University of Cape Town

Department of Statistical Sciences

Statistics Honours Project

Order Flow Analysis of Cryptocurrency Markets

Author:
Nesan Naidoo
Dominique Chetty

Supervisor:
Andrew Paskaramoorthy

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Abstract

Order flow analysis (OFA) examines how order book events influence price changes. Silantyev (2019) found that Trade Flow Imbalance (TFI) has greater explanatory power than Order Flow Imbalance (OFI) for Bitcoin mid-price movements. This study replicates Silantyev (2019) for October 1^{st}–23^{rd}, 2017 and extends it to October 2024 to assess the generalisability of his findings under a different time period. Using trade and quote data for the XBTUSD perpetual contract from BitMEX, linear regressions were applied across multiple sampling intervals. The results confirm that in the replication period, both OFI and TFI significantly explain simultaneous mid-price changes, with TFI showing stronger explanatory power. In the extension period, OFI's explanatory power declines sharply, while TFI remains relatively more robust. This suggests structural changes in the cryptocurrency market microstructure and liquidity since 2017. These findings offer insights for both market participants and researchers modelling order flow in cryptocurrency markets.

Contents

1 Introduction

1.1 Background and Context

Understanding price formation, which is the process by which supply and demand determine asset prices, is central to market efficiency, liquidity provision, and the development of trading strategies (Karpoff, 1987; Cont and Larrard, 2013). Order flow, which captures the sequence of buy and sell orders in a market, plays a key role in price formation as it acts as a direct signal of demand and supply imbalances (Chordia et al., 2002). In traditional markets, Order Flow Analysis (OFA) has emerged as a framework for studying buy and sell activity. This helps researchers and traders understand short-term price changes and market sentiment.

Over the last decade, cryptocurrency markets have emerged as an important and rapidly growing component of the global financial system, attracting attention from both academic researchers and market participants (McIntyre and Harjes, 2016). These markets differ from traditional ones in that they are more volatile, less regulated, and operate across multiple decentralised platforms. These structural differences raise important questions about whether analytical frameworks developed for traditional markets translate effectively to cryptocurrency contexts, making the study of order flow dynamics in these markets particularly relevant.

However, analysing price dynamics in both traditional and cryptocurrency markets presents significant challenges due to the complex nature of financial time series, which are typically non-linear, non-Gaussian, and non-stationary (Ruxanda et al., 2019). Non-stationarity implies that the statistical properties of the data change over time, making prediction difficult. Estimation is further complicated by "microstructure effects," which refer to noise introduced into the data by the trading process, such as bid-ask spreads, discrete tick sizes, and variations in order book depth (Aït-Sahalia and Jacod, 2014). Cryptocurrency price series share these characteristics with traditional financial markets but are also influenced by sentiment swings and the absence of clear fundamental pricing, making them even more volatile and difficult to model (Chu et al., 2017). Against this backdrop of complexity, researchers have developed various metrics within the OFA framework to capture order flow dynamics and their relationship with price changes.

1.1.1 Foundations in Traditional Equity Markets

Order flow analysis has deep roots in traditional equity markets, with researchers developing distinct metrics to capture different aspects of trading activity. Within this framework, Order Flow Imbalance (OFI) emerged as a key metric that quantifies the difference between buyer- and seller-initiated activity, including orders that are placed and cancelled (Chordia et al., 2002). Trade Flow Imbalance (TFI), which considers only executed trades, offers a complementary perspective by showing whether buyers or sellers are dominating actual transactions. Chordia et al. (2002) illustrated that aggregate order imbalances significantly impact market liquidity and price returns in equity markets more than trading volume, supporting the inventory paradigm where market makers adjust prices in response to buy-sell pressure to manage inventory risk. Building on this foundation, Cont et al. (2014) demonstrated in U.S. equities that OFI retained greater explanatory power for short-term price changes than TFI by capturing the net effect of all order book events including market orders, limit orders, and cancellations. Their analysis showed a strong, linear relationship between OFI and short-term mid-price changes, with this relationship inversely proportional to market depth (Cont et al., 2014). This established OFI as a central measure in price formation analysis and set the stage for testing whether these relationships hold in other market contexts.

1.1.2 Transition to Cryptocurrency Markets

While these findings hold true for traditional equity markets, cryptocurrency exchanges differ significantly in terms of order book depth, diversity of participants, fragmented exchange markets, and lack of regulation, leading to questions about whether OFI models translate effectively. McIntyre and Harjes (2016) adapted order flow analysis to model Bitcoin/USD spot rate fluctuations using data from the Mt. Gox exchange. They found a positive correlation between order flow and Bitcoin spot rates, with order flow explaining approximately 40% of the daily change in the U.S. Dollar/Bitcoin spot rate, echoing patterns observed in traditional FX markets (McIntyre and Harjes, 2016). Despite Bitcoin being traded on decentralized platforms, the relationship between order flow and price changes appeared similar to traditional currencies, suggesting that trader behaviour may be more consistent across markets than the trading systems themselves.

1.1.3 The Case for Trade Flow Imbalance

More recent research, however, has challenged the view that the relationship between order flow and price changes appeared similar to traditional currencies. Silantyev (2019) questioned whether OFI models truly translate to cryptocurrency markets. Using BitMEX order book data, he compared OFI and TFI in explaining mid-price changes and found that TFI consistently outperformed OFI, particularly over longer intervals (Silantyev, 2019). This was attributed to structural limitations in cryptocurrency markets, such as lower order book depth, slower order updates, and frequent cancellations that reduce the informational value of unexecuted limit orders. These issues are compounded by spoofing, where traders place fake orders they intend to cancel to mislead other participants (Silantyev, 2019). This leads to a key insight that in cryptocurrency markets, executed trades may carry more reliable information than overall order flow due to reduced noise from cancelled orders.

1.1.4 Recent Insights

Building on this research, Barucci et al. (2023) examined the market impact of order flow across cryptoasset markets, distinguishing between cryptocurrency-to-cryptocurrency exchanges and cryptocurrency-to-USD exchanges. They found that the explanatory power of order flow varies by market structure, as markets trading cryptoassets against each other exhibited greater efficiency and a stronger relationship between order flow and price changes (Barucci et al., 2023). Interestingly, they noted that these results differ from Silantyev (2019), as the explanatory power of order flow for mid-price changes decreases at higher frequencies. This suggests that the impact of order flow on price formation in cryptocurrency markets may vary depending on both market structure and the time period of analysis, revealing no consensus on the relative explanatory power of OFI versus TFI in cryptocurrency markets. These conflicting findings across different time periods and market conditions suggest the need for further validation of order flow models in cryptocurrency markets.

1.2 Problem Statement

Despite past research demonstrating that order flow analysis is central to understanding price formation in traditional financial markets, their effectiveness in cryptocurrency markets remains unclear. Existing studies provide mixed evidence on whether order book activity (OFI) or executed trades (TFI) better explain short-term mid-price changes. This highlights a lack of consensus on how order flow variables (TFI and OFI) affect prices in cryptocurrency markets. To address this, the current study replicates and extends the framework of Silantyev (2019) to test the generalisability of his findings under a different time period.

1.3 Research Question

1. To what extent does Order Flow Imbalance (OFI) and Trade Flow Imbalance (TFI) explain short-term price movements in cryptocurrency markets?
2. Are these relationships consistent across a different time period (October 2024)?

1.4 Research Aim and Motivation

This study aims to understand how price changes in cryptocurrency markets are affected by order flow and trade flow imbalances. Specifically, it evaluates the explanatory power of Order Flow Imbalance (OFI) and Trade Flow Imbalance (TFI) in predicting short-term contemporaneous mid-price changes for Bitcoin traded on the BitMEX exchange. To achieve this, the study replicates the methodology of Silantyev (2019) using datasets from October 1$^{\text{st}}$–23$^{\text{rd}}$, 2017, and October 2024. Extending the analysis to a more recent period allows assessment of the generalisability of previous findings. These results will clarify whether existing order flow models remain applicable in today's cryptocurrency markets or if new approaches are needed. This contributes to the broader literature on cryptocurrency market microstructure and provides insights for traders and researchers seeking to gain a deeper understanding of short-term price dynamics in cryptocurrency markets.

1.5 Research Objectives

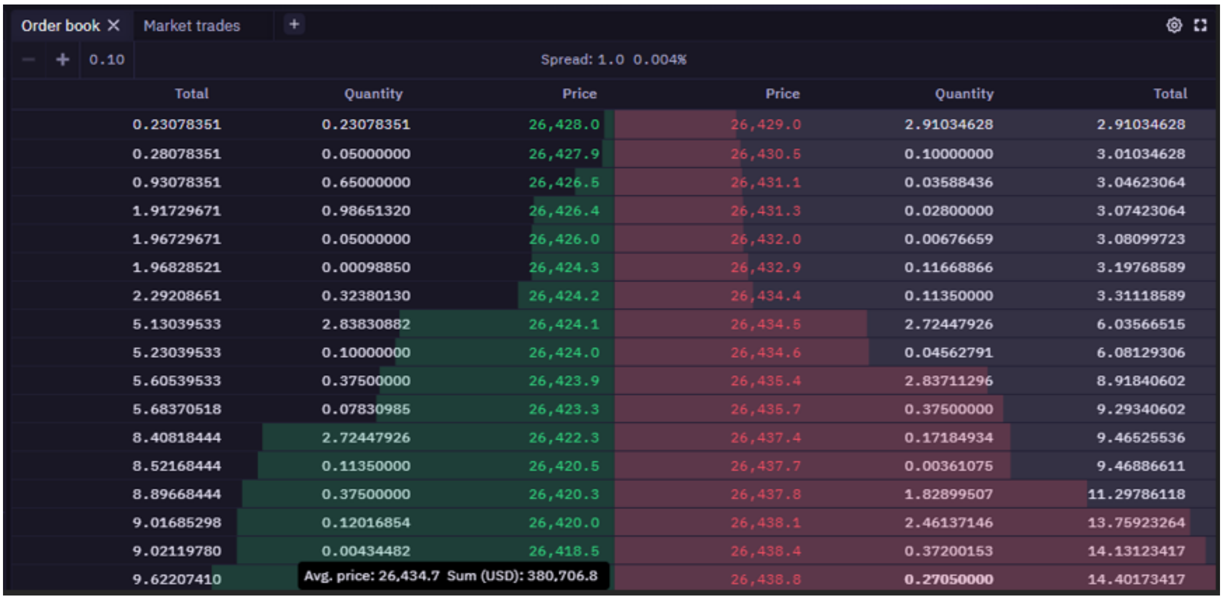
To achieve this aim, the study sets out the following key objectives:

- Conduct a literature review to place Silantyev (2019) within the broader context of order flow analysis in traditional financial and cryptocurrency markets.
- Explain the key concepts and models used in Silantyev (2019)'s research. This included order book mechanics and the two key measures of price changes, Order Flow Imbalance (OFI) and Trade Flow Imbalance (TFI).
- Replicate Silantyev (2019) using XBTUSD BitMEX data from October 2017.
- Assess the explanatory power of OFI and TFI on a different time period (October 2024).
- Account for limitations of this study and suggest further extensions to this research.

2 Preliminary Information

2.1 Definitions

2.1.1 Limit Order Book


Order book Market trades
0.10 Spread: 1.0 0.004%

Total	Quantity	Price	Price	Quantity	Total
0.23078351	0.23078351	26,428.0	26,429.0	2.91034628	2.91034628
0.28078351	0.05000000	26,427.9	26,430.5	0.10000000	3.01034628
0.93078351	0.65000000	26,426.5	26,431.1	0.03588436	3.04623064
1.91729671	0.98651320	26,426.4	26,431.3	0.02800000	3.07423064
1.96729671	0.05000000	26,426.0	26,432.0	0.00676659	3.08099723
1.96828521	0.00098850	26,424.3	26,432.9	0.11668866	3.19768589
2.29208651	0.32380130	26,424.2	26,434.4	0.11350000	3.31118589
5.13039533	2.83830882	26,424.1	26,434.5	2.72447926	6.03566515
5.23039533	0.10000000	26,424.0	26,434.6	0.04562791	6.08129306
5.60539533	0.37500000	26,423.9	26,435.4	2.83711296	8.91840602
5.68370518	0.07830985	26,423.3	26,435.7	0.37500000	9.29340602
8.40818444	2.72447926	26,422.3	26,437.4	0.17184934	9.46525536
8.52168444	0.11350000	26,420.5	26,437.7	0.00361075	9.46886611
8.89668444	0.37500000	26,420.3	26,437.8	1.82899507	11.29786118
9.01685298	0.12016854	26,420.0	26,438.1	2.46137146	13.75923264
9.02119780	0.00434482	26,418.5	26,438.4	0.37200153	14.13123417
9.62207410	Avg. price: 26,434.7 Sum (USD): 380,706.8		26,438.8	0.27050000	14.40173417

Figure 1: BTC/USD order book: Kraken

A limit order book (LOB) is the record of outstanding buy and sell limit orders for a traded asset at a given time (Cartea et al., 2015). Buy limit orders (bids) represent demand, and sell limit orders (asks) represent supply. The LOB operates as a double auction system, allowing both buyers and sellers to submit orders simultaneously. As shown in Figure 1, buy orders (bids) appear in green on the left side, ranked from highest to lowest price, while sell orders (asks) appear in red on the right side, ranked from lowest to highest price (Cartea et al., 2015). The best bid (highest buy price) and best ask (lowest sell price) sit at the top of their respective sides of the order book. The bid-ask spread between them represents the difference between what buyers are willing to pay and what sellers are willing to accept (Cartea et al., 2015). Trades occur whenever the highest bid meets the lowest ask. Within each price level, priority is given by the time the order was placed (Gould et al., 2013).

The state of the LOB evolves through three main types of events: new limit orders, market orders, and cancellations (Cartea et al., 2015; Gould et al., 2013). Limit orders provide liquidity by posting bids or asks at specified prices. Market orders consume liquidity by executing against the best available quote, and cancellations remove previously submitted limit orders from the book.

Participants are classified as market makers, who add liquidity via limit orders, and market takers, who remove liquidity with market orders (Cartea et al., 2015). In traditional equity markets, hybrid systems often involve intermediaries such as specialists or brokers. In contrast, cryptocurrency exchanges operate electronic LOBs. Therefore, all participants interact directly without intermediaries (Hileman and Rauchs, 2017).

The LOB plays a central role in price formation and liquidity. Incoming orders influence both the depth of the book and subsequent price dynamics. Aggressive or large orders cause stronger price movements in shallow order books, while in deeper order books with higher liquidity, these orders are absorbed with less impact on the price (Hautsch and Huang, 2012).

2.1.2 Order Flow Imbalance

Several interpretations of LOB imbalance have been proposed in the literature over the past few decades. Lee and Ready (1991) and Chordia et al. (2002) defined imbalance in terms of trades, aggregated by their direction. Another approach considered the aggregate order flow imbalance (OFI), which is composed of all types of order book events taking place in the limit order book (Cont et al., 2014). In this study, we used the latter perspective. Cont et al. (2014)'s definition treated OFI as a quantification of supply and demand inequalities in the LOB over a given time frame. The underlying principle is that any event which changed the state of the LOB can be classified as either changing demand or changing supply (Cont et al., 2014). Specifically,

- An arrival of a limit bid order increases demand.
- An arrival of a limit ask order increases supply.
- A market sell order, or full/partial cancellation of a limit bid order, decreases demand.
- A market buy order, or full/partial cancellation of a limit ask order, decreases supply.

(Cont et al., 2014) used a simplified model of the LOB in which the price impact of each order event is deterministic. This model relied on three assumptions:

- Liquidity is uniformly distributed across price levels.
- Every price level contains a fixed volume D, beyond the best bid and ask price.
- All limit order arrivals and cancellations occur at the best bid or ask price.

Under these assumptions, changes in the best bid (ΔP^b) and best ask (ΔP^a) prices over an interval $[t, t + \Delta t]$ can be expressed as

$$\Delta P^b = \frac{[L^b - C^b - M^s]}{D},$$

where

- L^b represents the volume of limit bid orders which increases the competitiveness of bids and tends to raise the best bid price,
- C^b are cancellations of existing bid orders, which removes demand and thus tend to decrease the best bid price ,
- M^s are market sell orders, which consume bid-side liquidity. This also decreases the best bid price .

Similarly, the change in the best ask price is given by

$$\Delta P^a = \frac{[-L^a + C^a + M^b]}{D},$$

where

- L^a represent the volume of limit sell orders, which add supply on the ask side. This makes the ask price more competitive and tends to decrease the best ask price,
- C^a are cancellations of ask orders, which remove supply and therefore tend to increase the best ask price ,
- M^b are market buy orders, which consume ask-side liquidity. This also increases the best ask price .

The above formulas assume the stylised parameter D , makes price changes depend solely on net order flow. However, this assumption does not hold in real markets. Limit order books are often irregular and contain features such as uneven depth, gaps, thin order levels, and hidden orders. As a result, D varies over time and is influenced by complex market dynamics. Nevertheless, Cont et al. (2014) suggests that net order flow remains strongly related to contemporaneous price changes in US equity markets. The formal definition of OFI is derived from the above definitions.

The impact of a single order book update can be expressed as:

$$e_n = I_{\{P_n^B \geq P_{n-1}^B\}} q_n^B - I_{\{P_n^B \leq P_{n-1}^B\}} q_{n-1}^B - I_{\{P_n^A \leq P_{n-1}^A\}} q_n^A + I_{\{P_n^A \geq P_{n-1}^A\}} q_{n-1}^A,$$

where

- P_n^B and P_n^A are the best bid and ask prices at update n respectively,
- q_n^B and q_n^A are the bid and ask volumes at update n respectively,
- and I is the price-conditional identity function.

For example, if q^B increased by a volume of v, there would be an increase in demand via a limit bid order, and since neither the best bid price nor the best ask price changed, e_n can be quantified as

$$e_n = q_n^B - q_{n-1}^B - q_n^A + q_{n-1}^A.$$

Therefore, the construction of Level I quote data equates to

$$-q_n^A + q_{n-1}^A = 0.$$

Since only one update can occur between observations, this results in $q_n^A = q_{n-1}^A$ and implies that

$$e_n = q_n^B - q_{n-1}^B = v.$$

Therefore, e_n measures the supply or demand impact of the nth order update.

Hence, order flow imbalance can be defined as the aggregation of impacts of e_n over the number of updates that occur $(N(t))$ during a time interval $[0, t]$:

$$OFI_k = \sum_{n=N(t_{k-1})+1}^{N(t_k)} e_n. \tag{1}$$

This study models the contemporaneous mid-price change, denoted as ΔMP_k, as the response variable. It is expressed in ticks, which are units of tick size. The tick size refers to the minimum price increment by which the price of an asset can change on the exchange (Gould et al., 2013). ΔMP_k is computed over the same time interval as the order flow imbalance (OFI_k) using:

$$\Delta MP_k = \frac{MP_k - MP_{k-1}}{\delta}.$$

The division of the mid-price change by the tick size aligns with the assumptions made in Section 2.1.1. Here, MP_k represents the mid-price, defined as $\frac{P_t^B + P_t^A}{2}$ at time t, and δ denotes the tick size (0.1 USD). It is important to note that in section 4.1.1, the term "tick" refers to individual quote or trade updates in the high-frequency dataset. However, unless otherwise specified, "tick" denotes the minimum price increment of $0.10.

As a result, this study used the following linear model to evaluate the regression of simultaneous mid-price change on OFI:

$$\Delta MP_k = \hat{\alpha}_{OFI} + \hat{\beta}_{OFI} \cdot OFI_k + \epsilon_k,$$

where

- $\hat{\alpha}_{OFI}$ is the intercept,

- $\hat{\beta}_{OFI}$ is the price impact coefficient,
- and ϵ_k is the error term.

This model was fit by using Ordinary Least Squares (OLS), and the chosen time intervals were 1s, 10s, 1 min, 5 min, 10 min and 1 hour.

2.1.3 Trade Flow Imbalance

Trade flow imbalance (TFI) measures the difference between the volume of already executed buy and sell trades (Cartea et al., 2015). Prior studies showed that trade flow imbalances were associated with short-term price changes in equity markets (Karpoff, 1987; Lee and Ready, 1991; Chordia et al., 2002). Some evidence also suggested that TFI has predictive value in trading strategies (Chan, 2017).

By definition, trade events are a subset of order book updates. Thus, intuitively, TFI may have lower explanatory power than OFI. However, trades differ from order activity because they incur both transaction fees and bid–ask spread costs. This means they reflect a stronger intent for trading (Cartea et al., 2015).

Formally, the trade flow imbalance over interval $[t_{k-1}, t_k]$ is defined as:

$$TFI_k = \sum_{n=N(t_{k-1}+1}^{N(t_k)} m_n, \tag{2}$$

where m_n is the signed indicator of the n-th update in $[t_{k-1}, t_k]$, which can be defined as

$$m_n = -I_{M^s} + I_{M^b},$$

such that:

- M^s represents the market sell orders,
- M^b represents the market buy orders,
- $N(t)$ is the number of updates occurring at Level I in $[0, t]$,
- and I is the indicator function that differentiates between market buy and sell events by assigning -1 to sells and $+1$ to buys.

This study used the following linear regression model to evaluate the extent to which trade flow imbalance impacts the contemporaneous mid-price changes in cryptocurrency markets:

$$\Delta MP_k = \hat{\alpha}_{TFI} + \hat{\beta}_{TFI} \cdot TFI_k + \epsilon_k,$$

where

- k is a time interval,
- $\hat{\alpha}_{TFI}$ is the intercept term,
- $\hat{\beta}_{TFI}$ is the trade impact coefficient,
- and ϵ_k is the error term.

Simarlarly to OFI, the model above is estimated by OLS across time intervals of 1s, 10s, 1 min, 5 min, 10 min, and 1h.

3 Methodology

This section describes the data that were used throughout the analysis. The data is available in this: Google Drive folder.

3.1 Data

3.1.1 Data Collection

The data used in this study covers two distinct periods: a replication dataset covering 1st October 2017 to 23rd October 2017, and an extension dataset covering October 2024.

Although the replication period (1–23 October 2017) matches that of Silantyev (2019), unavoidable discrepancies exist between the datasets due to differences in data retrieval methods. The original study obtained data through the BitMEX REST API, which streams real-time snapshots. In contrast, this study used BitMEX's AWS S3 historical archive, which aggregates daily CSV logs generated post-trade. These two sources differ slightly in their timestamp granularity and how order cancellations and partial orders fills are recorded, which may lead to small differences in the total number of trades and quote updates. Nevertheless, both datasets are drawn from the same underlying trading activity and are therefore comparable for replication purposes (see Section 4.1.2 for order arrival statistics comparison).

An R script file was created to automate the download of daily trade and quote CSV files, filter by the Bitcoin (XBTUSD) pair, and then merge the daily CSV files into two cleaned datasets: one for trades and one for quotes. The final replication dataset comprises approximately 8.5 million quote updates and 4.1 million trades, yielding a quote-to-trade ratio of 2.08. This means that there are approximately two quotes for every executed trade. For the extension, the same retrieval and cleaning procedure was applied to the October 2024 period. This produced a substantially larger dataset, consisting of approximately 41.9 million quote updates and 2.0 million trades. This yielded a quote-to-trade ratio of 20.89. This reflects a much higher level of quoting activity relative to trading in October 2024 compared to October 2017.

Each row in the quote dataset (Table 1 corresponds to an update to the best bid or ask price. New rows, therefore, reflect Level I order book events where a limit order is placed, cancelled, or a market order changes the top of the book.
BitMEX was selected as the primary data source based on the same criteria outlined in Silantyev (2019): high liquidity and minimal downtime. In 2017, BitMEX was the largest cryptocurrency derivatives exchange by daily trading volume, averaging roughly USD 3 billion per day, and it reported the lowest downtime among major exchanges at that time. See Appendix A

for BitMex exchange specification.

3.1.2 Data Format

Level I order book indicates any changes at the best bid and asks levels of the LOB. More formally, it is represented in the following format:

Table 1: Level I order book format: quote data.

Timestamp	Bid price	Bid volume	Ask price	Ask volume
2017-10-01 00:00:00.811455000	4327.3	59	4327.4	32508
2017-10-01 00:00:00.896560000	4327.3	58	4327.4	32508
2017-10-01 00:00:00.950556000	4327.3	58	4327.4	27508
2017-10-01 00:00:01.652617000	4327.3	57	4327.4	27508
2017-10-01 00:00:01.734221000	4327.3	57	4327.4	25508

Columns represent:

- Timestamp: nanosecond timestamp.
- Bid price: the highest price a market maker is willing to buy a cryptocurrency for.
- Ask price: the lowest price a market maker is willing to sell a cryptocurrency for.
- Bid volume: current contract volume available at the best bid price. Unitary.
- Ask volume: current contract volume available at the best ask price. Unitary.

The collected data also includes individual market orders. These are trades, which are represented by sequential time series, where each row corresponds to a market order:

Table 2: Trade data format.

Timestamp	Price	Volume	Side
2017-10-01 00:00:00.896560000	4327.3	1	Sell
2017-10-01 00:00:00.950556000	4327.4	1200	Buy
2017-10-01 00:00:00.950556000	4327.4	2000	Buy
2017-10-01 00:00:00.950556000	4327.4	1800	Buy
2017-10-01 00:00:01.652617000	4327.3	1	Sell

Interpretation of market orders:

- Timestamp: nanosecond timestamp.
- Price: trade price.
- Amount: trade volume.
- Side: buy/sell market order differentiator.

3.1.3 Benchmarking

Benchmarking is important in this study as it provides a reference point for which the impact of order flow in cryptocurrency markets can be measured against. Moreover, the results for XBTUSD would lack context without such a comparison. More established markets, such as equity index futures markets, offer an appropriate benchmark because they represent more mature assets with well-documented microstructures (Plerou et al., 2002; Chordia et al., 2002).

Following Silantyev (2019), the E-mini S&P 500 (ES-mini) futures contract was used as the benchmark asset. The ES-mini is traded on the Chicago Mercantile Exchange (CME) and is widely regarded as the most liquid equity index futures contract in the world. Its high liquidity made it an appropriate point of comparison for an asset such as Bitcoin. In Silantyev (2019)'s study, Level I trades-and-quotes (TAQ) data for the ES-mini were collected for May 2016, and the analysis of order arrivals in this established market was used as a baseline for evaluating the Bitcoin order arrival statistics.

In the present study, access to the original ES-mini dataset was not available. Therefore, this study relied on the results reported in Silantyev (2019) for the ES-mini order arrival statistics. For the extension period covering October 2024, Level I order book data for the ES-mini and similar assets (e.g SPDR S&P 500 ETF Trust) were not accessible due to paywall limitations. As a result, no benchmarking was carried out against another asset for October 2024.

4 Results and Analysis

Results for this section were obtained by adapting the Python code from Silantyev (2019) to R code. The code for this project is available at: https://github.com/NesanNaidoo/OFA-research-project.

4.1 Exploratory Data Analysis

4.1.1 Prices

First, the Augmented Dickey-Fuller (ADF) and KPSS tests for stationarity was conducted for all variants of k (1 sec, 10 sec, 1 min, 5 min, 10 min, 1 hour) in the ΔP_k variable. The ADF test was applied without an intercept or trend, because the trend and mean are already removed in a differenced-price series. Additionally, the KPSS test was performed for level stationarity around a constant mean. Table 9 confirms that the price series is stationary for every sampling period k at 1% significance level (see Appendix B.1).

Using the same methodology, the October 2024 price series data were also examined. Table 10 confirms that the price series is stationary for every sampling period k at 1% significance level (See Appendix B.1).

In this section, the term tick refers to individual quote updates in the high-frequency dataset. Hence, “tick-to-tick” mid-price changes compares two consecutive quote updates, and the “1000-tick window” represents a moving window of 1000 quote updates, rather than a fixed time duration.

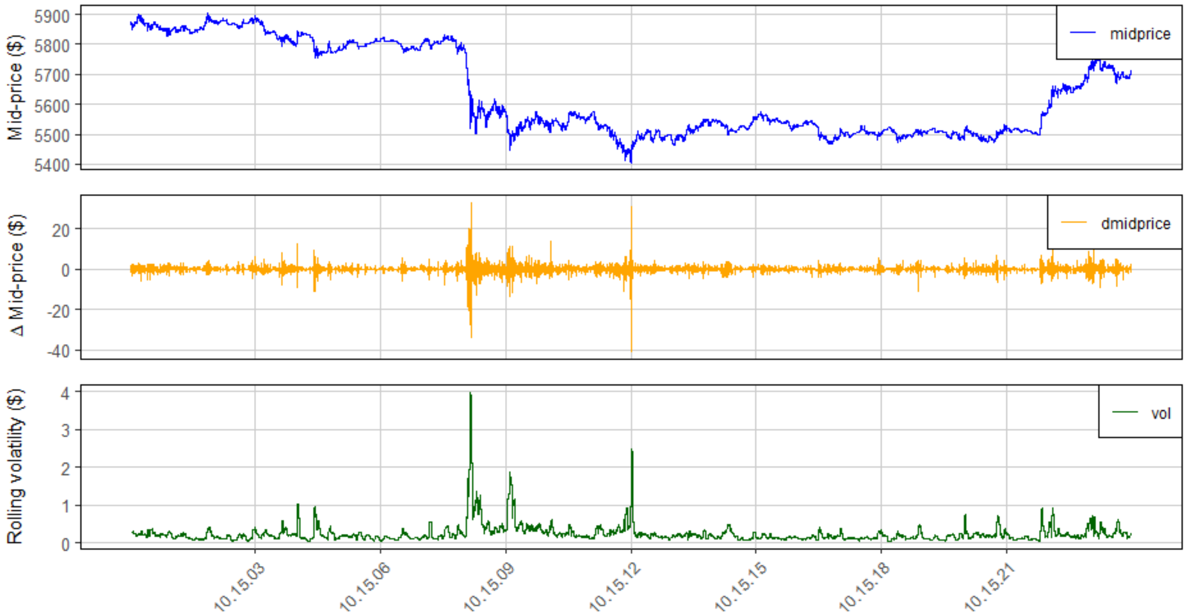


Figure 2: XBTUSD mid-price ($) (top), tick-to-tick changes ΔMP ($) (middle), and rolling volatility proxy ($) (bottom), based on a 1000-tick moving standard deviation of ΔMP. Date: 15 Oct 2017 (mm.dd.hh).

Figure 2 illustrates a typical trading day for XBTUSD in 2017. As a 24-hour market, cryptocurrency is traded continuously by traders worldwide (McIntyre and Harjes, 2016). The day opens with the price around $5,900, dips by approximately 10% to $5,400, and recovers to near $5,700 by the end of the day. This level of volatility is a key draw for day traders, as such dramatic movements are rare in traditional markets (Chu et al., 2017).

The middle plot displays the differenced tick-to-tick mid-price series (ΔMP). This represents the immediate momentum and direction of each price change. The concentration of the values is mainly around 0, suggesting that buyers and sellers are roughly balanced, so net price movements are small (Cont and Larrard, 2013).

The bottom plot illustrates a proxy for volatility, estimated as the rolling standard deviation of mid-price changes over a 1,000-tick window. Because both the mid-price and its changes are measured in USD, this volatility proxy is also in USD. Spikes in volatility tend to occur abruptly, which is likely due to shallow market depth during urgent trading periods, when liquidity providers are less active (Cont et al., 2014).

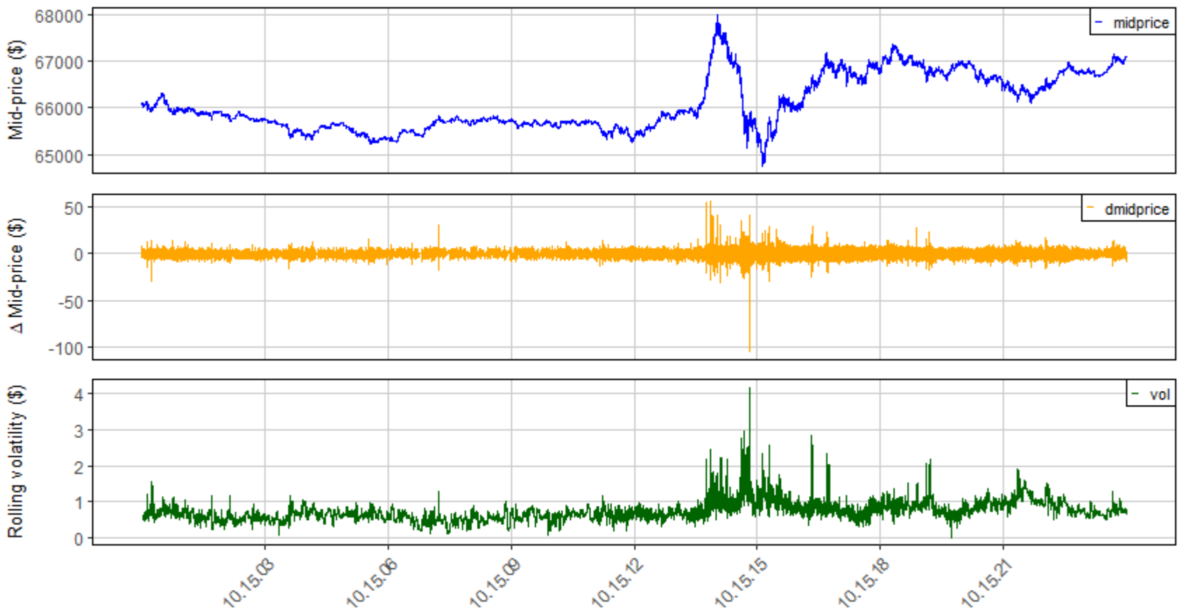


Figure 3: XBTUSD mid-price ($) (top), tick-to-tick changes ΔMP ($) (middle), and rolling volatility proxy ($) (bottom), based on a 1000-tick moving standard deviation of ΔMP. Date: 15 Oct 2024 (mm.dd.hh).

Figure 3 illustrates the trading activity for XBTUSD on October 15th, 2024. It demonstrates how the mid-price evolved throughout the day and allows for comparison with a typical trading day from October 2017. The top panel shows that the mid-price ranged between approximately $65,000 and $68,000, which is higher than the $5,400–$5,900 range observed in 2017. This reflects the appreciation in Bitcoin's long-term price level.

The middle panel displays the tick-to-tick mid-price changes (ΔMP), which fluctuate around zero for most of the day. This pattern suggests balanced trading activity, where buyer and seller pressures largely offset each other.

The bottom panel presents a proxy for volatility, estimated as the rolling standard deviation of ΔMP over a 1,000-tick window. During the first 13 hours, this measure remains near zero. As most tick-to-tick mid-price changes are zero, this proxy takes on small numerical values below $1. These low values do not imply low market volatility overall, but rather indicate that mid-prices remain stable for long periods between occasional sharp movements.

After the 13th hour, the top panel shows a sudden and sharp increase in the mid-price from around $66,000 to nearly $68,000, followed by an equally sharp decline to about $65,000. This event coincides with a spike in the volatility proxy, rising from near zero to around 4. The volatility spike likely reflects a temporary market imbalance, as sudden large orders can briefly deplete liquidity near the top of the order book.

Following this event, the mid-price gradually recovers, while the volatility proxy remains slightly higher than before. This suggests that traders became more cautious after the sharp price swings, leading to more uncertainty in market behaviour (Karpoff, 1987).

4.1.2 Orders

In October 2017, a key differentiating factor between cryptocurrency markets and established traditional equity markets was the speed at which orders arrived. Level I LOB updates were aggregated into 1-second buckets. These statistics were then benchmarked against ES-mini futures contracts for May 2016.

It is worth noting again that this study's replication dataset was not identical to that of Silantyev (2019) (see Section 3.1.1 for details on retrieval differences).
Table 3 shows that there are unavoidable discrepancies between this study's order arrival statistics and those reported in Silantyev (2019). This limitation means that the replication should be read as an approximation of Silantyev (2019) 's findings and not an exact reproduction. Table 3 also shows that cryptocurrency markets exhibited significantly lower arrival rates than the ES-mini contracts. The gap is clear when looking at the maximum arrival rates. The ES-mini Level I LOB updates reached 2,387 orders in a single second compared to the XBTUSD pair which only peaked at 48 orders in a second. This disparity likely reflects structural differences between the two markets, such as participant volume and trading infrastructure.
Table 3 also illustrates how Bitcoin's market activity evolved between 2017 and 2024. In 2017, the XBTUSD contract averaged around 5 orders per second, while by 2024 this had increased to nearly 20 orders per second, with peak activity reaching 342 orders in a single second. This increase suggests that trading on BitMEX became more active since 2017. The higher standard deviation in 2024 suggest more volatile order flow, with bursts of rapid activity (i.e a large number of orders are placed, modified, or cancelled within a short time) followed by quieter periods (i.e fewer orders coming in).

Table 3: Comparison of 1st order arrival rate statistics.

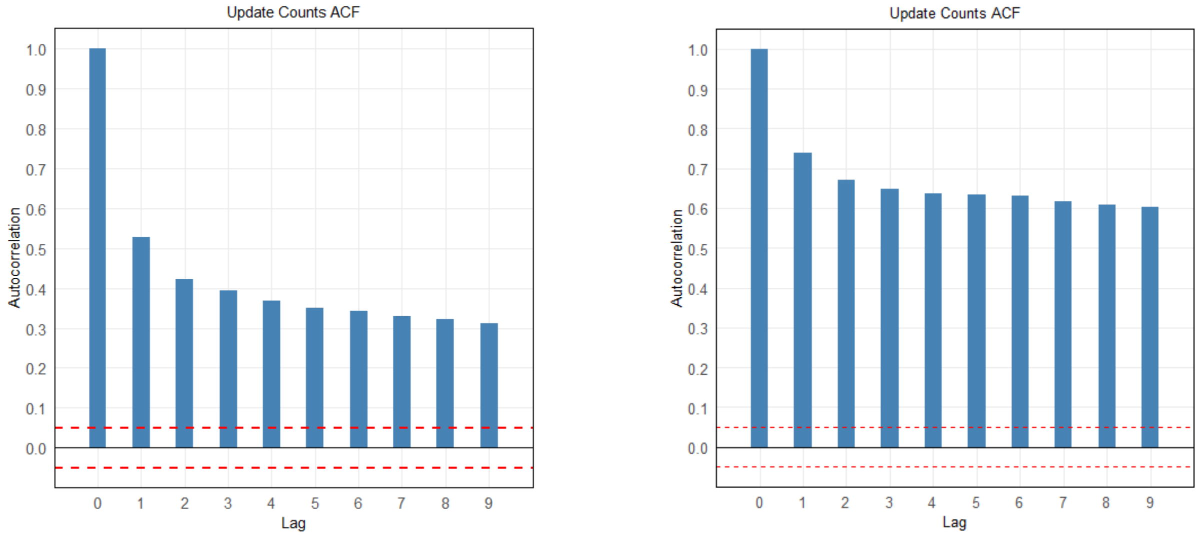
Statistic	XBTUSD (Oct 2017)*	Silantyev (2019) XBTUSD	Silantyev (2019) ESM16	XBTUSD (Oct 2024)*
Mean	5.47	4.93	57.66	19.68
SD	5.09	5.43	96.23	27.15
Min	1	0	0	1
25%	2	1	4	3
50%	4	3	20	9
75%	7	7	64	24
Max	48	48	2387	342

* The results we obtained for XBTUSD's order arrival statistics.

Table 4: Bid–Ask spread summary for XBTUSD in ticks (1 tick = 0.1 USD).

Period	Average Spread	Std. Dev.	Min Spread	Max Spread
Replication (Oct 2017)	2.91	11.04	1	3599
Extension (Oct 2024)	25.49	40.51	1	2938

Table 4 shows that in October 2017, the average bid–ask spread was about 2.91 ticks (1 tick = 0.1 USD). This suggests more orders were stacked near the mid-price, so a typical trade would not move the price much (Cont et al., 2014). However, by October 2024, the average spread had increased to 25.49 ticks (1 tick = 0.1 USD) and became much more variable with a standard deviation of 40.5 ticks (1 tick = 0.1 USD). This is reflective of higher Bitcoin prices (at $65,000–$68,000) and an uneven distribution of buy and sell orders in the order book. This means some prices had few or no orders, while others had more. This irregularity makes it harder to execute large trades without impacting the price (Cont et al., 2014).



(a) October 2017

(b) October 2024

Figure 4: XBTUSD 10-s update counts ACF, with 2 red dashed lines to represent significant value thresholds.

To examine order arrivals further, the autocorrelation function (ACF) of update volumes was computed by aggregating updates into 10-second intervals. Figure 4 shows that for both time periods, positive autocorrelation persists across multiple lags. The significant positive autocorrelations observed at higher lags indicate strong time dependence and raise the possibility of non-stationarity in update arrivals. To formally assess this, we applied the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests for both the replication and extension periods, as the KPSS test is known to be overly sensitive and can yield contradictory results for highly granular financial time series (Otero and Smith, 2005). Both the ADF and PP test statistics confirmed that update arrival volumes were stationary for the 10-second interval at the 5% significance level (see Appendix B.2). Figure 12 (in Appendix C.1) shows that update arrival volumes fluctuate around a stable, non-zero mean, supporting the conclusion that the series is stationary.

To validate the robustness of these results, this study further examined the model residuals for serial correlation and heteroskedasticity. The Ljung–Box test ($p < 0.001$) indicated significant autocorrelation in the residuals, while the Breusch–Pagan test ($p < 0.001$) confirmed heteroskedasticity. These findings support the interpretation that although the series is stationary, it exhibits conditional heteroskedasticity and short-term persistence driven by clustered market activity.

In the replication period, Figure 4a is approximately 0.55 at lag 1 and gradually decays to about 0.30 by lag 8. In the extension period, Figure 4b starts higher, at 0.74, and declines more slowly, remaining near 0.60 by lag 9. This slower decay indicates stronger and more persistent clustering of update volumes in the extension period. The difference between the replication and extension results can be attributed to the substantially larger dataset in the extension (41.9 million quotes), which allows for more accurate detection of clustering in order arrival activity (Cartea et al., 2015).

Overall, the EDA confirms that both price and order flow series are stationary and exhibit clustering patterns consistent with prior market microstructure research (Cont et al., 2014; Cartea et al., 2015). This short-term clustering suggests that the relationship between order flow and price changes unfolds over short time horizons, supporting the use of high-frequency intervals (1–60 seconds) alongside longer ones (1–60 minutes) to capture both immediate and more persistent effects.

4.2 Order Flow Imbalance

Following the framework of Cont et al. (2014), OFI was examined across multiple sampling intervals. Cont et al. (2014) considered intervals ranging from 1 second to 10 minutes and Silantyev (2019) extended this up to 1 hour in the context of cryptocurrency markets. To be consistent with both studies, this research applied sampling windows from 1 second to 1 hour to analyse the relationship between OFI and price changes for both the replication and extension period. This adjustment accounts for the lower arrival rates observed in the XBTUSD market in October 2017. Furthermore, this ensured that each aggregated interval contained a sufficient number of order book events for meaningful observation of both price changes and imbalances.

4.2.1 Stationarity Test

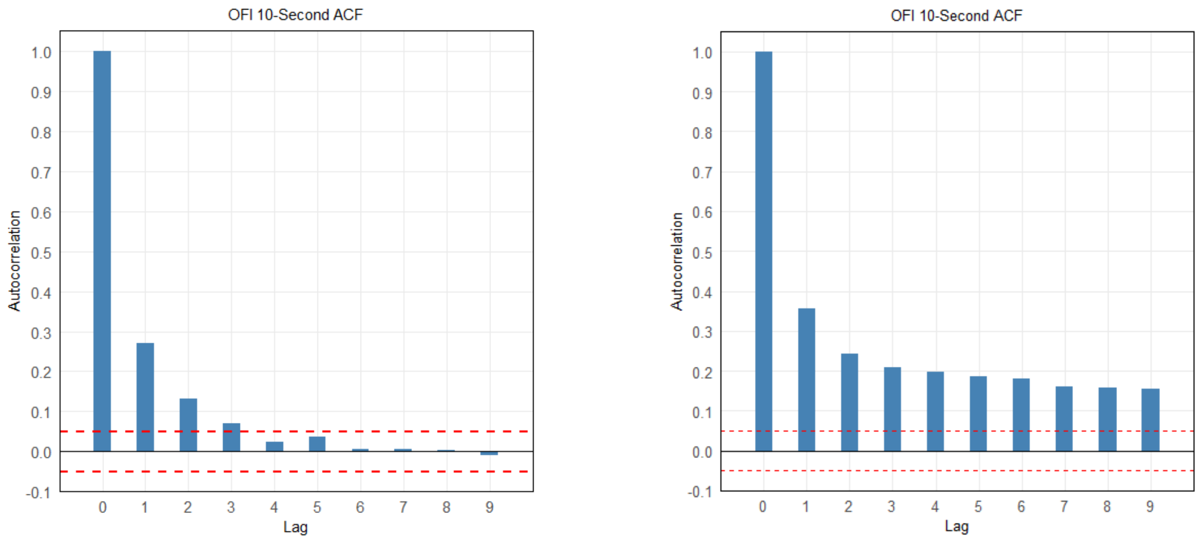
Before estimating the regression models, the stationarity of the non-differenced order flow imbalance (OFI_k) series was examined to avoid spurious regression results, where relationships appear significant even though they are not truly meaningful (Granger and Newbold, 1974). Overall, OFI is stationary across all aggregation intervals, with inconsistencies in high-frequency tests (1 sec - 1 min) typical for granular financial data (Otero and Smith, 2005).

First, the Augmented Dickey–Fuller (ADF) and KPSS tests were applied to OFI_k for both replication and extension periods (1 sec – 1 hour). In the replication period, both tests confirmed stationarity at the 1% level. In the extension period, the KPSS test suggested slight non-stationarity for the shortest intervals (1 sec – 1 min), but the ADF and Phillips–Perron (PP) tests supported stationarity across all intervals (see Table 15 and Appendix B.3).
Finally, diagnostic checks on model residuals revealed significant autocorrelation (Ljung–Box, $p < 0.001$) and heteroskedasticity (Breusch–Pagan, $p < 0.001$), indicating that OFI variabil-

ity changes over time due to bursts of intense trading activity which is a common feature of high-frequency markets (Andersen et al., 2003). Given these results, no differencing of OFI_k was applied before regression analysis.

4.2.2 Autocorrelation Function Plots

Next, the 10-second OFI autocorrelation function (ACF) was computed to check whether order flow imbalances are persistent in both the replication and extension period.



(a) October 2017

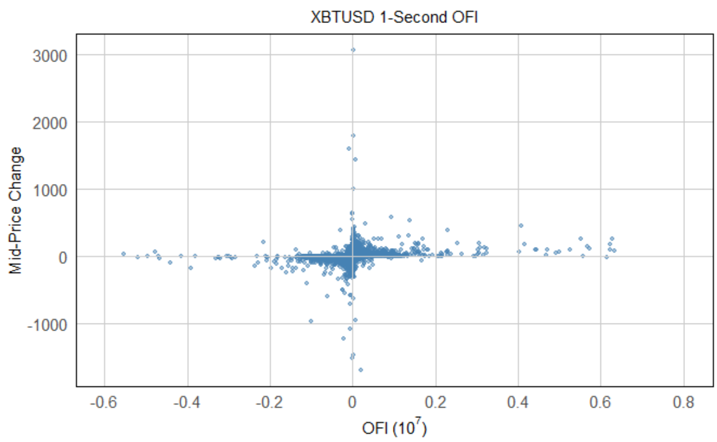
(b) October 2024

Figure 5: XBTUSD 10-sec order flow imbalance ACF, with 2 red dashed lines to represent significant value thresholds.

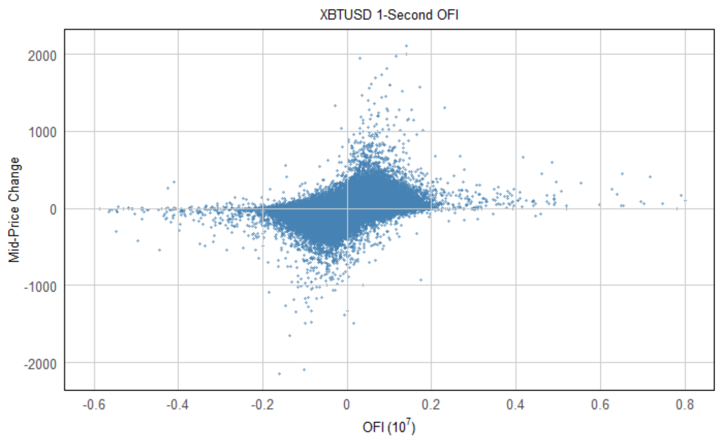
Figure 5a shows positive autocorrelation up to the third lag for October 2017. This indicates short-term persistence in both the direction and magnitude of order flow. This means that periods of positive imbalance, which reflect increasing demand or decreasing supply, are likely to be followed by similar periods, while negative imbalances tend to be followed by further negative imbalances. In October 2024 (Figure 5b), the autocorrelation decays more gradually and remains positive until the ninth lag. This reflects stronger and longer-lasting clustering of imbalances in the extension period. These results extend the findings from Section 4.1.2. In addition to the observed time dependence in absolute activity levels, there is also dependence in the sign of order flow activity.

4.2.3 Scatterplots of OFI vs. Mid price changes

The next step in the analysis examined the relationship between order flow imbalance and mid-price changes. This was measured in ticks (1 tick = 0.1 USD) aggregated over a one-second interval. The analysis was done by using the Ordinary Least Squares (OLS) model defined in Section 2.1.2 . This setup allowed examination of how shorter aggregation windows capture fine-grained dynamics while also revealing the effect of aggregation on model R^2 values. As the sampling interval increases, more events are combined, which reduces noise while also reducing short-term fluctuations in the order flow (Cont et al., 2014).



(a) October 2017 $R^2 \approx 7.4\%$

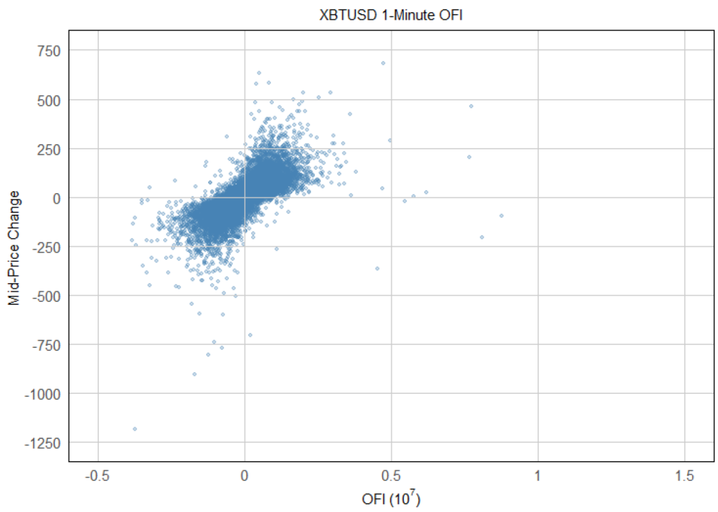


(b) October 2024 $R^2 \approx 25.2\%$

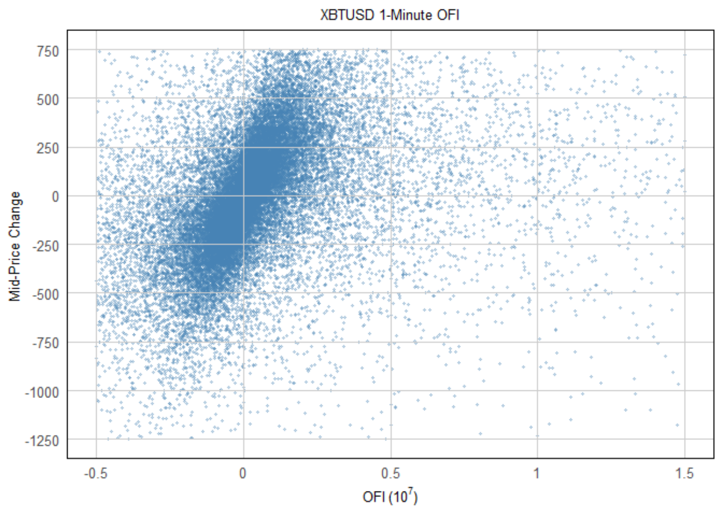
Figure 6: XBTUSD 1-sec order flow imbalance versus contemporaneous mid-price change in ticks (1 tick = 0.1 USD).

For the 1-second aggregation, the replication period (Figure 6a) exhibits a "sliding cross" pattern, with most observations clustered near the axes. The magnitude of mid-price changes increases as OFI approaches zero, producing a hyperbolic shape. The linear relationship is weak, with $R^2 \approx 7.4\%$.

In the extension period (Figure 6b), the "sliding cross" pattern is more pronounced than the replication period, due to its larger dataset. Observations remain concentrated near the origin, but mid-price changes show slightly greater variation. The correlation is stronger than in 2017, with $R^2 \approx 25.2\%$.



(a) October 2017 ($R^2 \approx 41\%$)



(b) October 2024 ($R^2 \approx 20.9\%$)

Figure 7: XBTUSD 1-min order flow imbalance versus contemporaneous price change in ticks (1 tick = 0.1 USD).

For the 1-minute aggregation, the replication period (Figure 7a) shows a clearer positive relationship between OFI and mid-price changes than it does at the 1-second aggregation (Figure 6). The observations are also tightly clustered along the upward trend, resulting in a strong linear fit ($R^2 \approx 41\%$).

In October 2024 (Figure 7b), the relationship remains positive but more dispersed. The wider spread of mid-price changes leads to a lower $R^2 \approx 20.9\%$, reflecting greater variability in price responses despite the overall trend.

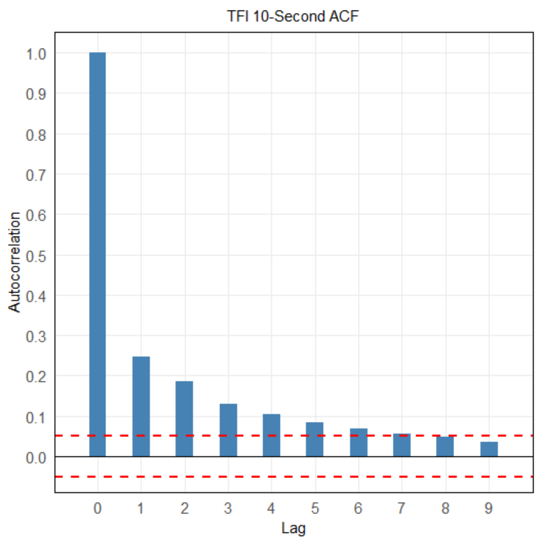
4.3 Trade Flow Imbalance

To ensure a direct comparison with the OFI results in 4.2, the analysis of TFI was conducted over the same set of sampling intervals: 1 s, 10 s, 1 min, 5 min, 10 min and 1 h.

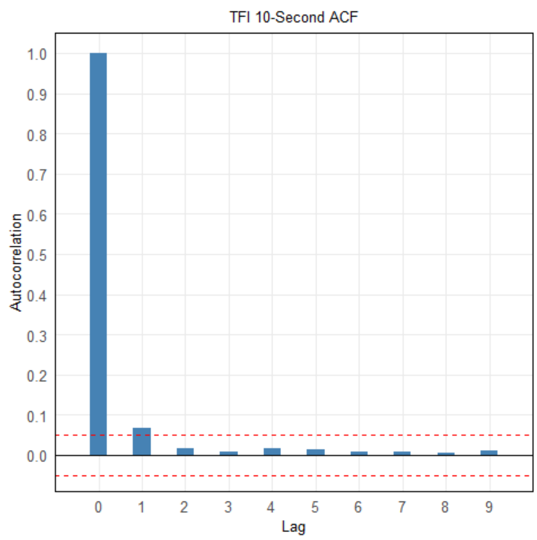
4.3.1 Stationarity Test

To reiterate, non-stationary time series can lead to spurious regression results (Granger and Newbold, 1974). Therefore, establishing stationarity ensures that the estimated relationships between TFI_k and contemporaneous mid-price changes are statistically valid. Overall, TFI is stationary across all aggregation intervals for both the replication and extension periods . ADF and KPSS tests confirmed stationarity at the 1% significance level (Tables 16–17).

4.3.2 Autocorrelation Function Plots



(a) October 2017

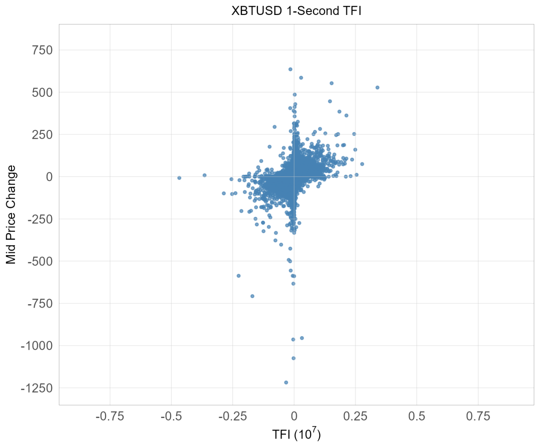


(b) October 2024

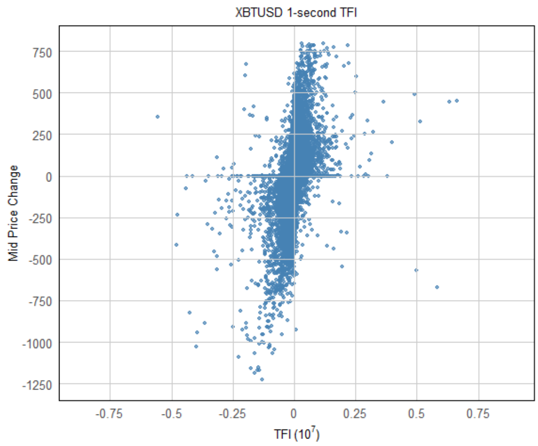
Figure 8: XBTUSD 10-sec trade flow imbalance ACF, with 2 red dashed lines to represent significant value thresholds.

In the replication period (Figure 8a), 10-second TFI is positively autocorrelated for lags 1–5, indicating short-term persistence in trade flow. In the extension period (Figure 8b), only lag 1 is significant, indicating weaker short-term memory. These results mirror the observed patterns in OFI and quantify the change in persistence between 2017 and 2024.

4.3.3 Scatterplots of TFI vs. Mid price changes



(a) October 2017 ($R^2 \approx 13.32\%$)

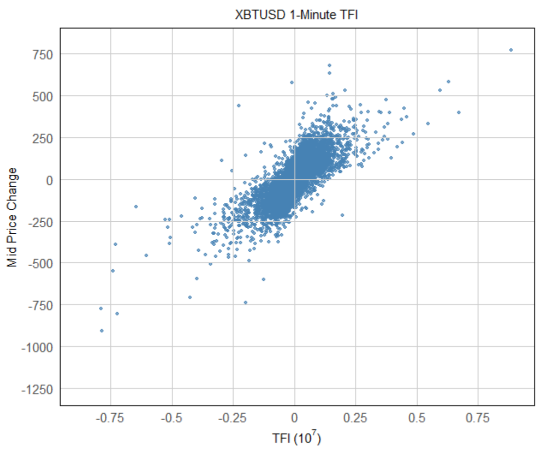


(b) October 2024 ($R^2 \approx 12.06\%$)

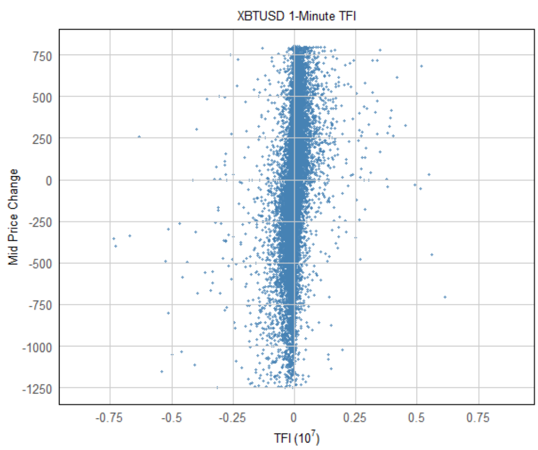
Figure 9: XBTUSD 1-sec trade flow imbalance versus contemporaneous mid-price change in ticks (1 tick = 0.1 USD).

For the 1-second aggregation, the replication period (Figure 9a), exhibits a "sliding cross" pattern, with most observations near the axes. The mid-price changes are observed to increase as TFI approaches zero. This pattern is similar to the 1-second aggregation of OFI in 2017 (Figure 6a) but with slightly more linear dispersion. The R^2 value is approximately 13.32%, indicating weak but measurable explanatory power.

In the extension period (Figure 9b), the observations are more dispersed along the mid-price change axis. The R^2 value is approximately 12.06%, indicating slightly weaker explanatory power than TFI in 2017.



(a) October 2017 ($R^2 \approx 58.56\%$)



(b) October 2024 ($R^2 \approx 16.22\%$)

Figure 10: XBTUSD 1-min trade flow imbalance versus contemporaneous price change in ticks (1 tick = 0.1 USD).

At the 1-minute aggregation, the replication period (Figure 10a) shows a moderate positive linear relationship between TFI and mid-price changes ($R^2 \approx 58.56\%$). Larger trade flow imbalances generally correspond to larger mid-price changes. This relationship is more linear than the 1-second aggregation during the same period (Figure 9a).

In October 2024 (Figure 10b), the pattern weakens considerably. Most TFI values cluster near zero, and mid-price changes become more variable. The R^2 drops to approximately 16.22%, indicating that TFI has substantially weaker predictive power in the recent period.

4.4 Regression Analysis

To formalize the relationship between order flow and price changes, regression models for both OFI and TFI (Sections 2.1.2 and 2.1.3 respectively) were estimated across all sampling windows. Results for the replication and extension periods are reported in Tables 5–6 for OFI and Tables 7–8 for TFI. Since the P-values are extremely small for all models except the 10-minute OFI in the extension period, the probability of non-significance (100% - p-value) is reported instead.

4.4.1 Order Flow Imbalance (OFI)

Replication Period

For illustration, the 1-second regression model is:

$$\Delta MP_{1sec} = -0.19173 + (8.383 \times 10^{-5}) \cdot OFI_{1sec},$$

where 10,000 units of net order flow correspond to an expected mid-price change of 0.65 ticks (1 tick = 0.10 USD).

As shown in Table 5, the slope coefficients ($\hat{\beta}_{\text{OFI}}$) are positive and highly significant across all intervals. This indicates that higher OFI is associated with mid-price changes in the same direction. Additionally, these beta coefficients do not differentiate between types of order book events. Hence, it generalises for cancellations, placements and trade order volume flows. The intercepts ($\hat{\alpha}_{\text{OFI}}$) become more negative as the interval increases. Explanatory power (R^2) increases with the sampling period k, reaching 55% at the 1-minute window and plateauing for longer intervals. Overall, the replication period demonstrates moderate predictive power of OFI for contemporaneous mid-price changes (Max $R^2 \approx 55\%$), which is consistent with the findings of Cont et al. (2014) and Silantyev (2019).

Extension Period

The 1-second regression model is:

$$\Delta MP_{1sec} = -0.3733 + (1.1072 \times 10^{-4}) \cdot OFI_{1sec}.$$

Here, 10,000 units of net order flow correspond to an expected mid-price change of 0.73 ticks.

Compared to the replication period, the slope coefficients remain positive at short intervals but lose significance at longer intervals, with the 10-minute slope not statistically significant. Furthermore, intercepts become positive at longer intervals, suggesting that mean-reverting behaviour is reduced, meaning that after a mid-price change, driven by order flow, the price is less likely to move back toward its previous level (Cont et al., 2014). Compared to the replication period, the R^2 values are lower across all intervals and approach zero at longer intervals (Table 6).

Table 5: Replication period (October 1st-23rd 2017): OFI regression model.

k	$\hat{\alpha}_{\text{OFI}}$	$\hat{\beta}_{\text{OFI}}$	$t(\hat{\beta}_{\text{OFI}})$	R^2 (%)	$\hat{\beta}_{\text{OFI}} \neq 0$ (%)
1 sec	0.0013	4.54e-05	353.71	7.40	100
10 sec	-0.0355	7.69e-05	371.22	40.97	100
1 min	-0.2776	8.43e-05	202.94	55.43	100
5 min	-0.8511	7.18e-05	84.84	52.09	100
10 min	-1.3485	6.77e-05	57.24	49.76	100
1 hour	-6.1830	6.43e-05	24.06	51.31	100

Table 6: Extension period (October 2024): OFI regression model.

k	$\hat{\alpha}_{\text{OFI}}$	$\hat{\beta}_{\text{OFI}}$	$t(\hat{\beta}_{\text{OFI}})$	R^2 (%)	$\hat{\beta}_{\text{OFI}} \neq 0$ (%)
1 sec	-0.3733	1.11e-04	847.21	25.21	100
10 sec	-1.7360	6.81e-05	265.00	20.86	100
1 min	-3.8186	3.06e-05	65.46	8.76	100
5 min	2.5649	5.95e-06	8.69	0.84	100
10 min	13.9163	9.54e-07	1.19	0.03	76.67
1 hour	127.9933	-3.51e-06	-2.69	0.96	99.26

4.4.2 Trade Flow Imbalance (TFI)

Replication Period

For illustration, the 1-minute regression model is:

$$\Delta MP_{1min} = 0.1303 + 1.1864 \times 10^{-4} \cdot TFI_{1min},$$

where 10,000 units of net trade flow correspond to an expected mid-price change of 1.32 ticks (1 tick = 0.10 USD). The intercept (0.1303) represents the expected price change when TFI is zero, capturing small movements due to spread or market noise.

As shown in Table 7, the slope coefficients ($\hat{\beta}_{\text{TFI}}$) are positive and highly significant across all intervals, indicating that higher trade flow imbalance generally pushes prices in the same direction. Intercepts ($\hat{\alpha}_{\text{TFI}}$) increase with the sampling interval k, consistent with lasting price impact from cumulative executed trades. Explanatory power (R^2) rises steadily with k, from 13.32% at 1 second to 75.16% at 1 hour. Compared to OFI, TFI has stronger predictive power across most intervals except at the 10-second sampling period. This is consistent with markets responding more strongly to executed trades than to order book imbalances (Silantyev, 2019).

Extension Period

For October 2024, the 1-minute regression model is:

$$\Delta MP_{1min} = 1.5443 + 4.2929 \times 10^{-4} \cdot TFI_{1min}.$$

Here, 10,000 units of net trade flow correspond to 5.84 ticks (1 tick = 0.10 USD).

Compared to the replication period, the slope coefficients remain positive and significant at most intervals, but explanatory power (R^2) is lower overall, peaking at 27.48% for the 1-hour sampling interval (see Table 8). TFI consistently outperforms OFI at longer sampling intervals (1 minutes to 1 hour); while at shorter intervals, price changes are more influenced by limit order book activity. Intercepts increase with k and remain positive. This reflects the point that cumulative trading pressure still contributes to lasting price changes over longer time frames.

Table 7: Replication period (October 1st-23rd 2017): TFI regression model.

k	$\hat{\alpha}_{\text{TFI}}$	$\hat{\beta}_{\text{TFI}}$	$t(\hat{\beta}_{\text{TFI}})$	R^2 (%)	$\hat{\beta}_{\text{TFI}} \neq 0$ (%)
1 sec	0.0122	7.68e-05	347.09	13.32	100
10 sec	0.0290	1.06e-04	333.86	37.53	100
1 min	0.1303	1.19e-04	216.25	58.56	100
5 min	0.9072	1.00e-04	121.25	68.95	100
10 min	2.0272	9.18e-05	89.44	70.74	100
1 hour	13.4080	8.60e-05	40.76	75.16	100

Table 8: Extension period (October 2024): TFI regression model.

k	$\hat{\alpha}_{\text{TFI}}$	$\hat{\beta}_{\text{TFI}}$	$t(\hat{\beta}_{\text{TFI}})$	R^2 (%)	$\hat{\beta}_{\text{TFI}} \neq 0$ (%)
1 sec	0.1061	3.50e-04	238.48	12.06	100
10 sec	0.3421	3.75e-04	154.02	11.98	100
1 min	1.5443	4.29e-04	91.44	16.22	100
5 min	7.3748	4.61e-04	48.31	20.73	100
10 min	14.7543	4.64e-04	35.38	21.91	100
1 hour	86.0347	4.80e-04	16.76	27.48	100

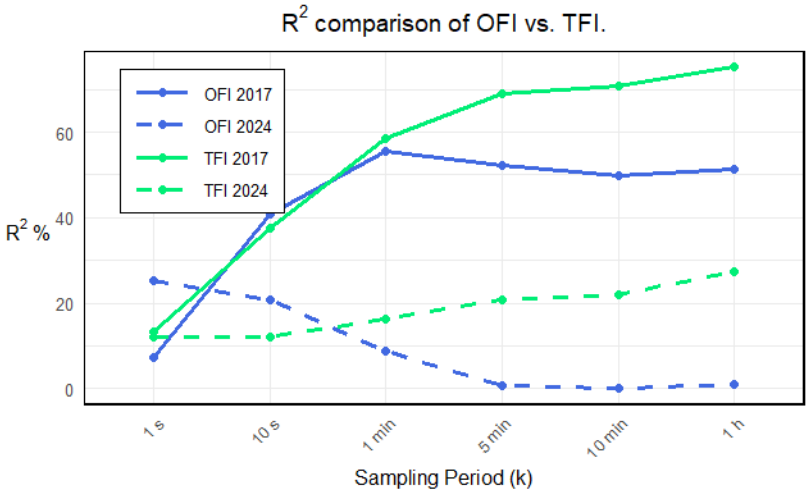


Figure 11: Explanatory power (R^2) of OFI (blue) and TFI (green) across different sampling periods k (1s, 10s, 1 min, 5 min, 10 min, 1 hour) for October 2017 and 2024 (dashed lines).

5 Discussion

5.1 Replication Period

The replication analysis reveals that TFI consistently outperforms OFI in explaining short-term price movements during October 2017, except at the 10-second interval. TFI achieves R^2 values ranging from 13.32% at 1-second intervals to 75.16% at 1-hour intervals (Table 7), while OFI peaks at 55.43% at 1-minute intervals (Table 5). This contradicts the findings in U.S. equity markets (Cont et al., 2014), where OFI demonstrated better performance. However, the results obtained in this study align closely with Silantyev (2019) (see Section 4). This confirmed that trade flow imbalance is more informative than order flow imbalance in explaining short-term mid-price movements in the Bitcoin derivatives market. This study's results differ marginally from Silantyev (2019), due to unavoidable discrepancies in the replication dataset, as mentioned in Section 3.1.1.

Three structural features explain why TFI outperforms OFI in the Bitcoin derivatives market: the number of available orders constantly changes (which violates OFI's assumptions), traders can freely manipulate the order book without penalties, and placing orders costs nothing while executing trades requires real commitment.

5.1.1 Constantly Changing Order Availability

OFI assumes that every price level contains a fixed volume D of limit orders, beyond the best bid and ask price, as stated in Section 2.1.1. This assumption works well in equity markets because liquidity is deep and regulated, but it appears to fail in cryptocurrency markets, where liquidity is fragmented and highly unstable (McIntyre and Harjes, 2016). The October 2017 data used in this study have an average bid-ask spread of 2.91 ticks (SD = 11.04), indicating inconsistent market depth. This means when spreads widen, fewer limit orders are placed near the best quotes, causing order volumes to fluctuate substantially across price levels and over time. A high standard deviation also suggests that the rate at which orders are replenished is uneven, unlike in stable markets, where new limit orders arrive at a rate similar to cancellations or executions.

When the volume of limit orders varies over time, identical buying or selling pressure can produce different price effects. For example, a buy order of 100 contracts may move the price by a single tick when supply is abundant, but by several ticks when liquidity is thin. Because OFI (see Section 2.1.2) assumes a constant depth parameter D, it treats these cases equivalently and may therefore understate price responses in unstable markets. By contrast, TFI, is based on executed trades (Equation 2) rather than order-book updates (Equation 1). Therefore, TFI more faithfully captures the realised impact of trades under varying liquidity conditions compared to OFI.

Imbalanced order availability creates additional complications. Consider the case where many sell orders at the best ask are suddenly cancelled. Under the assumptions outlined by Cont et al. (2014) and in Section 2.1.2, this reduces supply and makes OFI positive, suggesting upward price pressure even though the mid-price has not moved. If a new sell order then arrives and pushes the price down, OFI remains positive despite the falling price. This mismatch highlights how unevenly distributed liquidity can undermine OFI's predictive reliability.

5.1.2 Absence of Anti-Manipulation Regulation

According to Pasquale (2014), U.S. equity markets are governed by anti-spoofing regulations under the Dodd-Frank Act. In contrast, cryptocurrency markets lack comparable oversight (Hileman and Rauchs, 2017). Traders can freely place and cancel orders without any risk of those orders being filled. This allows traders to create fake buying or selling pressure without real commitment, injecting noise into the order book.

The replication period's quote-to-trade ratio of 2.08 suggests relatively modest order book manipulation compared to later periods, yet TFI still outperforms OFI. This indicates that even moderate levels of order cancellations and fake orders make OFI less reliable compared to executed trades, which prove genuine trading intent.

5.1.3 Orders Are Free, Trades Cost Money

The fundamental difference lies in commitment. Placing an order costs nothing and can be cancelled instantly with no penalty. Executing a trade, however, requires paying exchange commissions and accepting the bid-ask spread, which are the real costs that traders pay when they are serious about transacting (Cartea et al., 2015).

This cost difference means trades reveal genuine conviction from participants willing to pay for immediate execution, while orders often represent strategic positioning, price testing, or simple market monitoring (Cartea et al., 2015). In noisy cryptocurrency markets, this distinction makes executed trades substantially more informative than order placements (Silantyev, 2019).

This theoretical distinction is empirically supported by the intercept patterns in this study's regression results (Section 4.4). TFI intercepts remain positive and increase with sampling interval (from 0.0122 at 1 second to 13.4080 at 1 hour in 2017), which is in contrast to OFI's increasingly negative intercepts for the same period (see Tables 7 and 5, respectively). The positive TFI intercepts indicate that price changes from executed trades persist rather than reverse when trade flow returns to zero. This is consistent with trades carrying informational content from genuinely committed market participants (Cartea et al., 2015).

5.1.4 Order Flow Patterns Over Time

Both OFI and TFI show clustering in 2017, with OFI persisting to lag 3 and TFI to lag 5 (Figures 5a and 8a, respectively). This clustering happens because traders break large orders into smaller pieces to avoid moving the market too much (Chordia et al., 2002). When one side of the order book dominates for several consecutive intervals, directional pressure builds gradually. This confirms that price discovery unfolds step-by-step rather than all at once (Heusser, J., 2013).

As shown in Table 5, the negative regression intercepts for OFI are increasingly negative at longer intervals (from 0.0013 at 1 second to -6.1830 at 1 hour). Intuitively, the intercept represents the expected mid-price change when net order flow is zero. A negative intercept means that even without net buying or selling, the mid-price tends to move back to its previous level after a flow-driven move (Cont et al., 2014). This is called mean reversion. In other words, if a price jumps up due to buying pressure, it is likely to fall back partially, and if it drops due to selling pressure, it tends to recover slightly. One can think of the slope ($\hat{\beta}_{\text{OFI}}$) as pushing the mid-price in the direction of order flow, while the intercept ($\hat{\alpha}_{\text{OFI}}$) acts like a spring pulling it back when flow is zero (Cont et al., 2014).

5.2 Extension Period

Seven years later, the Bitcoin derivatives market on BitMex operates very differently. While TFI maintains its superiority over OFI, both metrics' explanatory power declined substantially (OFI: 55.43% to 8.76%; TFI: 58.56% to 16.22% at 1-minute intervals), as seen in Tables 6 and 8, respectively. The widening gap between TFI and OFI suggests that executed trades (Equation 2) have become relatively more informative than order book updates (Equation 1). This confirms that as markets become noisier, executed trades carry greater informational value. Three structural changes explain this deterioration: an increase in order book noise, algorithmic trading effects and market evolution.

5.2.1 Increase in Order Book Noise

The quote-to-trade ratio increased from 2.08 (2017) to 20.89 (2024). This represents a tenfold increase in orders that are placed and cancelled without execution. Simultaneously, the average bid-ask spread widened to 25.49 ticks (SD = 40.51) from 2.91 ticks (SD = 11.0). These changes create an environment where most order book activity represents positioning and signalling rather than genuine trading intent. Thus, making it increasingly difficult to distinguish real demand from strategic manipulation (Cartea et al., 2015).

The wider spread further enables manipulative behaviour by reducing the risk that fake orders get accidentally filled. Traders can place large orders far from the current price without fear of execution. This noise overwhelms the informational content in order flow, explaining why OFI's predictive power collapsed more severely than TFI's.

5.2.2 Algorithmic Trading Effects

OFI clustering in 2024 persists until lag 9 with slower decay (Figure 5b), suggesting stronger patterns of sustained order book activity. This likely reflects algorithmic trading strategies that generate waves of correlated order placements and cancellations (Cartea et al., 2015). Conversely, TFI clustering weakened substantially, with only lag 1 remaining significant (Figure 8b). This suggests the market now absorbs trade information into prices much faster, so buying or selling pressure does not persist as long. The contrast between OFI and TFI patterns reveals an important distinction: while algorithms constantly adjust their limit orders, actual trades in October 2024 reflect position adjustments rather than new information about Bitcoin's value (Cartea et al., 2015).

As shown by Table 6, OFI intercepts shifted from negative to positive at longer intervals (2.5649 at 5 minutes, 127.9933 at 1 hour), indicating that price changes driven by order flow in 2024 persist rather than reverse. This transformation reflects the unstable order availability and reduced market-making activity evident in the wider spreads and elevated order book noise. When fewer market makers provide consistent liquidity, prices do not quickly return to equilibrium after order flow shocks (Cont et al., 2014).

As shown by Table 8, TFI intercepts increased substantially with sampling interval (from 0.1061 at 1 second to 86.0347 at 1 hour), remaining positive across all intervals. The larger magnitude compared to 2017 suggests stronger baseline price movements, yet the consistent positive pattern confirms that executed trades continue to produce persistent price impacts rather than temporary disruptions. This reinforces the interpretation that trades carry informational content that becomes incorporated into prices permanently.

5.2.3 Market Evolution

The persistence of TFI's superiority across both periods demonstrates that this relationship is a durable feature of cryptocurrency market structure, confirming the generalisability of Silantyev (2019)'s findings. However, the dramatic deterioration in explanatory power reveals a paradox in how the market has matured. As cryptocurrency markets attract more sophisticated algorithmic traders, the order book has become cluttered with noise, yet the market has simultaneously become better at quickly incorporating genuine information from executed trades. This evolution confirms Barucci et al. (2023)'s observation that order flow explanatory power depends on market structure. Thus, showing that market changes over time increased algorithmic activity and order book manipulation, and are fundamentally reshaping how information moves into prices.

6 Conclusion

This study evaluated the explanatory power of Order Flow Imbalance (OFI) and Trade Flow Imbalance (TFI) in predicting short-term contemporaneous mid-price changes for Bitcoin, by replicating and extending Silantyev (2019)'s framework for the 1^{st}-23^{rd} October 2017 and October 2024. The aim was to clarify whether existing order flow models remain applicable in cryptocurrency markets or if market evolution has altered these relationships. The findings demonstrate that TFI consistently outperforms OFI across both periods, validating that executed trades provide more reliable price signals than order book activity in cryptocurrency markets. This contrasts with traditional equity markets where OFI demonstrates superior performance (Cont et al., 2014). Three structural features explain TFI's advantage: volatile market depth that violates OFI's fixed-depth assumption, the absence of anti-manipulation regulation that enables order book noise, and the commitment costs between placing orders and executing trades.

Notably, the market underwent a fundamental transformation between the replication and extension periods. Both OFI and TFI exhibited substantially reduced explanatory power in 2024. The quote-to-trade ratio surged from 2.08 to 20.89, while bid-ask spreads widened considerably. This created an environment dominated by non-executed order activity. Despite this deterioration, the relative gap between TFI and OFI widened, confirming that as markets become noisier, executed trades become increasingly valuable as informational signals.

These findings contribute to cryptocurrency market microstructure literature by investigating the generalisability of Silantyev (2019)'s results to a more recent period and documenting how market evolution fundamentally alters order flow dynamics. These results suggest that traditional equity market models, such as those by Cont et al. (2014), may not be directly applicable to cryptocurrency markets. Furthermore, these results extend Barucci et al. (2023)'s observation that order flow explanatory power varies by market structure. For market participants, the findings suggest that while order flow models remain relevant, their predictive power has diminished as cryptocurrency markets mature and attract algorithmic trading activity.

This study has several limitations. The replication dataset differs from Silantyev (2019)'s original data due to retrieval differences (see Section 3.1.1). Furthermore, the analysis focuses exclusively on BitMEX XBTUSD contracts, limiting generalisability across exchanges and trading pairs. The linear regression framework isolates specific order flow relationships but may not capture non-linear dynamics present in cryptocurrency markets. The extension period represents a single month in 2024, and external factors such as regulatory developments are not explicitly controlled.

Future research should examine multiple exchanges and trading pairs to assess whether TFI-OFI relationships generalise across the cryptocurrency ecosystem. Furthermore, incorporating non-linear and machine learning models could better capture complex order flow dynamics (Fang et al., 2024). Employing longitudinal studies across multiple periods and integrating statistical controls for external variables could enhance generalisability and causal inference of order flow. Investigating how specific algorithmic trading strategies affect order flow informativeness would clarify the mechanisms behind observed performance deterioration and inform whether predictive power can be recovered through more sophisticated modelling approaches.

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7 Appendix

A Exchange specification

BitMEX is primarily a derivatives exchange for cryptocurrency, rather than a spot market (Silantyev, 2019). All margin payments are conducted in Bitcoin. This means that participation requires only a Bitcoin deposit. A key feature of BitMEX is the leverage it offers. For the XBTUSD perpetual swap contract, maximum leverage can reach up to ×100 (BitMEX, n.d.).

The XBTUSD contract is a perpetual swap in which one contract represents 1 USD worth of Bitcoin. It does not expire but is subject to a margin funding mechanism. The contract tracks the underlying Bitcoin spot price via an index calculated from multiple spot exchanges (BitMEX, n.d.). BitMEX calculates the deviation between the XBTUSD price and the index price when the contract price exceeds the index to reduce tracking error. Long holders pay a funding fee to short holders, and vice versa when the contract price is below the index (Silantyev, 2019). This mechanism incentivises convergence between the swap and spot market prices.

BitMEX's fee structure is favourable to market makers relative to other exchanges. Market makers receive a rebate of 0.025%, while market takers pay a fee of 0.075% (BitMEX, n.d.).

B Stationarity Tests

B.1 Price Series

Table 9: 15th October 2017: ADF and KPSS test results for ΔP_k at different sampling periods k.

Sampling Period k	ADF Statistic	ADF CV 1%	KPSS Statistic	KPSS CV 1%
1 sec	-814.83	-2.58	0.061	0.739
10 sec	-257.00	-2.58	0.061	0.739
1 min	-129.04	-2.58	0.069	0.739
5 min	-54.14	-2.58	0.074	0.739
10 min	-37.22	-2.58	0.075	0.739
1 hour	-16.31	-2.58	0.089	0.739

Table 10: 15 October 2024: ADF and KPSS test results for ΔP_k at different sampling periods k.

Sampling Period k	ADF Statistic	ADF CV 1%	KPSS Statistic	KPSS CV 1%
1 sec	-907.97	-2.58	0.088	0.739
10 sec	-327.66	-2.58	0.086	0.739
1 min	-138.74	-2.58	0.086	0.739
5 min	-61.22	-2.58	0.092	0.739
10 min	-44.07	-2.58	0.101	0.739
1 hour	-19.44	-2.58	0.116	0.739

B.2 Orders

Table 11: (October 1st-23rd 2017): ADF and PP test for 10-second update arrival volumes at 5% significance level.

Test	Test Statistic	5% Critical Value
ADF (drift)	-176.855	-2.860
PP (Z−tau)	-365.807	-2.862

Table 12: (October 2024): ADF and PP test for 10-second update arrival volumes at 5% significance level.

Test	Test Statistic	5% Critical Value
ADF (drift)	-140.623	-2.860
PP (Z−tau)	-307.877	-2.862

B.3 Order Flow Imbalance

Table 13: (October 1st-23rd 2017): ADF and KPSS tests for Non-Differenced OFI.

Interval	ADF Statistic	ADF CV (1%)	KPSS Statistic	KPSS CV (1%)
1 sec	-762.61	-2.58	0.116	0.739
10 sec	-252.31	-2.58	0.070	0.739
1 min	-121.47	-2.58	0.064	0.739
5 min	-55.75	-2.58	0.060	0.739
10 min	-38.96	-2.58	0.061	0.739
1 hour	-16.78	-2.58	0.075	0.739

Table 14: (October 2024): ADF and KPSS Tests for Non-Differenced OFI.

Interval	ADF Statistic	ADF CV(1%)	KPSS Statistic	KPSS CV (1%)
1 sec	-755.20	-2.58	6.511	0.739
10 sec	-255.67	-2.58	2.331	0.739
1 min	-89.53	-2.58	1.064	0.739
5 min	-42.07	-2.58	0.640	0.739
10 min	-33.64	-2.58	0.546	0.739
1 hour	-15.45	-2.58	0.359	0.739

Table 15: (October 2024): ADF and PP Tests for Non-Differenced OFI : stationarity tests at 1% significance level .

Interval	ADF Statistic	ADF 1% CV	PP Statistic	PP 1% CV
1 sec	-755.20	-2.58	-1335	-3.434
10 sec	-255.67	-2.58	-471.906	-3.434
1 min	-89.53	-2.58	-155.269	-3.434

B.4 Trade Flow Imbalance

Table 16: (October 1^{st}-23^{rd}, 2017): ADF and KPSS tests for TFI.

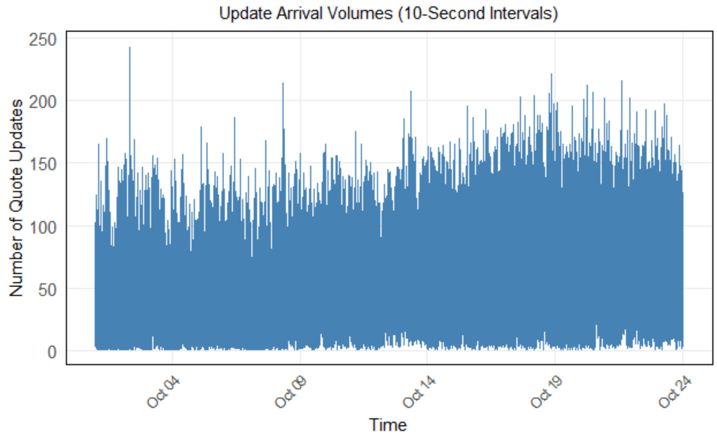
Interval	ADF Statistic	ADF CV (1%)	KPSS Statistic	KPSS CV (1%)
1 sec	-579.90	-2.58	0.328	0.739
10 sec	-231.46	-2.58	0.153	0.739
1 min	-109.52	-2.58	0.122	0.739
5 min	-54.15	-2.58	0.105	0.739
10 min	-37.21	-2.58	0.101	0.739
1 hour	-16.44	-2.58	0.107	0.739

Table 17: (October 2024): ADF and KPSS Tests for TFI.

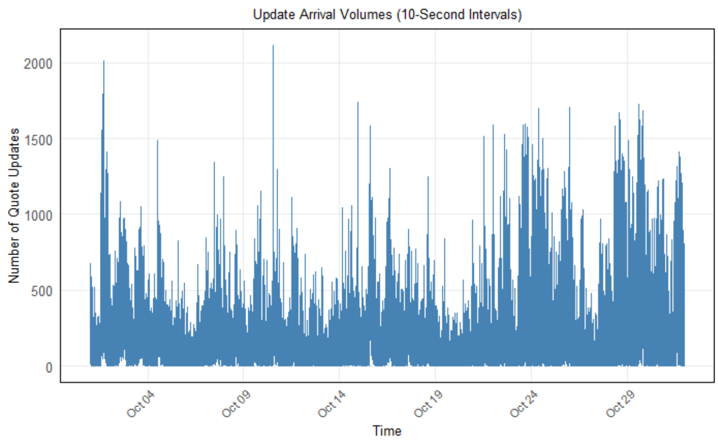
Interval	ADF Statistic	ADF CV(1%)	KPSS Statistic	KPSS CV (1%)
1 sec	-426.00	-2.58	0.104	0.739
10 sec	-281.67	-2.58	0.086	0.739
1 min	-137.91	-2.58	0.073	0.739
5 min	-62.26	-2.58	0.068	0.739
10 min	-44.55	-2.58	0.067	0.739
1 hour	-18.04	-2.58	0.063	0.739

C Time Series Plots

C.1 Update Arrival Volumes



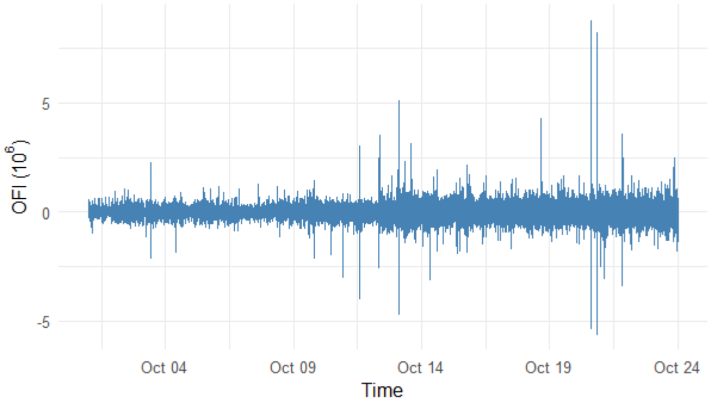
(a) October 2017



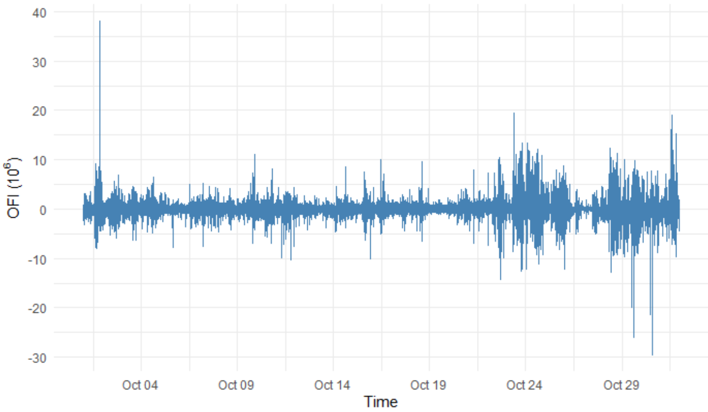
(b) October 2024

Figure 12: XBTUSD Update Arrival Volumes in 10 second intervals.

C.2 Order Flow Imbalance

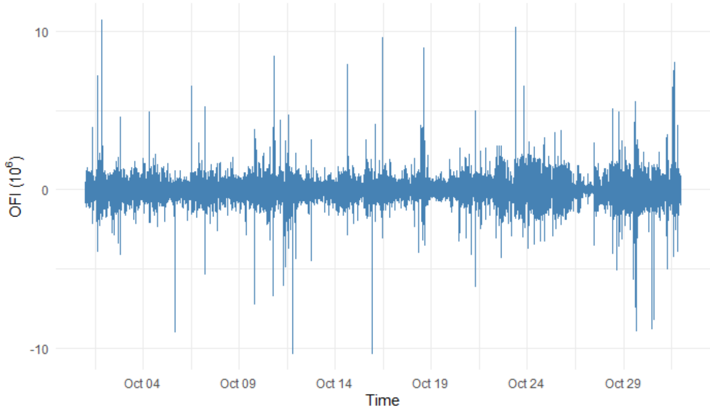


(a) October 2017

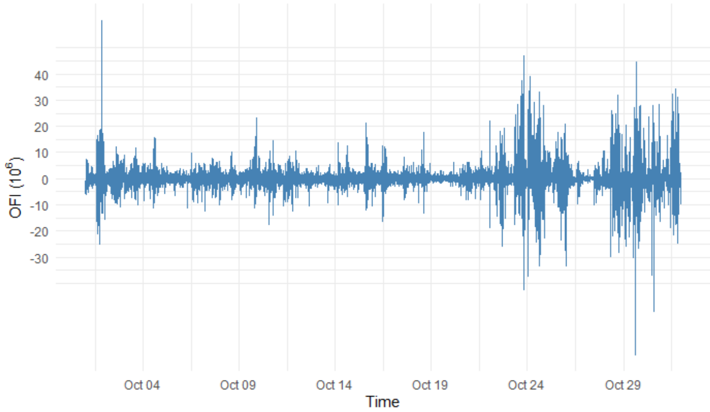


(b) October 2024

Figure 13: XBTUSD 10s OFI time series.



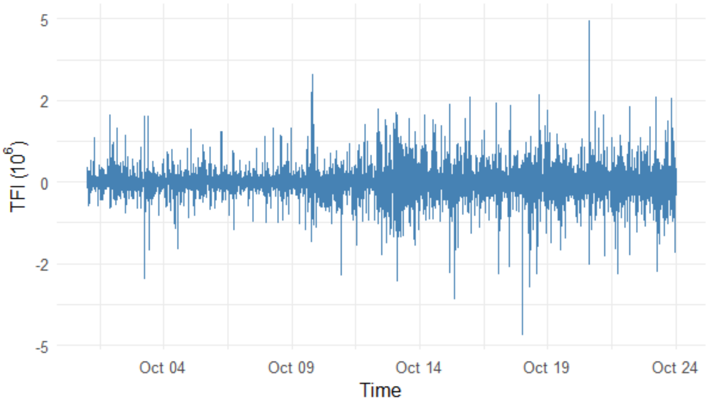
(a) OFI 1-second time series of XBTUSD in October 2024



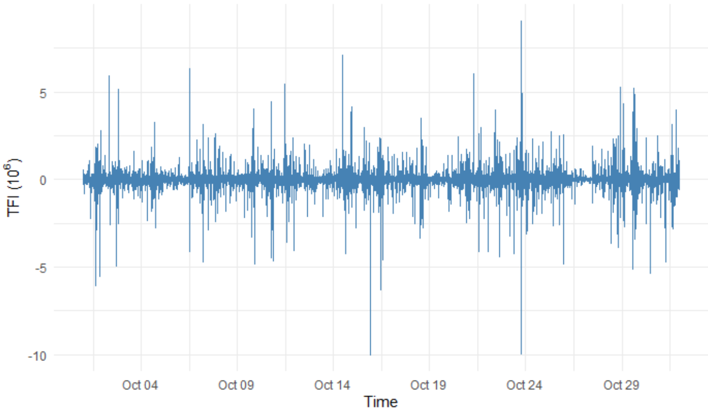
(b) OFI 1-minute time series of XBTUSD in October 2024

Figure 14: XBTUSD OFI time series to confirm stationarity.

C.3 Trade Flow Imbalance



(a) October 2017



(b) October 2024

Figure 15: XBTUSD 10s TFI time series.