CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

Price Impact of Order Book Events in Bitcoin Market

Bachelor's thesis

Author: Marek Erben
Study program: Economics and Finance
Supervisor: Mgr. Jan Šíla, MSc.
Year of defense: 2023

Declaration of Authorship

The author hereby declares that he or she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title. The author further declares that generative AI tools were used during the compilation of this thesis, with strict adherence to the principles of academic integrity, only to enhance the writing style.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, August 1, 2023

Marek Erben

Abstract

This thesis examines the price impact of order book events in the Bitcoin market. Using the data obtained from Binance exchange, the thesis shows that short-term price changes can be explained by high-frequency demand-supply interaction depicted in the Limit Order Book (LOB). The thesis demonstrates that the instantaneous price impact function has a non-linear shape, indicating that small and large orders have different effects on price, potentially leading to opportunities for price manipulation and quasi-arbitrage. Additionally, the analysis confirms the inverse relation between the price impact coefficient and market depth. Furthermore, the thesis observes that there are no clear intraday patterns for the price impact coefficient. These findings provide valuable insights into the understanding of Bitcoin's price dynamics, benefiting traders, investors, and policymakers seeking to understand the complexities of the cryptocurrency market.

JEL Classification	C58, G12
Keywords	Bitcoin, price impact, market microstructure, limit order book
Title	Price Impact of Order Book Events in Bitcoin Market

Abstrakt

Tato práce zkoumá vliv událostí v knize objednávek na cenu pro trh s Bitcoinem. S využitím dat z burzy Binance ukazuje, že krátkodobé změny cen lze vysvětlit pomocí vysokofrekvenčních interakcí mezi poptávkou a nabídkou zobrazenou v knize limitních objednávek. Odhadnutá funkce cenového vlivu má nelineární tvar. Tento výsledek naznačuje, že malé a velké objednávky mají rozdílný vliv na cenu, díky čemuž může docházet k cenové manipulaci a arbitráži. Analýza rovněž potvrzuje inverzní vztah mezi koeficientem cenového dopadu a hloubkou trhu. Dále práce konstatuje, že pro koeficient cenového dopadu neexistují jasné denní vzorce. Tato zjištění poskytují cenné poznatky pro pochopení cenové dynamiky Bitcoinu a jsou přínosem pro obchodníky, investory a regulátory, kteří se snaží pochopit komplexnosti trhu s kryptoměnami.

Klasifikace JEL	C58, G12
Klíčová slova	Bitcoin, vliv na cenu, mikrostruktura trhu, kniha limitních objednávek
Název práce	Dopad událostí v knize objednávek na cenu Bitcoinu

Acknowledgments

I am immensely grateful especially to Mgr. Jan Šíla, MSc., for his unwavering support, guidance, and valuable counsel throughout writing of my thesis. I am particularly thankful for the time he dedicated to me, his feedback was fundamental for refinement of the study. I am also thankful to my family and my partner for their constant support.

We gratefully acknowledge the financial support from the Czech Science Foundation under the project 'Deep dive into decentralized finance: Market microstructure, and behavioral and psychological patterns' [grant number 23-06606S].

Typeset in LaTeXusing the IES Thesis Template.

Bibliographic Record

Erben, Marek: *Price Impact of Order Book Events in Bitcoin Market*. Bachelor's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2023, pages 41. Advisor: Mgr. Jan Šíla, MSc.

Contents

List of Tables

List of Figures

Acronyms

LOB Limit Order Book

OFI Order Flow Imbalance

BTC Bitcoin

USD United States dollar

VAR vector autoregression

OLS ordinary least squares

TFI Trade Flow Imbalance

Chapter 1

Introduction

First cryptocurrency, Bitcoin, was introduced by Nakamoto (2008) as a decentralized digital currency, which relies on the technology called blockchain. In a blockchain-based system, transactions are validated and recorded on a distributed ledger, allowing secure peer-to-peer interaction between participants without the need for supervision from a trusted third party. Since the introduction of Bitcoin, many other cryptocurrencies have been introduced such as Ethereum, Dogecoin and Tether. Nevertheless, Bitcoin is still the most widely known and traded cryptocurrency with the highest market capitalization among cryptocurrencies. As of 23/7/2023, the market capitalization is 580 Billion USD which is twice the GDP of the Czech Republic in 2021[1]. Even though Bitcoin was presented as a currency, findings of Baur *et al.* (2018) suggest that the majority of the transactions are made for the purpose of speculative investment rather than for purchasing goods or services. Leading to a notion that Bitcoin is closer to a speculative investment asset instead of a medium of exchange.

Bitcoin is traded on various exchanges around the world, which, like stock exchanges, utilize a Limit order book, electronic continuous-time double- auction mechanism. But unlike more traditional financial markets, which are regulated, the markets for cryptocurrencies are mostly unregulated and open for trading 24 hours 7 days a week. The unique characteristics of cryptocurrency markets together with the high volatility of Bitcoin make them an interesting subject for market microstructure research.

This thesis studies whether short-term changes in the price of Bitcoin can be explained by the measure of high-frequency demand-supply interaction de-

[1]Information comes from the website https://blockworks.co/price/btc

picted in Limit Order Book (LOB). The aim is to examine the shape of the price impact function, the relationship of price impact to market depth, and to investigate intraday patterns of the price impact coefficient by applying the methodology developed by Cont *et al.* (2014).

The price impact can be defined as a correlation between an incoming buy or sell order and the price change associated with that order, buy trades should on average push the price up, while the opposite is true for sell orders. For traders each subsequent buy trade is typically costlier than the initial one due to their own influence on the price (vice-versa for sell orders). The size of the price impact is determined by the market depth. Lower market depth is associated with higher price impact as markets are less able to absorb large orders (Farmer *et al.* 2004; Weber & Rosenow 2006). Thus, the relationship between market impact and liquidity (market depth) is inverse.

Studying the price impact is essential for market participants as it provides insight into the price formation mechanics of the market, and can help with managing and mitigating risks and costs connected to orders. The optimal liquidation of a large block of shares is a particularly important application, which crucially involves making assumptions about price impact (Obizhaeva & Wang 2013; Almgren & Chriss 2001; Bertsimas & Lo 1998). For this reason, there exists a large body of literature that concerns itself with the price impact of trades (Hasbrouck 1991; Kempf & Korn 1999; Potters & Bouchaud 2003; Gabaix *et al.* 2003; Plerou *et al.* 2002). Bouchaud *et al.* (2003) connected the decline of the price impact of trades with limit orders, further supported by findings of Weber & Rosenow (2005) that the price impact of trades is diminished by the arrival of limit orders. These empirical findings suggest that focusing only on trades, without considering the impact of limit orders, overlooks a significant aspect of the price formation process (Cont *et al.* 2014).

As the Bitcoin market matures it starts to draw the attention of institutional investors, but they can be hesitant to enter the Bitcoin market when they do not know risks and specifics on how orders affect prices in this environment. There is a scarcity of studies that provide the insight about the price impact in cryptocurrency markets (see Silantyev (2019); Donier & Bonart (2015)) which my thesis aims to fill.

Cont *et al.* (2014) argue that over short time intervals, price changes are mainly driven by the OFI, which is defined as the imbalance between supply and demand at the best bid and ask prices. Cont *et al.* (2014) found that the relationship of instantaneous price impact of order book events is linear. However, my analysis suggests that the price impact is a non-linear increasing function. According to Huberman & Stanzl (2004) non-linearity of price function implies that in the Bitcoin market there are opportunities for price manipulation and arbitrage to make risk free profits. Cong *et al.* (2022) describe how such price manipulation can occur in the Bitcoin market in the form of wash trading which is able to distort price, volume and volatility by placing buy and sell orders at the same time for the same asset, and thus create the appearance of legitimate trading volume. Leading to reduction of investors' confidence and participation in financial markets Cong *et al.* (2022); Aggarwal & Wu (2006); Cumming *et al.* (2011). Such price manipulation is made possible because the Bitcoin market is largely unregulated.

I estimated the relation between price impact coefficient and the market depth. My results show that unit change in market depth(liquidity) will invoke more than a unit change in price impact coefficient. This result is crucial for traders who post large orders. Bitcoin market still exhibits relatively low liquidity compared to traditional financial markets. In this environment large orders are usually executed using lower than the best price in LOB and therefore push the price up (or down) for buy (or sell) orders. It follows from the estimated relation between market impact and market depth, that the price impact, which can be seen as a cost by traders, introduced by large orders is higher in the Bitcoin market. Thus, by placing a large order traders reveal to the market, that they have a new information about future price moves and deem such action as profitable despite the associated higher costs.

I also find that there is no clear intraday pattern, as seen on other financial markets. Most financial markets are open from 9:00 to 16:00, Cont *et al.* (2014) find that in the beginning the market is two times lower than on average during the day. In a shallow market the incoming orders are likely to trigger the mid-price change, so the price impact coefficient is high. I would attribute the fact that I was not able to observe such a pattern to the design of the Bitcoin market which is open 24/7.

The thesis is structured as follows: Firstly, Chapter 2 introduces to a reader the electronic order driven markets and literature related to price impact for more traditional financial markets and concludes with introduction of price impact literature for Bitcoin market. Chapter 3 describes Stylized Model of Limit Order Book, data and variables used and proposes a model of instantaneous price impact. Chapter 4 presents results of estimated models and discusses the interpretation of the results of my research. Lastly, Chapter 5 concludes my thesis by summarising and highlighting the key findings.

Chapter 2

Literature Review

2.1 Electronic Order-Driven Markets

Since the introduction of the first electronic order-driven market (NASDAQ) on 8.2.1971 in the USA, automated trading and dealing essentially supplanted the floor-based trading in equity markets. Today, majority of equity exchanges such as the NYSE, the Tokyo Stock Exchange, Toronto Stock Exchange, Vancouver Stock Euronext (Paris, Amsterdam, Brussels), and the London Stock Exchange and cryptocurrency exchanges such as Binance, Kraken, Bitfinex either fully or partially implemented an electronic continuous-time double-auction mechanism based on a fundamental concept of LOB. Unlike markets where a single market maker or specialist gathers all buy and sell orders and provides liquidity by setting bid and ask quotes, this electronical mechanism aggregates in real time all outstanding limit orders to a LOB which is accessible to all market participants, market orders are then mechanically matched and executed against the best present prices (quotes), thus allowing buyers and sellers to trade directly with each other. The most recent market actions and corresponding shifts in supply and demand lead to continuous updating of LOB in real-time.

Due to the accessibility of limit order book to all market participants, there is increased access to high-quality, high-frequency data of transactions, quotes, and order flow. Cont (2011) states that the time it takes for market orders to be executed on these electronic exchanges has decreased from more than 25 milliseconds in 2000 to less than 1 millisecond in 2010, while the frequency of order submission has grown, leading up to 100 000 updates per day in bid and ask quotations as well as regular changes in transaction costs. For Bitcoin data that I used the number of quotation updates reaches 150 000 updates per day.

The high-frequency data that LOB provides have completely changed the way how financial markets are studied. The abundance of information about market participants' actions that these data give can be used to draw distinct relations between order flow, liquidity, and asset price movements (Cont 2011). The study of this area is often referred to as market microstructure. According to Bouchaud *et al.* (2018) market microstructure describes how actions of individual traders affect the market as a whole and, in particular, how the price formation process can be derived from these actions. This creates a distinction between market microstructure and other fields of study, such as financial risk management, which generally tend to take price as an input in their models.

Results from the models of high-frequency data are often used as a basis for decision making in areas such as market making and regulation, or risk management. The models themselves also serve as a foundation for optimal trade execution as well as for market design.

2.2 Price Impact

The critical problem where market microstructure models are used is an optimal liquidation of a big block of shares given a defined time horizon (Bertsimas & Lo 1998; Almgren & Chriss 2001; Obizhaeva & Wang 2013). For this kind of a problem, it is essential to make assumptions about price impact, which is defined as the effect of a market participant's trading activity on the price of an asset or security. For traders, this price is the equivalent of trading costs, since each subsequent trade is more expensive because buy trades on average push the price up (the opposite is true for sell trades).

Bouchaud *et al.* (2018) states that there are two perspectives on interpretation for price impact that sit on the complete opposite of a spectrum. First, the efficient-market hypothesis states that at any given time, prices fully reflect all available information. This perspective explains the price impact by the fact that market participants accurately predict short-term price fluctuations with the new information available and make their trading decisions based on these forecasts. So for example when a trader is expecting a price increase he will purchase the asset ahead of this anticipated change. This action undeniably leads to positive correlation between trades and subsequent price change.

The other interpretation, that Bouchaud *et al.* (2018) mentions, is efficient-market sceptic perspective, it states that the information does not have an influence on price fluctuations rather that price fluctuations are a consequence of a completely unpredictable order flow which leads to certain dynamics within the LOB. In other words, prices move only because of trades. Then if everything else remains unchanged, an additional buy order will on average cause a price to rise. In this setting the price impact is a completely mechanical result of fluctuation in supply and demand (see Farmer *et al.* (2005)). Although both of these perspectives explain what causes the price impact, there is no consensus on which view is closer to reality.

Although price impact could be modelled by construction of a LOB model, such model would inherently predict price impact conditional on the placed order. In this thesis, however, I am going to focus on modelling price impact by joint analysis of order flow and price time series.

Toth *et al.* (2017) are concerning themselves with the question which perspective is closer to reality. They are comparing a price impact from the trades of Capital Fund Management in their proprietary dataset with the price impact of the rest of the market. The proprietary dataset They find that there is a little difference between public data and proprietary data on short time scales suggesting that the short term price impact is universal for all market participants. This leads to the notion that the short term price impact is a statistical property of the market and has nothing to do with the information content of the trades, which become apparent only within larger timescales. This result seems intuitive as liquid stocks are traded with very high frequency, in matter of seconds, much quicker than any relevant information can be incorporated to the prices by participants. This finding is very important since most of the empirical studies of price impact use public data with anonymised orders to calibrate their models which only assumed that the price impact of informed trade is the same as that of the uniformed trade.

Hasbrouck (1991) introduced a very popular method of modelling the price impact by jointly analysing the dynamics of price and order flow using vector autoregression (VAR) systems. VAR model uses ordinary least squares (OLS) estimation of coefficients of the assumed general noisy relation between variables. One of the key findings of Hasbrouck (1991) is that the price impact function of order flow is increasing and concave. This is supported by many other studies which concerned with price impact of market orders (Kempf & Korn 1999; Gabaix *et al.* 2003; Potters & Bouchaud 2003; Plerou *et al.* 2002)

Bouchaud *et al.* (2003) are analysing data from the Paris stock market and empirically find that the price process is almost exactly purely diffusive and that there is long range correlation of signs of the trades. They argue that if the price impact of a trade is permanent, it would lead to strong robust super-diffusion of the prices, however, that would contradict their empirical findings. Therefore, they introduce a 'propagator' or transient impact model (TIM), where price is represented as a linear superposition of the impact of all previous trades mediated by a propagator function in time and depicts the market's reaction to a specific trade. The key to the overall diffusive behaviour of the price process is in the shape of the propagator function and its decay in time which must follow a power law that leads to sub-diffusion of the prices to counter the super-diffusion which falls from the strong correlation of the trades sign.

Bouchaud *et al.* (2003) discuss theoretically that this fluctuation and response relation could emerge from the opposite tendencies of market makers and liquidity takers. Best scenario for market makers (liquidity providers) is when the bid and ask prices are as stable as possible and the order flow is balanced, because only in this setting they have ensured earning of the bid-ask spread from each round-trip trade. The observed imbalance of order flow, for example market maker receives many more sell orders than buy orders could be a signal that market maker's bid price is too high and that the liquidity takers have new information about the future price decrease. If it is the case, it leads to accumulation of large inventory of the asset, which can lead to a loss after the price decreases. However, the market maker can manage this inventory risk by changing prices, decreased bid price discourages selling and increases ask price encourages buying. This is exactly the mechanism of the mean reversion of the price (long-range anti-persistance in price changes).

The reason that liquidity takers break down their market orders into chunks that are traded over longer time horizons is to conceal their information about the price change and an effort to avoid any sudden price changes that would make the trades more costly. Bouchaud *et al.* (2003) argue that this is the explanation of the long-range persistence in the sign of the market orders (Bouchaud *et al.* 2003; Hasbrouck 1991; Lillo & Farmer 2004), which should lead to super-diffusion of the price process. These two effects offset each other and lead to overall diffusive price behaviour.

Cont *et al.* (2014) argue that it is exactly for this reason that focusing only on market orders amounts to ignoring a crucial part of the price formation process, which is realised through limit orders. This is further motivated in Eisler *et al.* (2012) who argue that in the modern market setting it is impossible to recognise between market maker and liquidity taker as informed traders can place limit orders as well to reduce their transaction costs. Therefore, limit buy order increases the upward pressure on price and cancelling the limit buy order reduces this pressure.

Hautsch & Huang (2012) focus on modelling market impact of limit orders from the outset using data of 30 different stocks on the Euronext Amsterdam exchange over a period of two months in the year 2008. They model the top three levels of depth on both sides of the market, along with the bid and ask quotes using a cointegrated VAR system model. Their empirical analyses provides further evidence that limit orders can have an impact on the price formation. One of the findings reveals that placing large aggressive limit orders can influence the market such that the market price moves towards the price of the posted large limit order. Aggressive limit order is such limit order that leads to a change of bid or ask price, which results in narrowing the difference between the two. Reasoning behind this process could be that placing a large limit order can signal to the market that significant buyer or seller shifts his valuation of the asset price based on an information, which can influence other market participants to accept this new price as a market price.

Cont *et al.* (2014) formalise the OFI, which is an aggregate of volumes of order book events such as market, limit and cancel orders into a single variable (measure) and it treats contributions of market events equally. They provide theoretical and empirical evidence that between high-frequency price changes and the OFI of individual stocks exists a linear relation and that this linear connection is robust across different stocks and time scales. Furthermore, they argue that OFI serves as a broader measure of supply/demand dynamics than trade imbalance (imbalance that consists of only market orders/trades).

Other notable study that tries to provide understanding of price impact of all order book events is Eisler *et al.* (2012). They start with discrete categorization of market events (market orders, limit orders and cancellations) and introduce History Dependent Impact Model (HDIM), which is able to associate each price change with one of these events. Eisler *et al.* (2012) find that by including all event types, the price becomes pure jump process. They also confirm that the interplay between limit orders and market orders is what prevents persistent trends in prices.

2.3 Bitcoin

Bitcoin financial literature is a rapidly growing field, Härdle *et al.* (2020) provide a broad overview of the blockchain technology, which serves as a backbone of cryptocurrencies and secondly the comprehensive summary of research possibilities. One of the mentioned study Ghysels & Nguyen (2019) examines the information content and liquidity of the limit order book on a leading Bitcoin exchange. Their study reveals, that trades and limit order at the best price (bid and ask) are the most informative, they also find existence of intricate dynamics between liquidity and volatility in the Bitcoin market. High asset volatility leads to worsened liquidity due to adverse selection, while low volatility environments see improved liquidity, where adverse selection refers to the a situation where traders with more information can take advantage of traders with less information.

Mark *et al.* (2022) developed a reflexivity index for the Bitcoin market and conclude that that about 80% of mid-price changes are determined within the market itself, which is significantly lower compared to equity, where the value is closer to 1. They further discuss that the level of endogeneity in the crypto market is similar to that found in foreign exchange markets for national currencies, which share certain key characteristics with Bitcoin.

Donier & Bonart (2015) present an empirical analysis of market impact of meta-orders in the Bitcoin/USD exchange market using a dataset of over one million meta-orders. Meta-orders are large orders, whose execution is spread over a certain time period. Their findings indicate that the Bitcoin market shows comparable response to trades and also the serial dependence of orders as is present on mature liquid financial markets. Thus they confirm that the square root impact law for individual meta-orders observed on the financial markets also holds true for the Bitcoin (BTC)/United States dollar (USD) market. The square root law is empirical law, that states that the price impact of a trade is proportional to the square root of the trade size. Donier & Bonart (2015) argue the presence of this law on the Bitcoin market, which, compared to financial markets, has different characteristics such as daily traded volume and volatility could imply that the square root law is universal across markets. However, they found that the Bitcoin market reacts to the total order flow rather than to the individual meta-orders, suggesting that market participants do not detect the meta-orders. This means that the effects of different meta-orders are not independent of each other, and their combined effect is not simply the sum of their individual effects. Instead, the impact of one meta-order can depend on the presence of other meta-orders leading to a more complex, non-linear relationship.

Donier & Bonart (2015) also show that typically 30-40% of daily traded volume is present in the LOB at the start of the day. This emphasizes the significant role that LOB in the Bitcoin market has since a large fraction of liquidity is not hidden. This is in stark contrast to traditional financial markets where less than 1% of daily traded volume is revealed in the morning Wyart *et al.* (2008).

Silantyev (2019) analysis short-term price impact of order book events with methodology developed by Cont *et al.* (2014). He uses quotes and trade data from BitMex exchange and computes both OFI and Trade Flow Imbalance (TFI) over different time intervals ranging from 1 second to 1 hour. OFI measures all order book events including market orders, limit orders and cancellations, whereas TFI measures only net volume of buy and sell trades. Silantyev (2019) finds that there are statistically significant positive linear relationships between each measure and mid-price changes across all time intervals and demonstrates that TFI is better at explaining contemporaneous mid-price changes than OFI at all time intervals, except the 10 seconds time interval. This is in contrast to findings in study by Cont *et al.* (2014) where authors found for classical financial markets that OFI is a broader measure, which contains more information about the price changes and in result leads to better explanation of price changes than TFI. Despite this finding I am following results of better established literature Cont *et al.* (2014) and use OFI in my analysis.

Guo & Antulov-Fantulin (2018) propose a temporal mixture model to forecast short-term volatility in prices in the Bitcoin market. They use data of realized volatility observations over short time periods and they reformat the order book data such that it constitutes a series of features and formulate the volatility prediction problem as a task of learning predictive models. They use a temporal mixture model to establish the dynamic effect of order book features on short-term volatility evolution and find that this type of model in most cases outperforms other modeling approaches, such as time series models and ensemble methods and that this type of approach is robust.

Chapter 3

Methodology

3.1 Quotes and Trades

Market participants can place two types of buy or sell orders. A limit order specifies the quantity q of a security to trade and a specific price P at which to trade the security and is posted to an electronic trading system. Price P must be a multiple of the minimal price change, called tick δ. The LOB is the collection of all outstanding limit orders from market participants, it shows the quantities of security available for trade at each price level. The bid (or ask) price is the maximum (or minimum) price for which the market participant is willing to buy (or sell) the security. Hence, we can think about the bid side of LOB as a demand and inversely ask side of LOB as a supply of the asset.

A market order is the second type of an order, it instructs to buy (or sell) a certain amount of an asset at the best price offered in the LOB. Upon arrival, the market order is immediately matched to the best available price in the LOB. If the market sell (or buy) order of size x is executed, then the quantity at the bid (or ask) price is decreased by x and the trade takes place.

A limit order remains in the order book until it is either executed against the market order or canceled by the market participant who placed the order. If a limit order matches the bid/ask prices or is close to them, it can be executed very quickly. On the other hand, if the market price shifts far from the desired price or the requested price is considerably different than the bid (or ask) price, the execution might take a considerable amount of time. It is important to note that the limit order can be subject to cancellation at any given moment. The cancellation holds true for most limit orders on electronic exchanges. According to Cont (2011) nearly 80% of limit orders on liquid stocks on the NYSE and

NASDAQ are canceled within a second of being posted.

The quote data contain information on how the bid and ask prices, along with the corresponding quantities quoted at these prices evolved over time. Every time a limit order is posted, realized against a market order, or canceled, these quantities change. The term "level-1 order book" is sometimes used for quote data because they match the data at bid/ask, which is the first level of the order book.

3.2 Quotes Data

My main data set consists of quotes data from Binance exchange for Bitcoin over a time period from 15/11/2020 to 14/2/2022. I have it stored by days, therefore, I have 457 files, one per each day. One entry in quotes data contains a timestamp, exchange and symbol flags, best bid and ask price, bid volume and ask volume for Bitcoin. The format of the timestamp includes date and time in milliseconds.

The average daily number of quote updates is 1 955.9 thousands. The average mid-price is 440 086.96 USD and it changes through the day on average 578 187 times. The average spread is 37 cents, the average best bid quote size is 513.28 BTC, and the best ask quote size is 552.55 BTC. There is one period between 13:20:36.595 and 15:10:27.582 on May 19, 2021 where there is empty LOB as both ΔP and OFI are zero. Similarly, on January 4, 2021, I was not able to compute the first 15 observations of ΔP and OFI since the first update to quotes occurred at 00:02:34.

Table 3.1: Exchange Data

timestamp	ask amount	ask price	bid amount	bid price
2021-11-15 00:00:00.135	2.405	65568.39	0.684	65568.38
2021-11-15 00:00:01.859	2.405	65568.39	0.594	65568.38
2021-11-15 00:00:02.153	3.341	65568.39	1.653	65568.38
2021-11-15 00:00:02.816	3.341	65568.39	1.652	65568.38
2021-11-15 00:00:02.989	3.319	65568.39	1.633	65568.38

Note: Data come from Binance exchange.

3.3 Stylized model of the Limit Order Book

Cont *et al.* (2014) assumes simplified model of an LOB which he calls a Stylized Model of the Limit Order Book (LOB). The main assumption of Stylized Model is that the depth D (the number of shares) is equal to constant value D at every price level including the best bid and ask. This implies that order arrivals and cancellations are limited to best bid and ask prices exclusively because a new best level is initialized every time when bid (or ask) size reaches the value of D. For the bid (or ask), the subsequent limit order arrives 1 tick above (or below) the best available quote. Under these assumptions, I have additive effects of the individual order events. When I take time interval $[t_{k-1}, t_k]$, let L_k^b represent the cumulative size of limit buy orders that have arrived during the given time interval and C_k^b denote the total size of buy orders that were canceled from the current best bid within the same time interval. In addition, I use the following definitions, M_k^b represents the total size of market buy orders that have been received at the current best ask during the time interval and P_k^b represents the bid price at time t_k. The quantities L_k^a, C_k^a, M_k^a are defined analogously for limit sell order, sell order cancellation, and market sell order, the P_k^a is the ask price. Cont *et al.* (2014) argues that thanks to this simplified order book model there exists simple linear relations between order flows $L_k^{b,a}$, $C_k^{b,a}$, $M_k^{b,a}$ and price changes $\Delta P_k^{b,a} = \left(P_k^{b,a} - P_{k-1}^{b,a}\right)$:

$$\Delta P_k^b = \delta \left\lceil \frac{L_k^b - C_k^b - M_k^a}{D} \right\rceil \tag{3.1}$$

$$\Delta P_k^a = -\delta \left\lceil \frac{L_k^a - C_k^a - M_k^b}{D} \right\rceil, \tag{3.2}$$

where δ is tick size. These relations allow us to compute price change over period $[t_{k-1}, t_k]$ directly.

For example when $D = 10$, and in given time interval occur first market sell order of size 16, $M_k^a = 16$. The bid price change will be $-\delta$ and bid size on the new price will be 4. After that will arrive limit buy order of size 7, $L_k^b = 7$. That will change the price by δ back to previous value and on the new price the bid size will be 1. Lastly, I record limit buy cancel order of size 14, $C_k^b = 14$, which will change the bid price by 2 ticks -2δ and on the new price the bid size will be equal to 7. So the overall change is equal to -2δ.

$$\Delta P_k^b = \delta \left\lceil \frac{L_k^b - C_k^b - M_k^a}{D} \right\rceil = \delta \left\lceil \frac{7 - 14 - 16}{10} \right\rceil = -2\delta$$

The proposed relations are without parameters, the effect of all order book events is cumulative and relies solely on their net imbalance. I am following Cont *et al.* (2014) also in that the following analysis is carried out for mid-price changes normalized by tick size $\Delta P_k = \frac{P_k^b + P_k^a}{2\delta}$, instead of analyzing bid and ask prices separately.

$$\Delta P_k = \frac{\mathrm{OFI}_k}{2D} + \epsilon_k, \tag{3.3}$$

$$\mathrm{OFI}_k = L_k^b - C_k^b - M_k^a - L_k^a + C_k^a + M_k^b, \tag{3.4}$$

where OFI_k is the order flow imbalance and ϵ is the truncation error.

3.4 Variables

I define the variables that I will use same as Cont *et al.* (2014). I begin with taking every observation of bid and ask, which is formed by the bid price P^b, the bid queue size q^b and the ask price P^a and size q^a. I label them with the index n and calculate the differences between consecutive observations of P_n^b, q_n^b, P_n^a, q_n^a as follows:

$$e_n = q_n^b I_{\{P_n^b \geq P_{n-1}^b\}} - q_{n-1}^b I_{\{P_n^b \leq P_{n-1}^b\}} - q_n^a I_{\{P_n^a \leq P_{n-1}^a\}} + q_{n-1}^a I_{\{P_n^a \geq P_{n-1}^a\}}, \tag{3.5}$$

where I is the the price-conditional identity function.

In line with Cont *et al.* (2014), each variable e_n is a signed contribution of one order book event to supply/ demand and only one of the following events between any two observations of e_n can occur:

- $P_n^b > P_{n-1}^b$ or $q_n^b > q_{n-1}^b$ signifying an increase in demand
- $P_n^b < P_{n-1}^b$ or $q_n^b < q_{n-1}^b$ signifying an decrease in demand
- $P_n^a < P_{n-1}^a$ or $q_n^a > q_{n-1}^a$ signifying an increase in supply
- $P_n^b < P_{n-1}^b$ or $q_n^b < q_{n-1}^b$ signifying an decrease in supply

When new limit buy order arrives, there is a situation where demand increases. Further, one of the following things could happen, either price P^b does not change and only the quantity q^b increases. In this case $e_n = q^b_n - q^b_{n-1}$ which is the size of that order. Or P^b increases, this means that the new limit buy order was price improving order and initiated new best bid quote. And in this case $e_n = q^b_n$. If there is decrease in demand, there will be a situation where either a market sell order or a limit buy order cancellation will arrive. Cont *et al.* (2014) notes that variable e_n does not differentiate between market orders or cancel orders. If q^b decreases and price remains the same, we have $e_n = q_n - q_{n-1}$, which represents size of either market sell order or order buy cancellation. If P^b decreases $e_n = -q^b_{n-1}$ represents last order in the queue after the best bid was removed by market sell order or limit buy cancellation. Symmetric reasoning is done also for ask side.

I am following Cont *et al.* (2014) in the use of the same two uniform time grids $\{T_0, ..., T_n\}$ and $\{t_{0,0}, ..., t_{I,K}\}$ with time steps $T_i - T_{i-1} = 30min$ and $t_{k,i} - t_{k-1,i} = \Delta t = 10s$.[1] Within each 30 minute time interval $[T_{i-1}, T_i]$ I compute 180 price changes and OFIs indexed by k:

$$\Delta P_{k,i} = \frac{P^b_{N\left(t_{k,i}\right)} + P^a_{N\left(t_{k,i}\right)}}{2\delta} - \frac{P^b_{N\left(t_{k-1,i}\right)} + P^a_{N\left(t_{k-1,i}\right)}}{2\delta} \tag{3.6}$$

$$OFI_{k,i} = \sum_{n=N\left(t_{k-1,i}\right)+1}^{N\left(t_{k,i}\right)} e_n, \tag{3.7}$$

Where the first order book event in the interval $[t_{k-1,i}, t_{k,i}]$ is indexed $N\left(t_{k-1,i}\right) + 1$ and the index $N\left(t_{k,i}\right)$ is assigned to the last order book event in the same time interval $[t_{k-1,i}, t_{k,i}]$. The tick size δ is equal to 1 cent in my data.

I begin with loading the data day by day into a data frames. For each of the data frames, I compute e_n for every row except the first one, because I do not have data to be able to compute it and I also compute mid price for every row. Then I began to resample this data frame by timestamp for 10 second intervals and for each resampled data frame I sum the e_n to form OFI for that time interval and ΔP by taking the first mid price value and subtracting it from the last mid price value in resampled data frame. This gives me data frame with mid price changes and OFI over 10 second intervals.

The depth is computed by running the following equation for every 30

[1] The choosing process of that interval is described in the section 5 of Chapter 3.

minute long time interval. The equation takes the average of bid and ask queue sizes immediately prior or after a change of price considering the stylized order book model's description of depth.

$$D_i = \frac{1}{2}\left[\frac{\sum\limits_{n=N(T_{i-1})+1}^{N(T_i)}\left(q_n^b I_{\{P_n^b<P_{n-1}^b\}} + q_{n-1}^b I_{\{P_n^b>P_{n-1}^b\}}\right)}{\sum_{n=N(T_{i-1})+1}^{N(T_i)} I_{\{P_n^b\neq P_{n-1}^b\}}} + \frac{\sum\limits_{n=N(T_{i-1})+1}^{N(T_i)}\left(q_n^a I_{\{P_n^a>P_{n-1}^a\}} + q_{n-1}^a I_{\{P_n^a<P_{n-1}^a\}}\right)}{\sum\limits_{n=N(T_{i-1})+1}^{N(T_i)} I_{\{P_n^a\neq P_{n-1}^a\}}}\right] \tag{3.8}$$

where I is the the price-conditional identity function.

3.5 Choice of Timescale

I compute $\Delta P_{k,i}$ and $OFI_{k,i}$ according to equations 3.6 and 3.7 and estimate equation 4.1 for five different $\Delta t \in \{1s, 5s, 10s, 1min, 2min, 5min\}$. I am making these computations for only one day, because for the whole period of 457 days it would be computationally demanding. I choose the date randomly and I split the computation to two parts, for timestamps $\Delta t \in \{1s, 5s, 10s\}$ and $\Delta t \in \{1min, 2min,$
$5min\}$. For the first group I directly compute variables $\Delta P_{k,i}$ and $\mathrm{OFI}_{k,i}$ according to equations 3.6 and 3.7 and continue with OLS estimation of equation 4.1. And for the second group of larger timescales I needed to pool data across 30 days to preserve large number of observations $\Delta P_{k,i}$ and $\mathrm{OFI}_{k,i}$ per separate 30 min intraday intervals. For example when $\Delta t = 5$ minutes, there would be 6 observations for single half hour subsample, which would not produce reliable estimates, therefore when I pool across 30 days, I got 180 observations in one half hour sample. And after that I continue with estimation of equation 4.1.

The average R^2 and Newey-West t-statistics for OFI across time are presented in Figure 3.1. The goodness of fit is for this particular sample best for 10 second timescale reaching 51.8%. What is interesting is the drop of R^2 to 23.5% when $\Delta t = 30s$ and that it remains constant roughly around 23% after that. The OFI variable remains statistically significant at a 95% level in 100% for all different Δt's.

Since, the difference of goodness of fit between 10 second timescale and 5

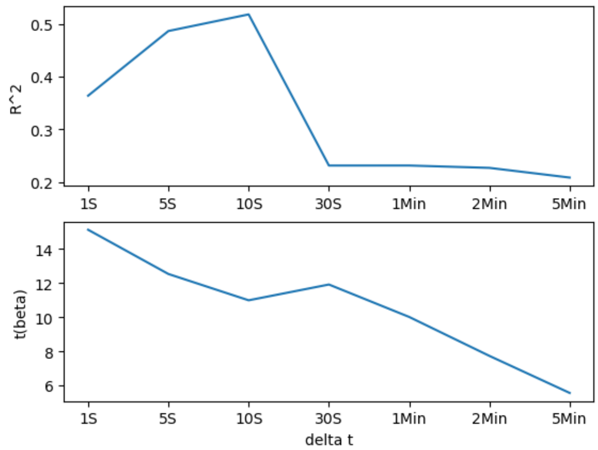

Figure 3.1: Average R^2 and Newey-West t-statistics for OFI coefficient across time for different Δt for November 15, 2020

second timestamp is 3.15%, I compute the variables $\Delta P_{k,i}$ equation 3.6 and $OFI_{k,i}$ equation 3.7 for both timescales and estimate model 4.1 for half hour time intervals To obtain 48 different R^2 estimates for each timescale. Average R^2 for 5 second time scale is 46.59% and for the 10 second timescale is 46.66%. This leads me to choosing the 10 seconds timescale.

3.6 Model Specification

Real world order books have much complex dynamics than stylized model of LOB specified by Cont *et al.* (2014). The arrivals and cancellations of limit orders take place at all price levels and the depth has non-trivial distribution across levels as stated in Potters & Bouchaud (2003); Zovko & Farmer (2002). Additional errors are created by hidden liquidity together with data-reporting issues as shown by Avellaneda *et al.* (2011). Motivated by the stylized order book example, Cont *et al.* (2014) assumes a simple linear relationship between price changes and OFI. This relationship holds locally for short time intervals $[t_{k-1,i}, t_{k,i}] \in [T_{i-1}, T_i]$, where $[T_{i-1}, T_i]$ are longer intervals and proposes the following model.

$$\Delta P_{k,i} = \beta_i OFI_{k,i} + \epsilon_{k,i}, \tag{3.9}$$

where β_i is the price impact coefficient for i-th time interval and $\epsilon_{k,i}$ is an error term, that summarizes influences of other factors, for example deeper levels of order book or hidden liquidity. In the study, Cont *et al.* (2014) allows β_i and the distribution of $\epsilon_{k,i}$ to vary with index i. This flexibility is included to account for the well-known effects of intraday seasonality. I am specifying the model in the same way, because I want to be able to see or explore intraday seasonality effects for cryptocurrency market and to be able to compare my results with the results of the study by Cont *et al.* (2014). The Stylized Model of Limit Order Book (LOB) implies the inverse relationship between the price impact coefficient β_i and market depth D_i to be $\beta_i = \frac{1}{2D_i}$ and also interprets $\frac{1}{2\beta_i}$ as an implied order book depth. To empirically examine this inverse relationship a more general model is proposed:

$$\beta_i = \frac{c}{D_i^{\lambda}} + \nu_i, \tag{3.10}$$

where c, λ are constants and ν_i is a noise term. The stylized order book model corresponds to values $c = \frac{1}{2}$ and $\lambda = 1$.

Cont *et al.* (2014) formulate equations 3.9 and 3.10 and interpret them as a representation of the instantaneous price impact of order book events arriving within the time interval $[t_{k-1}, t_k]$. Whenever an order is placed or canceled at time $\tau \in [t_{k-1}, t_k]$, it contributes a signed quantity e_τ to supply or demand. According to Cont *et al.* (2014) these contributions are likely unbalanced in any given time interval, but when the contributions from that given time interval are summed it results in OFI_k. The price adjustment is done by market-makers, who are striking to have order flows balanced so that for each roundabout trade they make profit of the difference between bid and ask price (bid-ask spread). Bouchaud *et al.* (2018) describes a mechanism of price adjustment as follows; when market-maker receives a significantly higher number of buy orders compared to sell orders, they have several options to address this order-flow imbalance. One approach is to raise the ask-price, discouraging potential buyers from entering the market. Alternatively, they can increase the bid-price to attract more sellers. In some cases, market-makers might opt to implement both strategies simultaneously to mitigate the order-flow imbalance. When an individual order sign aligns with the prevailing order direction in given time interval ($sgn\,(e_\tau) = sgn\,(\mathrm{OFI}_k)$), than it reinforces OFI and can affect the price. However, if the order sign goes against the majority of orders in given time interval ($sgn\,(e_\tau) = -sgn\,(\mathrm{OFI}_k)$), then its instantaneous price impact is mitigated by the majority to zero. In this model all events (limit orders, cancellations, and market orders) have a linear price impact, on average equal to β_i during the i-th time interval.

Chapter 4

Results

4.1 Estimation, Results and Discussion of Model 3.9

For each of the 457 days I estimate 48 models 3.9, one for each half hour time interval of the day. I am using an ordinary least squares (OLS) to estimate the regression:

$$\Delta P_{k,i} = \hat{\alpha}_i + \hat{\beta}_i OFI_{k,i} + \hat{\epsilon}_{k,i} \tag{4.1}$$

with separate half-hour subsamples indexed by i. Figure 4.1 represents a scatter plot of $\Delta P_{k,i}$ against $OFI_{k,i}$ for subsample 11/1/2021 from 21:00 to 21:30. I chose this time interval because in this half hour subsample there is the highest number of posted quotes as well as the highest number of non-null mid-price changes. I am using Newey-West standard errors with 4 lags to control for heteroscedasticity and autocorrelation in the time series data. I find that $\hat{\beta}_i$ is statistically significant in 99% of samples, and $\hat{\alpha}_i$ is significant in 14% of the samples. The average t-statistics for $\hat{\alpha}_i$, $\hat{\beta}_i$ are 0.09 and 33 billion (ranging from -1.3 to 731 trillion).

To check for nonlinear dependence I estimate an augmented regression:

$$\Delta P_{k,i} = \hat{\alpha}_i^Q + \hat{\gamma}_i OFI_{k,i} + \hat{\gamma}_i^Q OFI_{k,i}|OFI_{k,i}| + \hat{\epsilon}_{k,i}^Q. \tag{4.2}$$

Cont *et al.* (2014) got the coefficient $\hat{\gamma}_i^Q$ statistically significant only in 17% of samples, whereas I have this coefficient statistically significant in 60% of my samples, suggesting that in my data there is some nonlinear dependence.

The average goodness of fit of quadratic model is higher at 50.5% compared to 46%, average of the linear models. Cont *et al.* (2014) were able to achieve

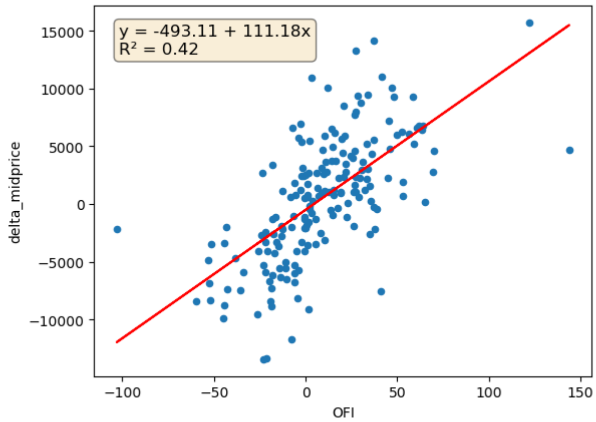

Figure 4.1: Scatter plot of $\Delta P_{k,i}$ against $OFI_{k,i}$, January 11, 2021 21:00-21:30 pm.

R^2 of 76% for Schlumberger (SLB) stock and 65% on average across stocks for a linear model and use this high goodness of fit as an evidence for the fact, that the activity at the top of the order book is a primary driver for short-term price changes. Also, I would like to draw attention to the high volatility of Bitcoin, where the change of mid price ΔP ranges from 150 USD to -100 USD over a 10 second time interval. This is in contrast to Cont *et al.* (2014), where for similar graph the price changes range from -4 cents to 4 cents.

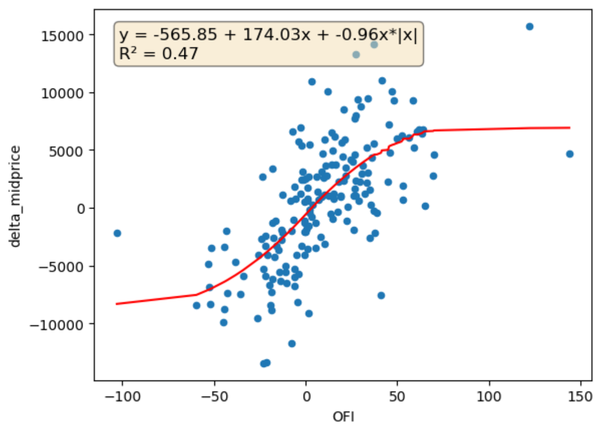

Figure 4.2: Non-linear price impact function of $\Delta P_{k,i}$ against $OFI_{k,i}$, January 11, 2021 21:00-21:30 pm.

Huberman & Stanzl (2004) define quasi-arbitrage as a trading strategy that leads to an infinite expected payoff as well as infinite Sharpe ratio. A round-trip trading strategy refers to a series of trades that starts and ends with the same position, but includes trades in between that aim to exploit price differences. They argue that the required condition for a market to be viable is the absence of quasi-arbitrage, breaking this condition might indicate potential price manipulation. They conclude that the absence of quasi-arbitrage is equivalent to the linearity of the price impact function. This means that the immediate impact of a trade on the price must increase linearly with the volume of the trade. Therefore, the nonlinear price impact function, which was empirically found for the Bitcoin market, implies the feasibility of price manipulation in the Bitcoin market.

Cong *et al.* (2022) conclude that unregulated cryptocurrency exchanges are using wash trading and they estimate that over 70% of reported volume could originate from this practice. Wash trading, simultaneously buying and selling the same instruments, is primarily done by cryptocurrency exchanges to artificially inflate the perceived trading volume. This can attract other market participants, who may interpret high trading activity as an indicator for investing opportunity. The price manipulation can arise when a wash trader places the buy orders with progressively higher prices, given that the trader is at the same time on the selling side of these transactions, there is no financial loss incurred. However, to the external market participants the upward price trend appears to be genuine and stimulating other additional trading activity (Cong *et al.* 2022; Aggarwal & Wu 2006; Cumming *et al.* 2011). Although most developed financial markets have strict regulations prohibiting wash trading, the limited regulatory oversight in Bitcoin exchanges makes them susceptible to such practices.

Further, Cong *et al.* (2022) categorize Binance exchange among the more reputable exchanges based on the top 700 ranking for finance/investment on SimilarWeb.com and find that Binance exchange behaves closer to the regulated exchanges which are averse to wash trading. Nevertheless, they establish that more than 45% of total trading volume potentially comes from wash trading.

4.2 Relationship between the Price Impact Coefficient and Market Depth 3.10

For the estimation of the equation 3.10 I use time series of D_i computed for every half hour according to equation 3.8, and I collect estimated price impact coefficient $\hat{\beta}_i$ from the linear estimation of equation 4.1, resulting in a new dataset with 21 936 data points. The relationship specified in equation 3.10 is estimated in two steps with the following two regressions:

$$log\hat{\beta}_i = \hat{\alpha}_{L,i} - \hat{\lambda} log D_i + \hat{\epsilon}_{L,i} \tag{4.3}$$

$$\hat{\beta}_i = \hat{\alpha}_{M,i} + \frac{\hat{c}}{D_i^{\hat{\lambda}}} + \hat{\epsilon}_{M,i}. \tag{4.4}$$

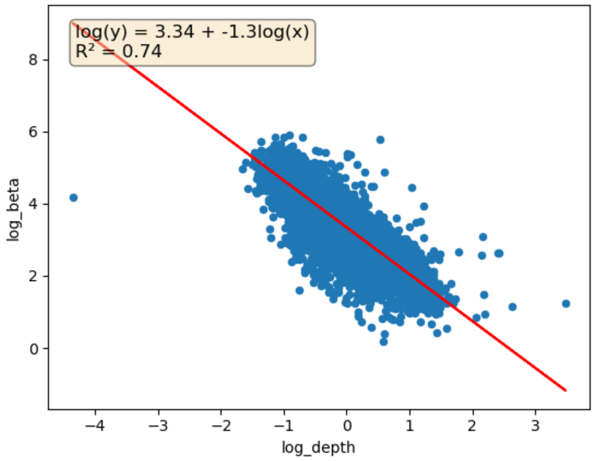

Figure 4.3: Log-log scatter plot of the price impact coefficient estimate β_i against average market depth D_i.

As in Cont *et al.* (2014) I estimate both regressions using OLS using Newey-West standard errors with 4 lags to control for heteroscedasticity and autocorrelation.

I first proceed with the estimation of regression 4.3 to obtain $\hat{\lambda}$. The results of this regression can be seen in Figure 4.3 and are as follows: the coefficient $\hat{\lambda}$ equals to 1.3, and the R^2 of regression is 74% which is by 18% lower compared to R^2 that Cont *et al.* (2014) was able to achieve. Afterward, I make the transformation of the time series of market depth $\frac{1}{D_i^{\hat{\lambda}}}$ so that I can use it in regression 4.4 and obtain the coefficient $\hat{c}$. The results of this regression can be seen in Figure 4.4. Even though I confirm that the relationship between price impact coefficient β_i and market depth D_i is inverse, I conclude that the proposed relation $\beta_i = \frac{1}{2D_i}$ does not hold in the Bitcoin market. Rather, the relationship appears to have a form $\beta_i = \frac{29}{D_i^{1.3}}$.

To interpret this result I will use the estimated equation 4.3. The $\hat{\lambda}$ coefficient is in the exponent and therefore has a higher impact than the coefficient $\hat{c}$, which functions only as a multiplying constant in the relationship and can be neglected for the purpose of simplification. The equation 4.3 implies that for Bitcoin market the depth affect the price impact coefficient by 30% more on average, compared to the financial markets. So for example, when a large buy order (order for which desired quantity exceeds the supply at ask side) is placed by a trader, it forces the buyer to purchase at higher price levels to fulfill the order. The increase in price represents a price impact cost to the trader as he buy now for less favorable price. The price impact cost is therefore 30% higher in Bitcoin market. When such trade occurs, it signals that the trader must have strong believes about the future price movements and he deems such order profitable despite the higher costs from price impact.

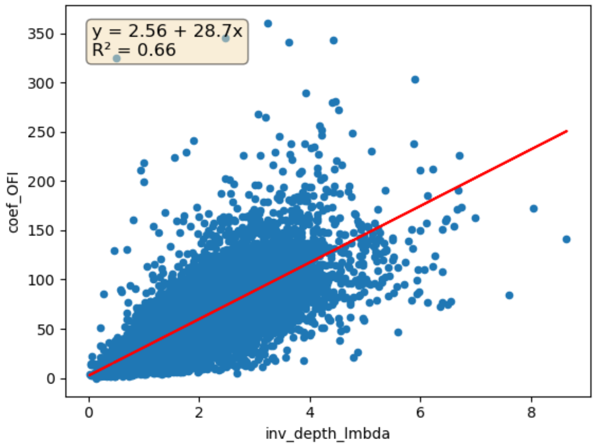

Figure 4.4: Scatter plot of the price impact coefficient estimate β_i against average market depth D_i.

4.3 Intraday Patterns of the Price Impact Coefficient

In this section, I want to examine whether there exists a clear intraday pattern for instantaneous price impact using the link between price impact and market depth established in the previous section. The diurnal patterns were computed such that I averaged $\hat{\beta}_i$ for BTC for each half-hour interval across days to obtain 48 mean values for every half-hour. Then I normalized the diurnal pattern by grand average $\hat{\beta}_i$. I used the same procedure for depths D_i. I also re-estimated equation 4.3 and equation 4.4, with the data pooled across days, so for each half-hour interval, I got 457 observations of price impact coefficient $\hat{\beta}_i$ and market depth D_i which I used to obtain 48 values of $\hat{\lambda}_i$ and $\hat{c}$. These 48 values were also normalized by their mean and then were also plotted into Figure 4.5.

In more traditional financial markets, the diurnal pattern of market depth

Figure 4.5: Diurnal patterns of the price impact coefficient $\hat{\beta}_i$, the average depth D_i and the parameters $\hat{c}_i$, $\hat{\lambda}_i$.

follows a predictable pattern (Ahn *et al.* 2001; Lee *et al.* 2015), which, combined with the equation 3.10 means that instantaneous price impact must also have a predictable intraday pattern. This interesting observation is indeed supported by the findings of Cont *et al.* (2014). However, as it can be seen in Figure 4.5, in the Bitcoin market, the deviations of every diurnal pattern from the grand average are not that large (only about 20% in both directions). This suggests that there is no clear intraday pattern of the price impact coefficient β_i. The biggest drop in depth is at 21:00 when the value is 20% lower than the average. This corresponds to the highest increase in the price impact coefficient, which is 15% higher than average. This is reasonable since, in the shallow market, the incoming market orders have a pronounced influence on mid-prices.

Dyhrberg *et al.* (2018) find that trading activity is low during the morning, corresponding to the opening of European markets. The increase in trading activity to its peak occurs with the opening of the US markets. Then during the day, trading activity gradually decreases and drops rapidly with the closing of the Asian markets. In Figure 4.5, the highest peak of the market impact coefficient coincides with the closing of the New York Stock Exchange. This may provide further support to the findings of Dyhrberg *et al.* (2018) that the majority of trades on cryptocurrency exchanges come predominantly from the United States during regular trading hours.

The absence of any clear intraday pattern can be attributed to the different market designs of the cryptocurrency exchanges. Most notably, they are traded 24 hours, 7 days a week. The continuous trading can lead to more uniform distribution of price impact. The second explanation could be that in the Bitcoin market algorithmic trading is prevalent. Thus, automated trading algorithms can execute an order at any given moment, which could further smooth the impact coefficient over the day.

Chapter 5

Conclusion

This thesis presents an analysis of the short-term price fluctuations of Bitcoin, the leading cryptocurrency, by examining the high-frequency interaction between demand and supply depicted in the Limit Order Book (LOB). The study follows established literature and methodology developed by Cont *et al.* (2014), and it investigates the shape of the price impact function, the relationship of price impact coefficient to market depth, and intraday patterns of the price impact coefficient.

The research reveals that the price impact of order book events in the Bitcoin market is a non-linear increasing function, contradicting the findings of Cont *et al.* (2014) who argued for a linear relationship. The non-linearity of the function suggests that there may be opportunities for price manipulation and quasi-arbitrage in the Bitcoin market, leading to risk-free profits. The study additionally reveals that in the Bitcoin market, the market depth has about 30% greater influence on the price impact coefficient compared to more traditional financial markets. This finding suggests that large orders have a significant impact on the market price and that traders who post these orders are likely to be highly informed. Interestingly, the study finds no clear intraday pattern of the price impact coefficient in the Bitcoin market. This could be due to the unique characteristics of the design of the Bitcoin market, such as the 24/7 operation of the Bitcoin market and the high level of automated trading.

Overall, the findings of this thesis contribute to the growing body of literature on price impact in markets, particularly cryptocurrencies, and provide valuable insights for market participants, notably institutional investors considering entering the Bitcoin market. The research also highlights the need for further investigation into the regulatory aspects of the Bitcoin market given the potential for price manipulation and the lack of clear intraday patterns.

Bibliography

Aggarwal, R. K. & G. Wu (2006): "Stock market manipulations." *The Journal of Business* **79(4)**: pp. 1915–1953.

Ahn, H.-J., K.-H. Bae, & K. Chan (2001): "Limit orders, depth, and volatility: Evidence from the stock exchange of hong kong." *The Journal of finance* **56(2)**: pp. 767–788.

Almgren, R. & N. Chriss (2001): "Optimal execution of portfolio transactions." *Journal of Risk* **3**: pp. 5–40.

Avellaneda, M., J. Reed, & S. Stoikov (2011): "Forecasting prices from level-i quotes in the presence of hidden liquidity." *Algorithmic Finance* **1(1)**: pp. 35–43.

Baur, D. G., K. Hong, & A. D. Lee (2018): "Bitcoin: Medium of exchange or speculative assets?" *Journal of International Financial Markets, Institutions and Money* **54**: pp. 177–189.

Bertsimas, D. & A. W. Lo (1998): "Optimal control of execution costs." *Journal of financial markets* **1(1)**: pp. 1–50.

Bouchaud, J.-P., J. Bonart, J. Donier, & M. Gould (2018): *Trades, quotes and prices: financial markets under the microscope.* Cambridge University Press.

Bouchaud, J.-P., Y. Gefen, M. Potters, & M. Wyart (2003): "Fluctuations and response in financial markets: the subtle nature ofrandom'price changes." *Quantitative finance* **4(2)**: p. 176.

Cong, L. W., X. Li, K. Tang, & Y. Yang (2022): "Crypto wash trading." *Technical report*, National Bureau of Economic Research.

Cont, R. (2011): "Statistical modeling of high-frequency financial data." *IEEE Signal Processing Magazine* **28(5)**: pp. 16–25.

Cont, R., A. Kukanov, & S. Stoikov (2014): "The price impact of order book events." *Journal of financial econometrics* **12(1)**: pp. 47–88.

Cumming, D., S. Johan, & D. Li (2011): "Exchange trading rules and stock market liquidity." *Journal of Financial Economics* **99(3)**: pp. 651–671.

Donier, J. & J. Bonart (2015): "A million metaorder analysis of market impact on the bitcoin." *Market Microstructure and Liquidity* **1(02)**: p. 1550008.

Dyhrberg, A. H., S. Foley, & J. Svec (2018): "How investible is bitcoin? analyzing the liquidity and transaction costs of bitcoin markets." *Economics Letters* **171**: pp. 140–143.

Eisler, Z., J.-P. Bouchaud, & J. Kockelkoren (2012): "The price impact of order book events: market orders, limit orders and cancellations." *Quantitative Finance* **12(9)**: pp. 1395–1419.

Farmer, J. Doyne, L. Gillemot, F. Lillo, S. Mike, & A. Sen (2004): "What really causes large price changes?" *Quantitative finance* **4(4)**: pp. 383–397.

Farmer, J. D., P. Patelli, & I. I. Zovko (2005): "The predictive power of zero intelligence in financial markets." *Proceedings of the National Academy of Sciences* **102(6)**: pp. 2254–2259.

Gabaix, X., P. Gopikrishnan, V. Plerou, & H. E. Stanley (2003): "A theory of power-law distributions in financial market fluctuations." *Nature* **423(6937)**: pp. 267–270.

Ghysels, E. & G. Nguyen (2019): "Price discovery of a speculative asset: Evidence from a bitcoin exchange." *Journal of Risk and Financial Management* **12(4)**: p. 164.

Guo, T. & N. Antulov-Fantulin (2018): "Predicting short-term bitcoin price fluctuations from buy and sell orders." *arXiv preprint arXiv:1802.04065* .

Härdle, W. K., C. R. Harvey, & R. C. Reule (2020): "Understanding cryptocurrencies."

Hasbrouck, J. (1991): "Measuring the information content of stock trades." *The Journal of Finance* **46(1)**: pp. 179–207.

Hautsch, N. & R. Huang (2012): "The market impact of a limit order." *Journal of Economic Dynamics and Control* **36(4)**: pp. 501–522.

Huberman, G. & W. Stanzl (2004): "Price manipulation and quasi-arbitrage." *Econometrica* **72(4)**: pp. 1247–1275.

Kempf, A. & O. Korn (1999): "Market depth and order size." *Journal of Financial Markets* **2(1)**: pp. 29–48.

Lee, C. M. C., B. Mucklow, & M. J. Ready (2015): "Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis." *The Review of Financial Studies* **6(2)**: pp. 345–374.

Lillo, F. & J. D. Farmer (2004): "The long memory of the efficient market." *Studies in nonlinear dynamics & econometrics* **8(3)**.

Mark, M., J. Sila, & T. A. Weber (2022): "Quantifying endogeneity of cryptocurrency markets." *The European Journal of Finance* **28(7)**: pp. 784–799.

Nakamoto, S. (2008): "Bitcoin: A peer-to-peer electronic cash system." *Decentralized business review* p. 21260.

Obizhaeva, A. A. & J. Wang (2013): "Optimal trading strategy and supply/demand dynamics." *Journal of Financial markets* **16(1)**: pp. 1–32.

Plerou, V., P. Gopikrishnan, X. Gabaix, & H. E. Stanley (2002): "Quantifying stock-price response to demand fluctuations." *Physical review E* **66(2)**: p. 027104.

Potters, M. & J.-P. Bouchaud (2003): "More statistical properties of order books and price impact." *Physica A: Statistical Mechanics and its Applications* **324(1)**: pp. 133–140. Proceedings of the International Econophysics Conference.

Silantyev, E. (2019): "Order flow analysis of cryptocurrency markets." *Digital Finance* **1(1-4)**: pp. 191–218.

Toth, B., Z. Eisler, & J.-P. Bouchaud (2017): "The short-term price impact of trades is universal." *Market Microstructure and Liquidity* **3(02)**: p. 1850002.

Weber, P. & B. Rosenow (2005): "Order book approach to price impact." *Quantitative Finance* **5(4)**: pp. 357–364.

Weber, P. & B. Rosenow (2006): "Large stock price changes: volume or liquidity?" *Quantitative finance* **6(1)**: pp. 7–14.

Wyart, M., J.-P. Bouchaud, J. Kockelkoren, M. Potters, & M. Vettorazzo (2008): "Relation between bid–ask spread, impact and volatility in order-driven markets." *Quantitative finance* **8(1)**: pp. 41–57.

Zovko, I. & J. D. Farmer (2002): "The power of patience: a behavioural regularity in limit-order placement." *Quantitative Finance* **2(5)**: p. 387.