. Depth is reported with millions of USD.

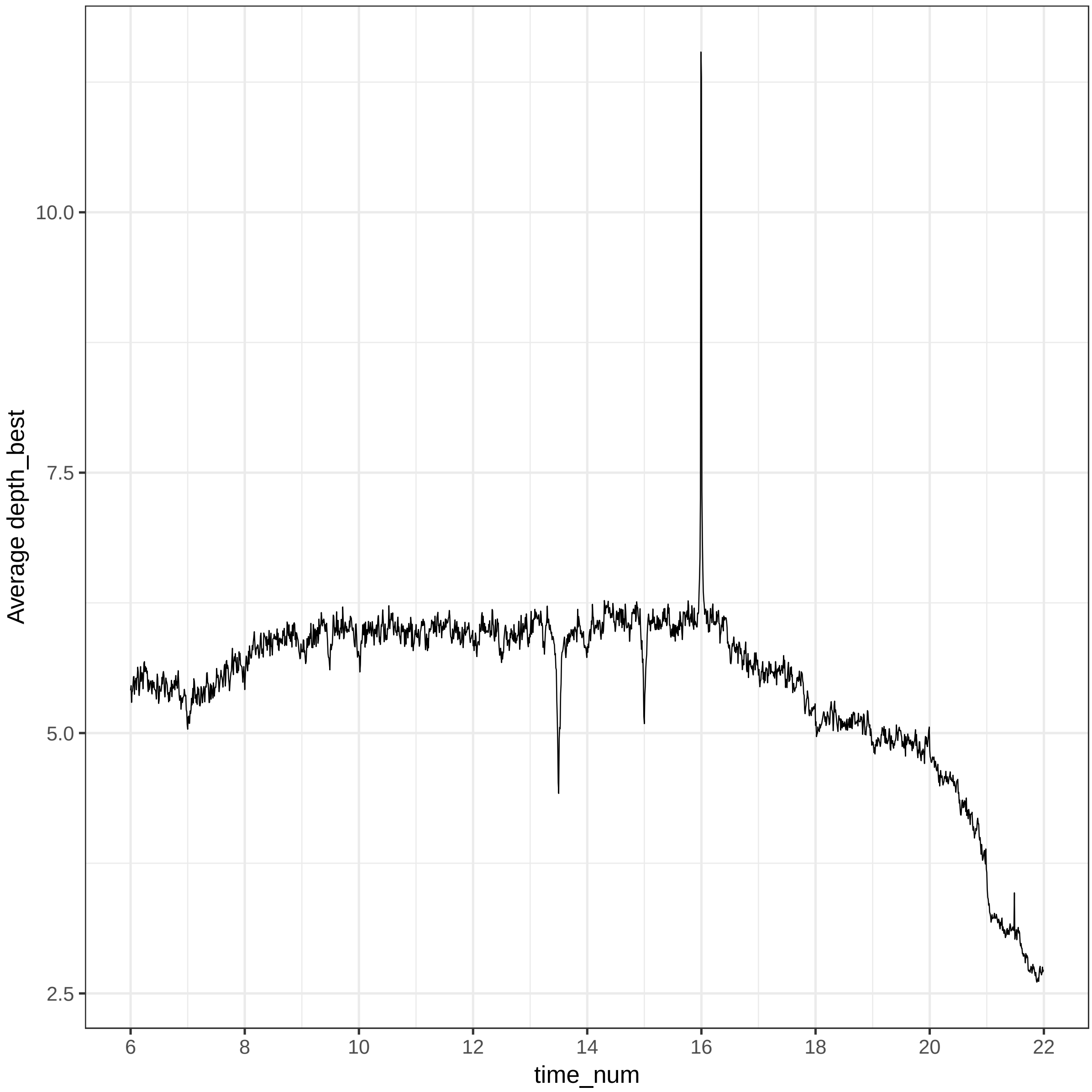


Figure 25: Mean Time-Weighted Average Depth at the Top 10 Best Bid or Offer Levels — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports time-weighted average depths in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. Depth is reported with millions of USD.

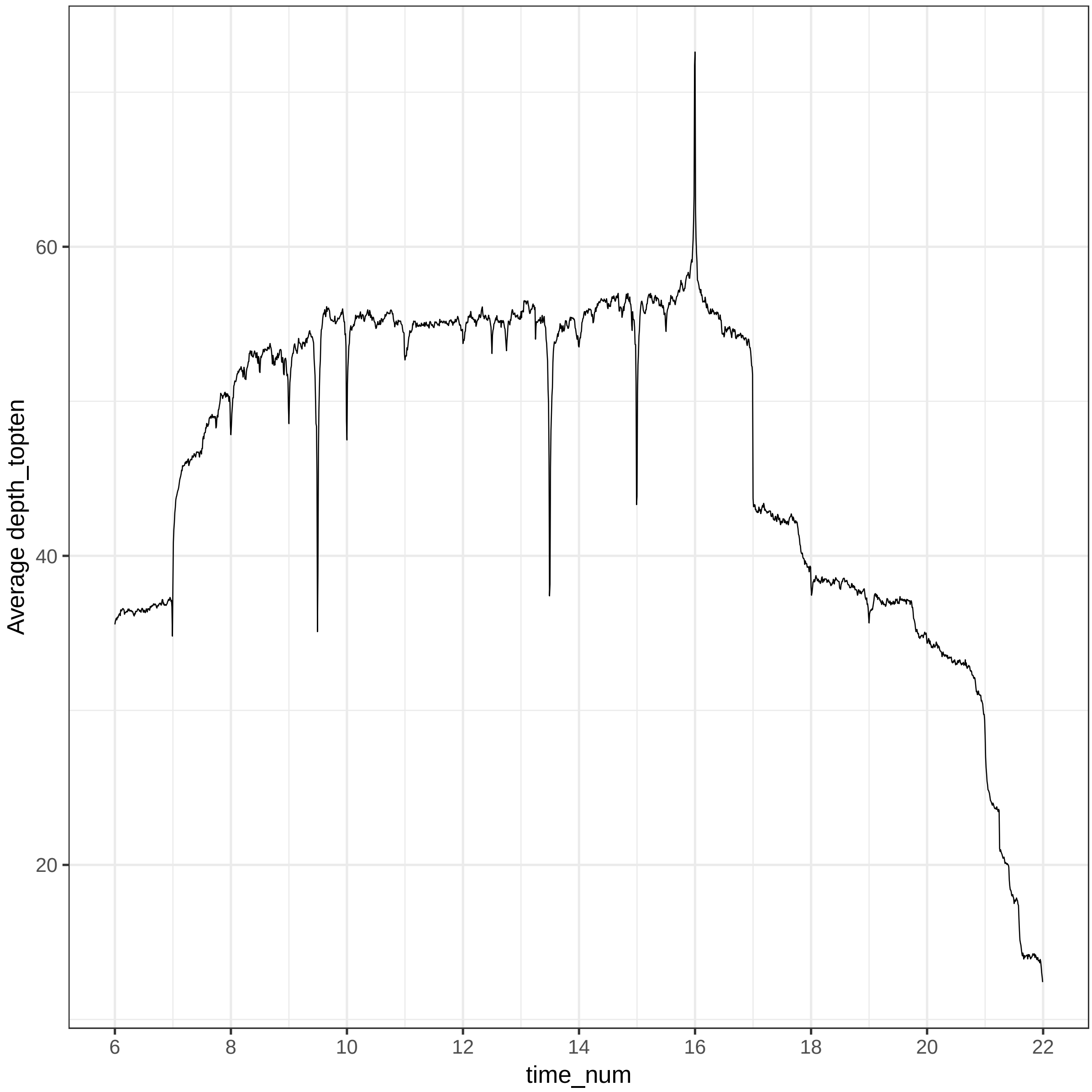


Figure 26: Mean Time-Weighted Average Depth at the Top 10 Best Bid or Offer Levels — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports mean time-weighted average depths in AUDUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. Depth is reported with millions of USD.

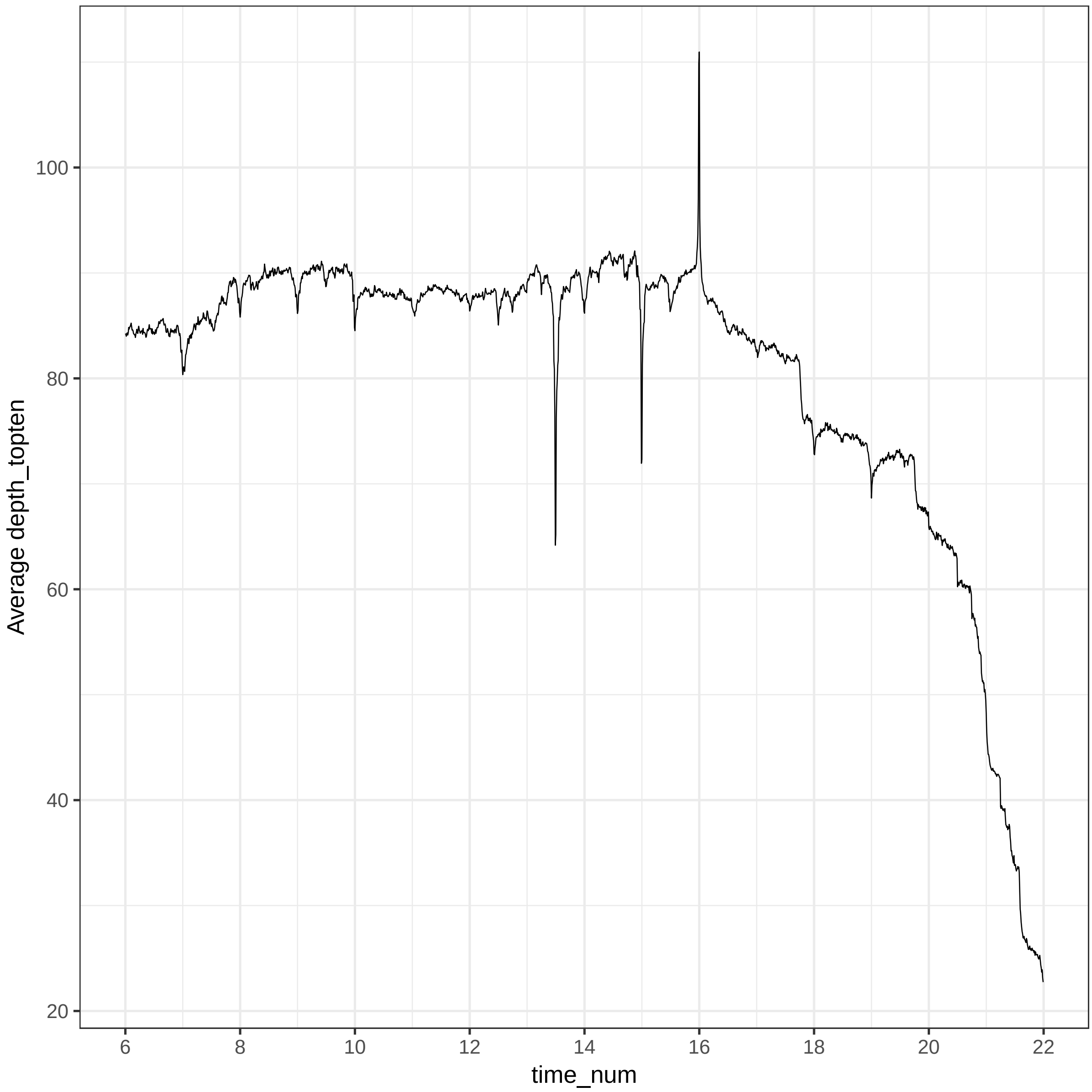


Figure 27: Volatility — Mean of High Minus Low of Trade Prices in Each 30 Seconds — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports time-weighted average depths in GBPUSD for 30-second time intervals from 6am to 10pm, with means calculated across all dates in our sample. Reported in absolute values.

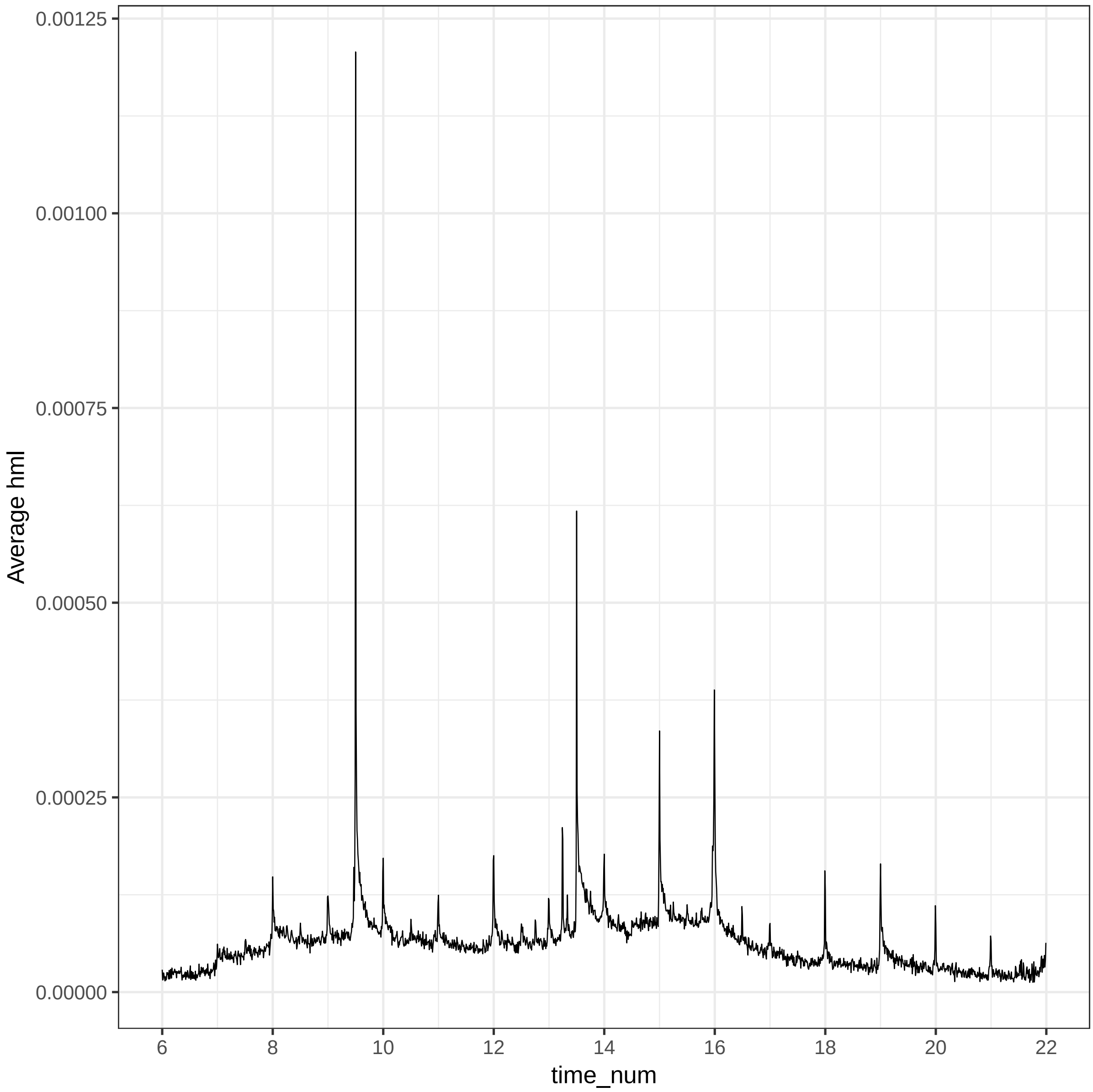


Figure 28: Volatility — Mean of High Minus Low of Trade Prices in Each 30 Seconds — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports the mean, across the entire sample, of the highest minus the lowest trade price in a 30 second interval, from 6am to 10pm. Reported in absolute values.

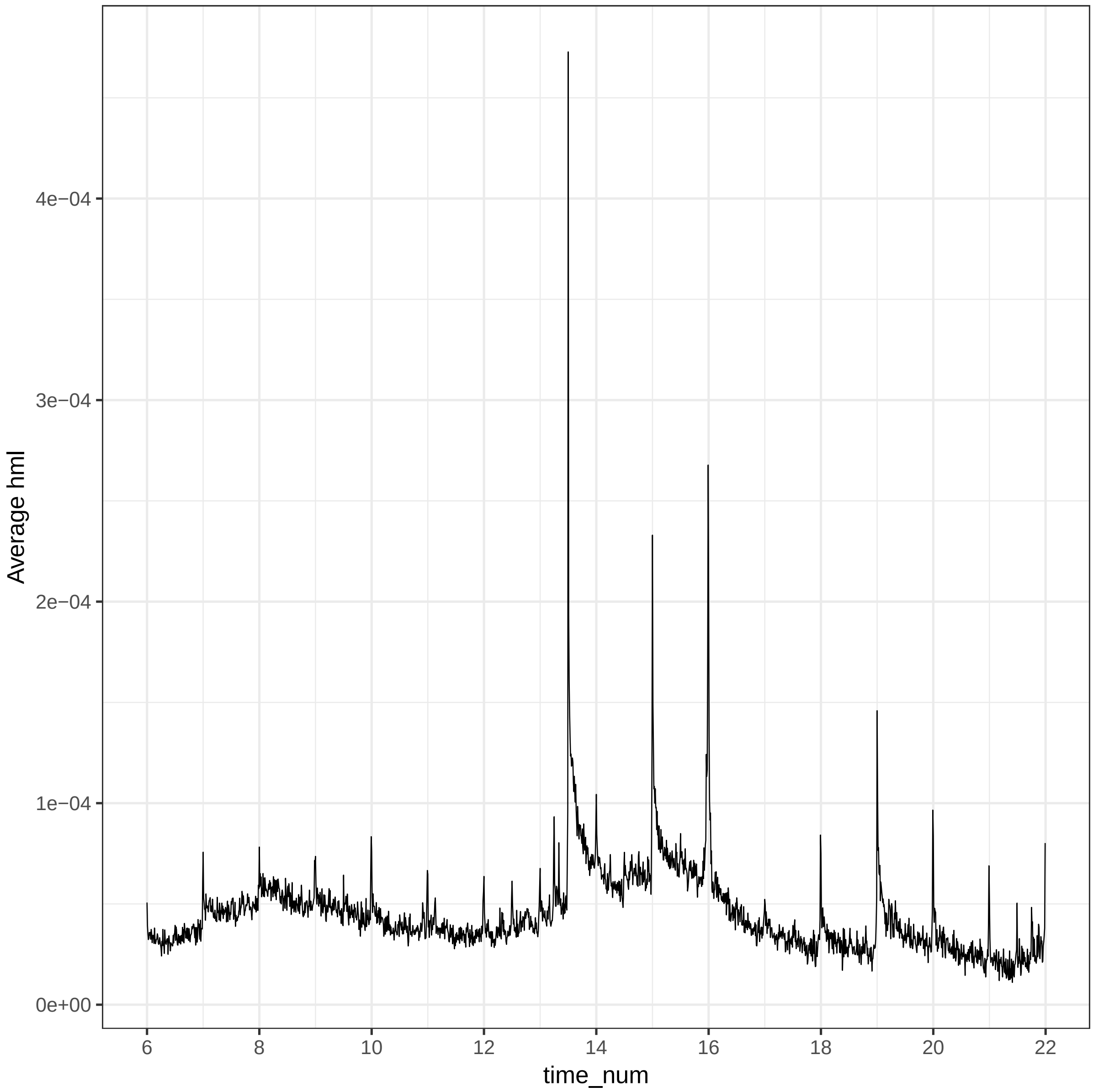


Figure 29: Mean Total Number of Messages Entire Sample — 6am to 10pm — GBPUSD
This Figure reports the total number of messages in each 30 second interval, calculated as a mean across the entire sample. Reported in absolute values.

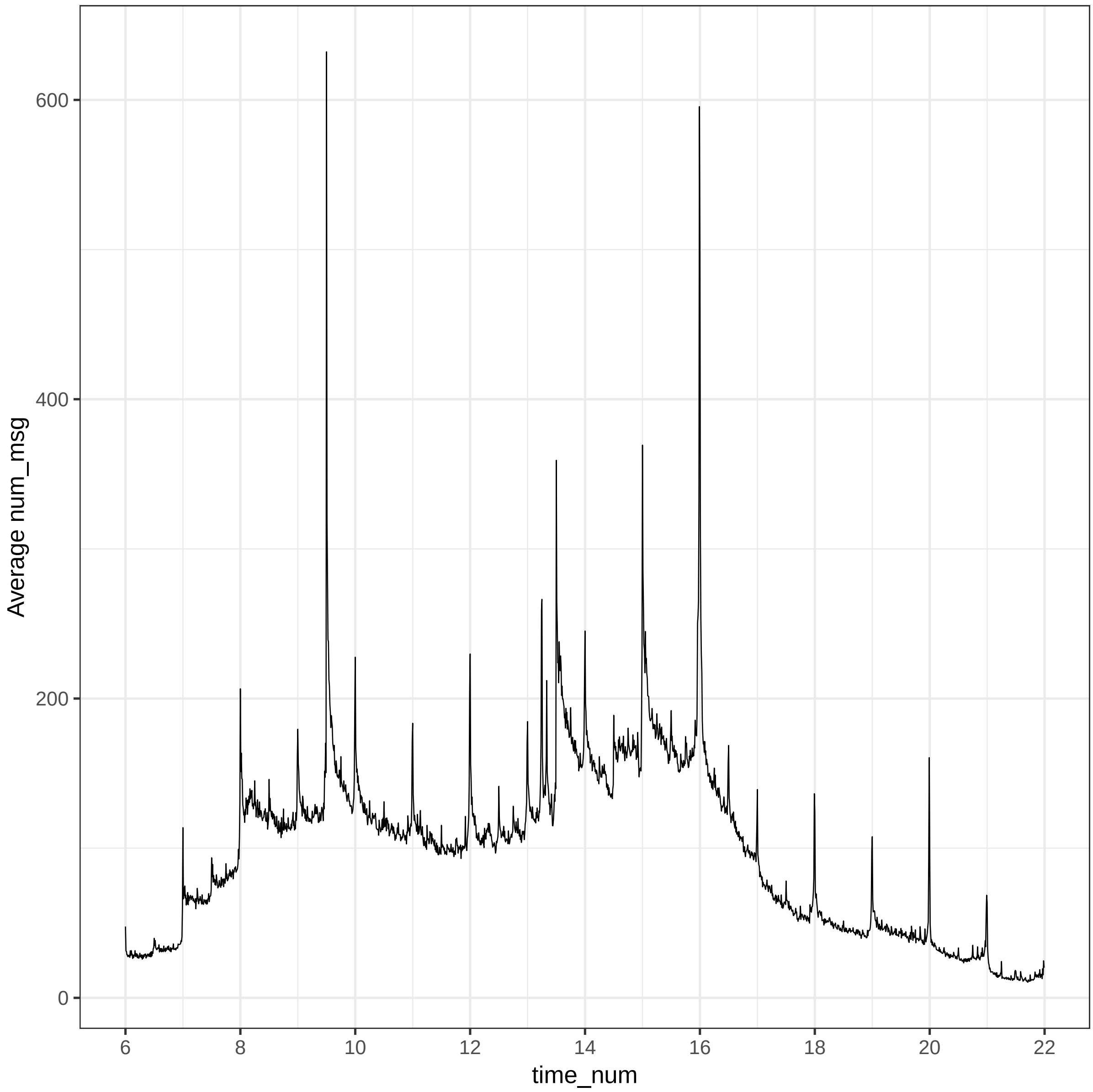


Figure 30: Mean Total Number of Messages Entire Sample — 6am to 10pm — AUDUSD
This Figure reports the total number of messages in each 30 second interval, calculated as a mean across the entire sample. Reported in absolute values.

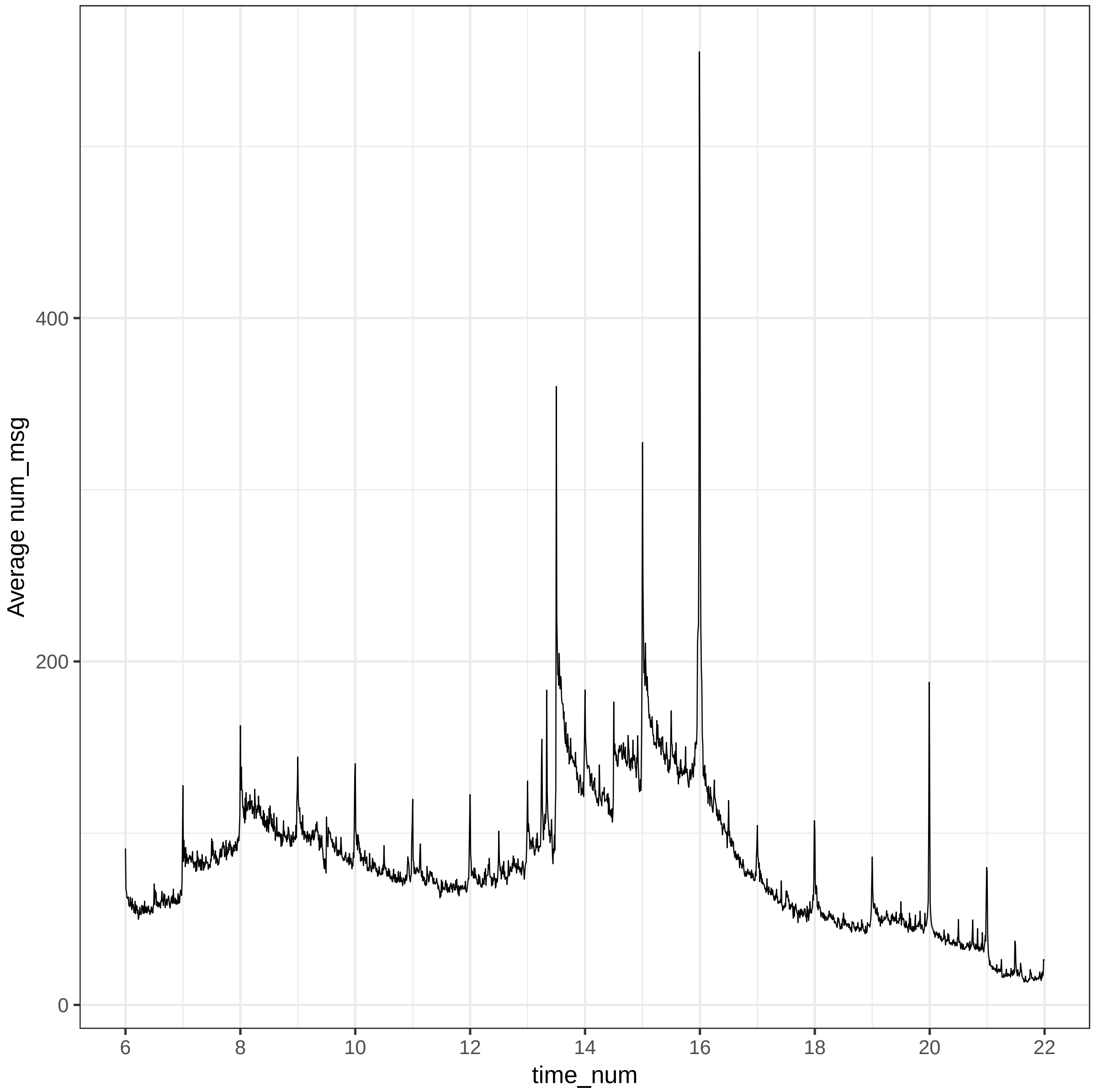


Figure 31: Mean Order-book Slope — Entire Sample — 6am to 10pm — GBPUSD
This Figure reports the total number of messages in each 30 second interval, calculated as a mean across the entire sample. Reported in absolute values.

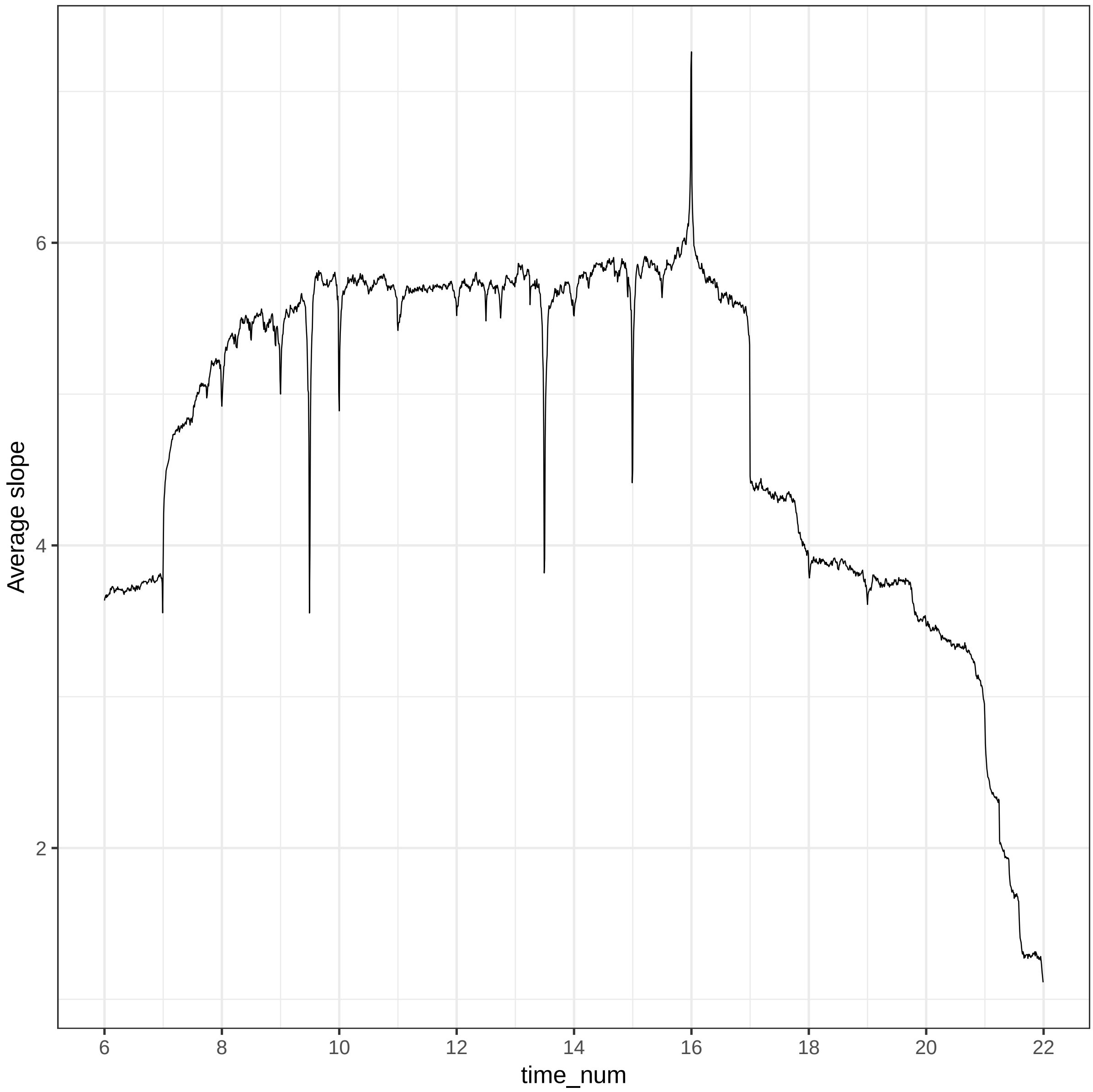


Figure 32: Mean Order-book Slope — Entire Sample — 6am to 10pm — AUDUSD
This Figure reports the mean order-book slope, calculated as the depth at the best bid(ask) less the depth at the top ten buy(sell) levels, divided by 9. This is then calculated as a time-weighted average and then as a mean across the entire sample..

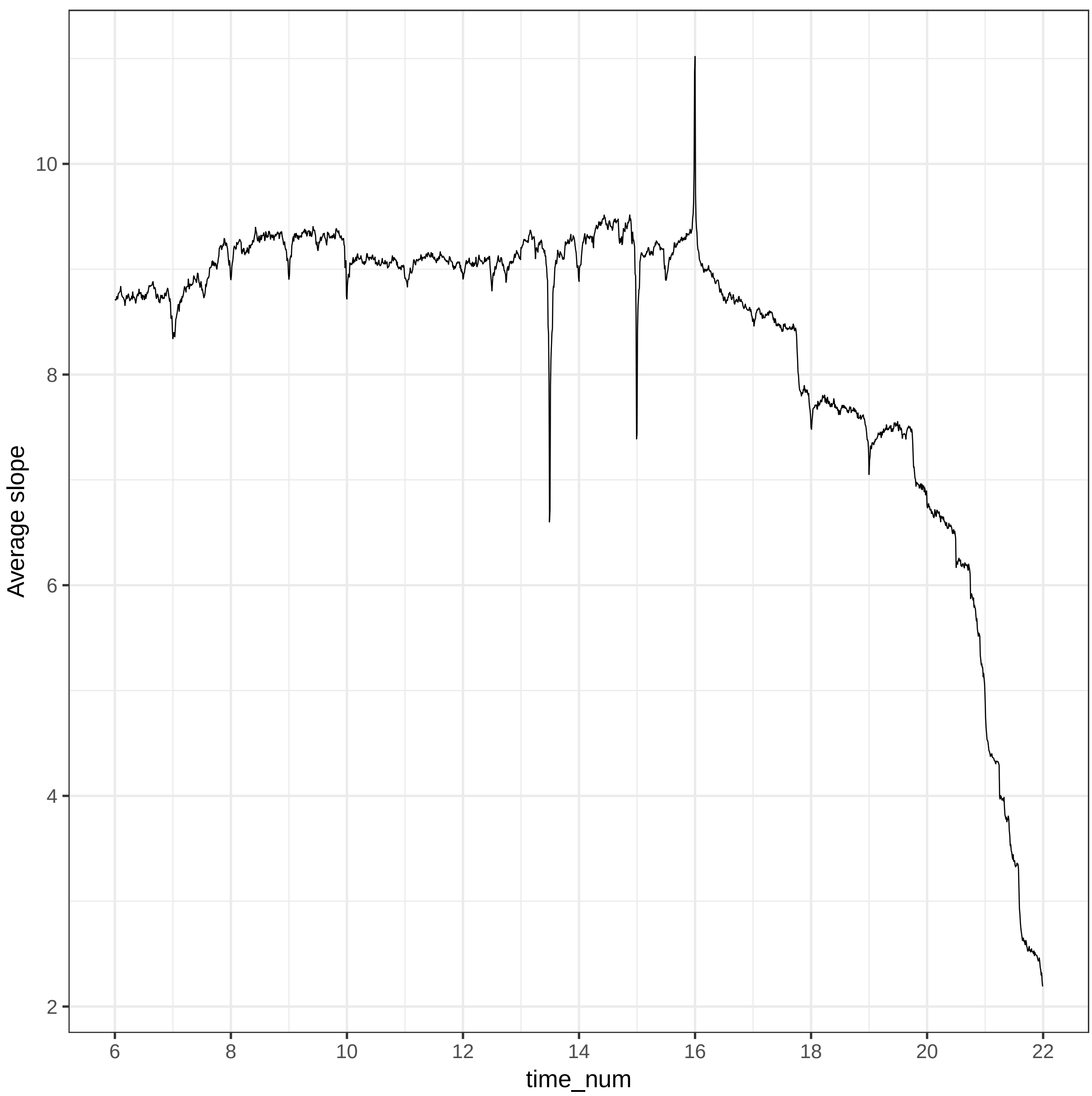


Table 33: Summary Statistics During the full trading day from 8am to 8pm — by Currency-Year
Volume is total volume during the trading day from 8am to 8pm. Depth is computed as the average of depth at bid and offer sides of the book (at the best bid and offer and the top 10 levels or all levels). Mean number of messages ('#msg'), quote life ('q.lif'), unique TCIDs ('#TCIDs'), number of trades ('#trades') and number of aggressor trades ('#agr.trades') are calculated across all currency-dates. #agr.trades is smaller than #trades because it doesn't include the component orders that make up a trade - of which there are least 2. Quoted spread ('Qtd.Sprd') is time-weighted, effective spreads ('Eff.Sprd.') and price impact (PI) is volume-weighted in basis points.

Pair	Year	# TCIDs	Volume	Depth best	Depth top	Depth total	#msg	q.life	# trades	#agr. trades	Qtd. sprd	Eff. sprd	PI 1ms	PI 1s	PI 5s
	2012	223.2	14950.3	8.1	121.1	283.4	187219.2	245.2	10332.6	4224.4	1.46	1	0.88	0.98	1.07
	2013	222.9	18177.2	5.8	88.7	239.8	191810.9	180.44	12881.1	5511.4	1.76	3.9	0.89	1.18	1.27
audusd	2014	198.5	12218.4	6.3	87	252.6	156363.4	216.48	8556.1	3701.5	1.91	1.3	0.96	1.18	1.28
	2015	183.2	12843.6	5.7	76.5	249	212718.8	146.06	9606.6	4277	2.54	1.6	1.16	1.53	1.6
	2017	138.9	6540.8	6.2	87.4	314.9	186881.7	119.85	4868.5	2107.5	2.04	1.4	1.14	1.34	1.39
	2012	88.2	1001.3	1.6	4.3	32.4	10415.1	944.36	821.7	396.9	6.79	3.7	2.37	2.52	2.73
	2013	88.9	1288.1	2	5.1	34.6	15273	563.57	1048	497.7	6.86	3.5	2.21	2.3	2.48
eurhuf	2014	79.4	1203.8	1.9	5.1	32.8	21162.4	410.13	1013.3	484.7	6	3	2.2	2.1	2.23
	2015	71.1	1215.7	1.9	4.4	30.7	18946.8	422.73	1036.8	500.2	7.89	3.9	2.95	2.66	2.84
	2017	58.1	620.3	2	8.3	41.4	49627.6	88.96	535	252.8	4.41	2.7	1.38	1.65	1.93
	2012	115.5	3674.7	1.9	4.1	35	47752.5	384.83	2805.3	1351.4	2.88	1.5	1.32	1.27	1.4
	2013	107.9	3541.1	2	4.1	33.9	80000.9	170.29	2780.8	1321.6	3.37	1.8	1.48	1.46	1.7
eursek	2014	97.3	2779.7	2	4.3	32.1	77906	128.82	2270.4	1089.8	3.44	1.7	17.22	4.1	9.53
	2015	92.3	3575.4	2.2	4.3	43.6	177314.6	147.86	2912.2	1405	4.88	2.3	1.83	1.92	2.26
	2017	80.7	2337.5	3.1	15.3	106.1	84043.1	50.18	1885.1	889.5	2.7	1.5	0.97	1.37	1.5
	2012	151.2	2047.7	3.4	28.6	48.6	170697.9	101.25	1504.5	724.6	1.28	0.8	0.52	0.91	1.07
	2013	132.8	1678.7	2.4	33.1	57.8	125233.2	78.14	1258.5	616.9	1.62	1	0.53	1.06	1.17
eurusd	2014	114.8	1349.7	2.5	39	61.6	71431.9	120.46	970.4	462.4	1.58	1.1	0.62	1.01	1.11
	2015	113.1	1697.3	2.2	37.5	56.5	167992	141.97	1158.5	562.3	2.22	1.6	0.9	1.71	1.81
	2017	77.8	1196.2	1.3	15.4	55.7	151302.6	38.14	1047.9	489.3	1.28	1	0.66	1.05	1.12
	2012	206.3	10615.7	4.5	72.2	135.8	184067	130.59	8114	3609.1	1.16	0.8	0.59	0.74	0.79
	2013	219.8	14557.4	3.6	57	154.2	238280	103.12	10980.5	4927.6	1.38	0.9	0.81	1	1.07
gbpusd	2014	198.3	10354.9	4	51.2	146.4	205683	150.28	7906.4	3599.1	1.31	0.8	0.69	0.87	0.91
	2015	180.2	11219	3.3	41.5	152.9	251627.8	175.88	8832	4145.6	1.8	1.1	0.78	1.05	1.11
	2017	150	8049.7	3.6	47.1	296.1	222747.3	71.86	6312	2874.6	1.76	1.1	0.9	1.17	1.2

Table 34: Media event : Mean volume of aggressive and passive trades, by fix quarter, before and after (*) the event, for GBPUSD and AUDUSD. Volume is first summed across all TCIDs in each participant group, for each currency-date-fix quarter combination, and then averaged across currency pairs and dates. Absolute value ('Tot') in million of base currency, quarterly volume ('Q') as share of total. P-value of two-sample t-test for difference in mean of the ratio (first half)/(second half).

Participant			Before					After			
Aggr. Trades:	Tot	Q1	Q2	Q3	Q4	Tot*	Q1*	Q2*	Q3*	Q4*	p-value
Agency Broker	29.4	0.26	0.28	0.20	0.26	26.7	0.29	0.24	0.24	0.23	0.31
Asset Manager	15.0	0.20	0.27	0.31	0.22	26.0	0.12	0.60	0.21	0.08	
Commercial Bank	45.8	0.25	0.29	0.25	0.21	38.2	0.28	0.30	0.23	0.19	0.52
Custodian	24.2	0.29	0.32	0.22	0.18	27.3	0.33	0.26	0.23	0.18	0.13
Dealer	63.4	0.32	0.28	0.24	0.16	65.5	0.29	0.29	0.22	0.20	0.70
Dealer - R	110.5	0.32	0.31	0.22	0.15	98.8	0.31	0.32	0.21	0.17	0.63
Hedge Fund	9.6	0.10	0.27	0.42	0.21	14.9	0.19	0.41	0.13	0.27	0.57
Private Bank	27.5	0.36	0.11	0.36	0.16	8.3	0.24	0.28	0.12	0.36	
Prop Trader	14.4	0.28	0.26	0.23	0.23	17.4	0.30	0.28	0.22	0.20	0.67
Prop Trader - HFT	56.3	0.35	0.28	0.21	0.17	57.8	0.34	0.26	0.22	0.17	0.20
Passive Trades:											
Agency Broker	46.6	0.30	0.24	0.26	0.20	27.0	0.22	0.30	0.27	0.21	0.92
Asset Manager	21.7	0.25	0.31	0.34	0.11	6.3	0.21	0.32	0.16	0.32	
Commercial Bank	41.1	0.25	0.32	0.24	0.19	47.0	0.30	0.29	0.23	0.19	0.77
Custodian	29.3	0.27	0.30	0.25	0.18	23.1	0.28	0.26	0.26	0.20	0.01
Dealer	63.0	0.31	0.31	0.23	0.16	78.5	0.30	0.30	0.23	0.18	0.06
Dealer - R	109.0	0.33	0.31	0.22	0.15	109.5	0.31	0.31	0.21	0.16	0.33
Hedge Fund	7.2	0.20	0.34	0.14	0.33	11.3	0.14	0.19	0.44	0.22	0.66
Private Bank	17.5	0.25	0.37	0.11	0.27	5.9	0.40	0.17	0.17	0.26	
Prop Trader	8.6	0.27	0.28	0.26	0.19	9.4	0.27	0.22	0.22	0.29	0.59
Prop Trader - HFT	37.1	0.38	0.26	0.23	0.14	26.7	0.38	0.25	0.19	0.19	0.18

Table 35: Mean number of trades and proportion of seconds with trades during the fix. Calculated as a mean across all seconds in a given year.

Pair	Year	Mean #Trades	% Sec. w Trades
audusd	2012	1.34	0.48
audusd	2013	1.49	0.52
audusd	2014	1.25	0.47
audusd	2015	0.49	0.27
audusd	2017	0.27	0.15
eurhuf	2012	0.07	0.05
eurhuf	2013	0.07	0.06
eurhuf	2014	0.08	0.06
eurhuf	2015	0.04	0.03
eurhuf	2017	0.03	0.03
eursek	2012	0.59	0.36
eursek	2013	0.56	0.33
eursek	2014	0.55	0.29
eursek	2015	0.23	0.14
eursek	2017	0.16	0.11
eurusd	2012	0.05	0.04
eurusd	2013	0.04	0.03
eurusd	2014	0.04	0.03
eurusd	2015	0.03	0.02
eurusd	2017	0.04	0.03
gbpusd	2012	1.19	0.48
gbpusd	2013	1.38	0.51
gbpusd	2014	1.16	0.44
gbpusd	2015	0.50	0.27
gbpusd	2017	0.46	0.23

Table 36: Mean number of messages, quote life, unique TCIDs, number of trades and number of aggressor trades, daily by time window (fix or control). The mean is first taken with respect to all trades for a given currency pair-date combination, and then averaged across all currencies.

Period	#msg	q.life	#TCIDs	#trades	#agr.trades
control	25384.2	103.96	79.2	915.3	411.0
fix	1342.5	111.60	29.6	123.7	57.2

Table 37: Mean trading volume and depth of orderbook and best prices, top ten levels and total. Depth is computed as average of bid and offer, daily by time window (fix or control). Each measure is first averaged across all observations for a given date-currency pair combination, the aggregated into a single daily mean.

Period	Volume	Depth best	Depth top	Depth total
control	1218.2	3.4	38.6	120.4
fix	213.6	5.4	46.9	129.0

Table 38: Mean quoted and effective spreads and price impacts. Quoted spread is time-weighted, effective spreads and price impact is volume-weighted. Unit: basis points. The mean is first taken with respect to all trades for a given currency pair-date combination, and then averaged across all currencies. Daily by time window (fix or control).

Period	Qtd.sprd	Eff.sprd	Pr.impact 1ms	Pr.impact 1s	Pr.impact 5s
control	2.61	1.8	1.20	1.38	1.49
fix	2.15	1.7	1.03	1.12	1.23

Table 39: Media event: Mean price impact (5sec), by fix quarter, before and after (*), for GBPUSD and AUDUSD. Basis points. P-value for two-sample t-test of difference in mean price impact across the entire fix.

Participant	Q1	Q2	Q3	Q4	Q1*	Q2*	Q3*	Q4*	p-value
Agency Broker	1.4	0.8	1.2	0.6	0.8	1.0	0.7	-0.4	0.14
Asset Manager	1.0	-1.3	2.1	-1.0	1.0	0.0	0.0	1.3	
Commercial Bank	0.4	0.3	0.6	0.8	0.4	0.7	0.5	0.5	0.44
Custodian	0.6	0.8	0.8	0.8	0.5	0.5	0.8	0.5	0.95
Dealer	0.7	0.7	0.5	0.6	0.6	0.8	0.6	0.9	0.13
Dealer - R	1.2	0.9	0.7	1.0	0.6	0.7	0.6	0.8	0.67
Hedge Fund	0.0	0.4	0.0	1.0	1.1	1.1	0.1	1.1	0.33
Private Bank	-4.1	-0.8	3.1	1.1	1.1	-0.6	0.6	0.0	
Prop Trader	0.4	0.5	0.2	0.6	0.7	0.7	0.8	1.0	0.15
Prop Trader - HFT	0.6	0.6	0.7	0.9	0.7	0.8	1.0	0.7	0.79

Table 40: Correlation of flows (net position change) during the control window, for GBPUSD and AUDUSD. Net position change is computed as the sum of signed trade volume across all TCIDs in each category, using trades in the control window of 12pm to 2pm only.

	Broker	Ass.mngr	Cm.bank	Cstd	Dealer	Dealr-R	Hedge	Prop
Agency Broker								
Asset Manager								
Commercial Bank	-0.01	-0.10						
Custodian	-0.01	0.01	-0.12					
Dealer	-0.11	-0.15	-0.10	-0.15				
Dealer - R	-0.12	-0.13	-0.46	-0.10	-0.45			
Hedge Fund	0.05	-0.06	-0.06	-0.01	-0.07	-0.16		
Prop Trader	0.14	0.26	-0.14	-0.07	-0.09	-0.27	0.03	
Prop Trader - HFT	0.12	0.23	-0.18	-0.10	-0.21	-0.35	0.13	0.47

Table 41: Pct. negative bid-ask spread (mean, 30 seconds)

year	audusd	eurhuf	eursek	eurusd	gbpusd
2012	0.00	0.00	0.02	0.01	0.00
2013	0.02	0.01	0.02	0.01	0.01
2014	0.03	0.00	0.02	0.02	0.05
2015	0.02	0.00	0.02	0.00	0.02
2017	0.07	0.09	0.00	0.00	0.07

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