Bitcoin Inelasticity Hypothesis

Master's Thesis

Submitted in partial fulfillment of the requirements for the degree of Master of Arts in Economics and Business Administration

Author

Diego Hager

Georg-Kempf-Strasse 14

8046 Zürich

14-918-361

diego.hager@uzh.ch

Supervisors

Prof. Dr. Claudio Tessone

Professor of Blockchain and Distributed Ledger Technologies

Department of Informatics

University of Zurich

Prof. Dr. Felix Kübler

Professor of Financial Economics

Department of Banking and Finance

University of Zurich

Date of Submission: 31.07.2022

Task Assignment

The exercise aims to estimate the parameters of and fit the model proposed by Gabaix and Koijen (2021) to bitcoin transaction data.

The research question is stated as:

Does the model of Gabaix and Koijen (2021) explain bitcoin price fluctuations ?

Executive Summary

The thesis uses bitcoin data to estimate parameters, with which it is then tried to assess whether the model proposed in Gabaix and Koijen (2021) can explain the mean and standard deviation of bitcoin returns. The model uses the price elasticity of demand to generate observed prices and is stated in perturbations around a baseline.

The results suggest that the model does not account for the full picture of return patterns observed. The moments resulting from the simulation are far larger in absolute terms than the observed moments and the estimation results are hardly statistically significant. Albeit, a parameter of the model, the speed of mean reversion of flows, has not been estimated, a back-of-the-envelope calculation implies a negative and very large value to counter the effects of the estimation results. A sensible estimation of this parameter is beyond the scope of this thesis.

Bitcoin is well suited for price elasticity estimations because it is only marginally influenced by supply shocks i.e., all the shocks can be ascribed to the demand side. Moreover, the full record of transactions is in theory available to the public. A wide range of studies point to the effects trading has on prices, yet only recently has literature emerged arguing for inelastic financial markets. The model presented in Gabaix and Koijen (2021) uses flows to funds to drive asset prices away from their fundamental values. This mechanism influences the stochastic discount rate in the model. For the estimations, two datasets are used. One dubbed 'daily data' is provided by Stütz et al. (2020).[1] This dataset consists of bitcoin transaction data aggregated on a daily and an entity level, transactions of bitcoin holders with only one address are omitted. The second called 'block-level data' has been downloaded through the *GraphSense* API (Haslhofer et al., 2021). This dataset has been aggregated on a block-level and contains all transactions.

Both datasets entail information about on-chain transactions. With this information, the estimations are performed on the transformed data. The data used is stated in deviations from its rolling averages. The rolling averages serve as a baseline. The results of the estimations suggest a positively inelastic demand and contrarian investing agents. The simulations suggest that the model overpredicts the volatility in bitcoin markets and overstates the premium paid by investors, in absolute terms.

[1] A special thank to the authors of Stütz et al. (2020) and especially Rainer Stütz for rerunning their computations and providing me with the data.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In Summary: This chapter argues why the topic is chosen, introduces bitcoin, and the concept of elasticity in financial markets.

Main Points:

- The model of Gabaix and Koijen (2021) uses price elasticity of demand and flows into assets to generate asset prices.
- Bitcoin seems well suited to test this price mechanism in financial assets.
  - Bitcoin is volatile and lacks a 'fundamental value' i.e., has no 'non-monetary' value.
  - Bitcoin transactions are recorded and available publicly.
  - Bitcoin has an inelastic supply, which is algorithmically determined and adapts to increases in computing power. I.e., there are only minimal supply shocks.
  - Bitcoin prices are mainly driven by demand-side effects.
- Demand is a known driver of volatility and influences the behavior of financial markets.

Gabaix and Koijen (2021) introduces inelastic prices to financial market price generation and discusses their effects on different aspects of finance. The authors propose a way to model financial market fluctuations by incorporating the mechanism of inelastic prices. A consequence of an effect of trading on prices would be that tastes play a role in price generation. I.e., someone buying bitcoin (Nakamoto, 2008) because he likes the idea of decentralized finance would influence the exchange rate of bitcoin. Even though, this decision might not be influenced by the fitness of bitcoin to archive any of his ideas about decentralized finance.

That tastes play a role in the price generation of financial markets is exemplified by the Keynesian beauty contest (Keynes, 1936). The story goes like this: market participants try to guess what others will like and therefore try to buy cheap, what others want to buy at higher prices later. This stands in sharp contrast to what Fama (1970) expects to be at the origin of price discovery. His efficient market theory indicates that the only determinant for the price of a financial asset is its expected return, which is independent of tastes but relies on the fundamentals of the asset in question.

The difference between the efficient view and the taste-driven view on price generation or discovery is not if prices can be predicted or not. Fashions are unpredictable, too.

The views differ in the way how prices change. In an efficient setting, prices are set because of foresight. Agents trade at a certain price because they know the future expected return. In a setting with inelastic prices, fads and whims can drive prices substantially away from fundamentals. Bubbles can build up and burst as everyone tries to sell what others want to sell and buy what others want to buy just a step ahead of others.

Noise is many times said to be the culprit that prices differ from their fundamentals at times. As Black (1986) puts it: '*The price of a stock will be a noisy estimate of its value.*' (p. 534). Black implies the existence of an inherent value with this statement. In the realms of stocks and bonds, this makes sense because owning a stock means owning a fraction of a company, which in turn owns real assets.

Because of this consensus assumption, that there exists a ' fundamental value' of a company that can be measured and fixed with enough information, it makes sense to talk about the fundamental value of a stock. However, for bitcoin, this assumption seems not to hold up well. Hence, it is difficult to distinguish noise from deviations driven by fundamentals.

Keynes used another metaphor in his book: the game 'Old Maid'. In this card game, players try to form pairs of cards and pass them on to their neighbor, without being left with the odd card.[2] The similarity between the two metaphors is intended, yet the difference is that in the game 'Old Maid' there is one losing player and in the beauty contest there is one winning player. The old maid metaphor highlights the fact that in markets participants lose because they are too late to get rid of the 'odd queen'.

Similarly, 'The Dollar Auction' (Shubik, 1971), describes a situation where a dollar is sold to bidders with the caveat that the two last bidders pay the price they bid. The dollar auction has shown that prices can reach irrational highs, if players do not want to be the biggest loser on the table, despite the costs being sunk at the time of the next bid.

Viewed in a pessimistic light, bitcoin seems to push both stories to their limits. One can get stuck with an essentially worthless thing without obvious fundamental value. With production costs that are sunk at the time of production (Dwyer, 2015), one can get captured in a cycle of overpaying for not to be the biggest loser. These mechanisms would create a self-enforcing upward price spiral for bitcoins.

Because the transaction data of bitcoin is publicly stored on the blockchain, it lends itself to an investigation of the inner workings of price discovery or price generation in its markets.

Bitcoin is a relatively new cryptographic asset, widely believed to archive the objective of decentralized proof of ownership. As adoption is unclear, the value of bitcoin will be heavily influenced by believers in its technology and speculators, betting that they can sell it later for a higher price.

Even in stock markets, where prices can be anchored to fundamental values, much of the price variation originates not in news and fundamentals (Cutler et al., 1988). How about bitcoin markets, where the assumption of a measurable 'value' seems less straightforward? Nevertheless, it has been shown that the existence of a fundamental value can reduce volatility (Hommes et al., 2005). Bitcoin lacks this break on volatility and therefore is especially interesting to use as an object of study what Gabaix and Koijen (2021) call: *the origins of financial market fluctuations.* A fundamental value of

[2] `https://bicyclecards.com/how-to-play/old-maid/`.

bitcoin would, among other things, need to depend on the wide adoption of bitcoin as a means of payment, as a store of value, or something, similar, i.e. nothing measurable at the time of writing.

Or put differently by paraphrasing Blacks quote without the implicit assumption of an inherent value: '*The price of bitcoin will be noisy*'.

This property of ostensible distilled financial noise is why I believe bitcoin is a great possibility to study the origins and effects of noise in financial markets. An interest in gaining an understanding of how prices form in a market, beyond the level of metaphor, is what drove me to choose the paper Gabaix and Koijen (2021) as the subject of my master's thesis. In this thesis, I want to learn about the role played by price elasticity or the price impact of trading in financial noise. To achieve this goal, I use the model proposed by Gabaix and Koijen (2021) and combine it with the transaction data of bitcoin.

This thesis continues in the following way: The remainder of this chapter first, introduces bitcoin and thereafter financial market elasticity. Chapter 2 summarizes first the theory on which the price generation in financial markets builds in general and later distinguishes between market macrostructure and microstructure in this sequence. The chapter 3 reviews more recent literature, first on bitcoin and second on the price impact of trading. The subsequent chapter 4 introduces the model of Gabaix and Koijen (2021) in a schematic way. Starting, as is done in the original paper, with the two-period model and later expanding the scope to the infinite-horizon model. The data used is detailed in chapter 5. This chapter starts with an overview of the data structure of the blockchain, then dives deeper into the block-level data, and closes with the daily data provided by Stütz et al.. The estimations for the model are outlined in chapter 6. In this chapter, first, the implementation and some of the adaptions necessary for bitcoin are discussed. Later the data transformations are detailed and finally, the results of the estimations are discussed. In the chapter 7 the simulation is outlined. The simulation is done with the model presented in Gabaix and Koijen (2021) and the final chapter 8 concludes the thesis.

1.1 Bitcoin

In this section characteristics of bitcoin are outlined and eventually, some milestones in bitcoin history are presented.

In this thesis, the term bitcoin is used for the digital asset. Fiat currency in circulation, such as the Swiss franc and the dollar is referred to as cash. The terms 'price' and 'exchange rate' are used interchangeably and refer to the bitcoin-dollar exchange rate i.e., the number of dollars needed to buy one bitcoin.

Bitcoin has been referred to as a 'synthetic commodity money' by Selgin (2015). There are two facets of this definition worth pointing out:

First, inelastic scarcity which makes bitcoin not subject to supply shocks i.e., bitcoin does only negligibly react to advancements in computational technology (Selgin, 2015). Further, the supply is known with near certainty, i.e there are no supply shocks, this feature distinguishes bitcoin from commodities (Gronwald, 2019).

The feature of fixed and near-to-known supply is due to the changing difficulty of the creation process ('mining'). To create bitcoins a computational problem needs to be solved. The network participant who first solves the problem gets the newly created coins as a reward. The process is designed in such a way that a new block is mined, and newly created bitcoins are distributed roughly every 10 minutes. The supply of bitcoins approaches a maximum of 21 million (Nakamoto, 2008). It started with a reward of 50 bitcoin per block and halves approximately every 4 years. The current block reward is 6.25 bitcoins per block and will reach zero around the year 2140.[3]

As the reward diminishes, the incentive for mining will slowly shift from block rewards to fees paid by agents to the miners who include the transaction in the new block, therefore validating the transactions. See Böhme et al. (2015), Dwyer (2015) or Antonopoulos (2017) for further information on the inner workings of the bitcoin network and Dowd (2014) for a comparison to earlier digital currency proposals.

Dwyer (2015) and Selgin (2015) note the similarity of the inelastic supply of bitcoin to the

[3] At the time of writing in 2022. For an overview of the current block-reward see: `https://bitcoinvisuals.com/chain-block-reward`.

'computer controlled money' proposed by Friedman (2005). The rule is reversed however, it is not the case that the quantity created is set such that the nominal interest rate is zero. Contrary, the supply is fixed such that if demand is positive, a rise in value compensates for a zero interest rate. The deflationary pressure built in the foundations of bitcoin is intended as a reward for early adopters and thus facilitates adoption (Huber and Sornette, 2022). The deflationary effect has the disadvantage, that it makes bitcoin prone to hoarding, which impedes its use as a medium of exchange (Dowd, 2014). It has been shown that many users hold bitcoin as a speculative investment or store of value (Glaser et al., 2014).

Second, the absence of nonmonetary value i.e., there is no additional value in holding bitcoin than to use it as a medium of exchange, unit, or store of value (Selgin, 2015). The usefulness of bitcoin for the first two use cases is disputed because of its high volatility. The second two by the fact that it is not backed by an economy based on analog goods and that it lacks the possibility for credit and lending (Yermack (2015) and Senner and Sornette (2019)).

The missing non-monetary value makes bitcoin sensitive to demand-side factors connected to its usefulness as a medium of exchange, a trait often reported. Despite having extreme swings and displaying bubbles in the price path, Gerlach et al. (2019) and Dyhrberg (2016) find similarities in the behavior of the bitcoin return volatility to gold and cash. They, therefore, place bitcoin somewhere between those assets in terms of volatility risk and attribute positive hedging properties to bitcoin. Dyhrberg (2016) further indicates that the return of bitcoin holdings is affected by its usefulness as a medium of exchange. More recent studies note that bitcoin volatility shows a negative correlation when compared with U.S. stock market volatility and tends to be pro-cyclical (Conrad et al. (2018) and Walther et al. (2019)).[4]

Hedging properties are discussed further in Bouri et al. (2017a), they find beneficial properties in shorter and longer time horizons.[5] In Bouri et al. (2017b) the hedging properties are reassessed, and the authors qualify the hedging properties. They, however, note the beneficial properties of bitcoin as a diversifying asset. Fang et al. (2019) note the changing nature of correlations between bitcoin,

[4] A recent investigation of the statistical properties of different cryptographic currencies has been done by Phillip et al. (2018)

[5] Interestingly, Bouri et al. (2017a) describe that if the bitcoin market is bullish, it does not react to heightened global uncertainty in the short term.

equities, and bonds.

Similarly, in-depth investigations of bitcoin price correlations with different variables measuring supply and demand side market forces done by Ciaian et al. (2016a) and Ciaian et al. (2016b) find that the variables indicating the attractiveness of bitcoin for investors and users are the most germane and that the variables relevant for the short term differ from the ones relevant for the long term. Likewise, Bouri et al. (2017b) find different hedging effects for weekly and daily data. A more detailed literature review concerning bitcoin with a greater focus on the subject of the thesis can be found in chapter 3.1.

An important distinction between cash and bitcoin is anonymity. Where a payment in cash cannot be traced back, transactions in bitcoin can, see e.g., Ron and Shamir (2013), Ron and Shamir (2014) and Meiklejohn et al. (2013) for examples of how this can be done. There is, however, the possibility to remain pseudonymous on the blockchain. Yet, if a peer wants to exchange bitcoins in cash i.e., leave the blockchain, regulations make it increasingly difficult to stay pseudonymous.[6]

1.1.1 Historical Aspects

In what follows, the history of bitcoin is outlined with some important events. It is done so, shortly and by no means completely.[7] I will not introduce technological changes triggered by bitcoin. For an early review see Bedford Taylor (2013).

A widely known fact is that the initial block, the genesis block, contains a message which reads: 'The Times 03/Jan/2009 Chancellor on brink of second bailout for banks. This quote refers to a headline of an article in the magazine *The Times*. The first documented retail use case in the history of bitcoin was an exchange of 10'000 bitcoins for two pizzas in the year 2010. Further in the year 2010, a vulnerability allowing for the creation of an arbitrary number of bitcoins was exploited. The blockchain was forked below the transactions, such that these transactions do not appear in the valid blockchain, and the bitcoin protocol was updated, such that the vulnerability no longer exists. This deletion of the transactions and the subsequent update of the bitcoin protocol sparked a wide discus-

[6] There are services to obscure the identity of transacting peers. See Möser and Böhme (2016) and the references therein for more information.

[7] For more detail see: `https://en.wikipedia.org/wiki/History_of_bitcoin` and the links therein.

sion about the control of the bitcoin network. In 2013 the infamous trading platform *Silkroad* was closed down by the FBI. *Silkroad* was selling illegal substances, services, and other things through a darknet webpage using bitcoins as a medium of exchange. 2014 was the year where the crypto bourse *Mt. Gox* was hacked and had to file bankruptcy protection in Japan (for a case study see Bolici and Rosa (2016)). The Swiss Railway operator began selling bitcoins at their ticket machines in 2016. Bitcoin cash was created as a hard fork from the bitcoin blockchain in the year 2017. The difference between the two is the block size limit, which is 1MB in bitcoin and 8MB in bitcoin cash. The larger storage capacity should allow for more transactions stored on the ledger. In 2021 bitcoin became an allowed currency to pay taxes in the Swiss canton Zug and bitcoin became also legal tender in El Salvador.

In short: Bitcoin supply is algorithmically determined and adapts to advances in computational power. Hence, bitcoin prices are mainly influenced by demand-side factors. In contrast to cash, all transactions are stored on the public ledger with a pseudonym. Some aspects of bitcoin price behavior make it potentially useful for hedging, yet the results are mixed. In recent times, bitcoin has been adopted as a means of payment by some governmental agencies.

1.2 Elasticity in Financial Markets

This section describes the evolution of research concerning the price elasticity of demand in financial markets.

That market prices are influenced by non-fundamentally driven demand was presumed for a long time. Early investigations concentrated on demand curves. Downward sloping demand curves would imply finite elasticities. In contrast to efficient market models, with horizontal demand curves and therefore infinite elasticities, downward sloping demand curves would entail some room for market inefficiency.

Shleifer (1986) documented the possible presence of downward sloping demand curves and therefore the presence of finite elasticities in financial markets. He looked at S&P 500 index inclusions and documented that an index inclusion is accompanied by an abnormal return. Shleifer attributed the abnormal return to the inflow of index fund demand for the included stock. His suggestion was later confirmed (Lynch and Mendenhall, 1997).

The studies by Loderer et al. (1991) and Bagwell (1992) went a step further and indicate elasticity effects in financial markets.

Loderer et al. (1991) looks at firm stock offerings from regulated firms and finds paltry evidence that stock offerings transmit negative information to the market. The authors suggest that price changes originate from price elasticities. This suggestion is later confirmed by Levin and Wright (2002).

Bagwell (1992) investigates the effects of share repurchases via Dutch auctions and reports evidence that the price increases at announcement days originate from market elasticities. Bagwell further notes that the supply elasticity correlates with firm-level characteristics, notable is the increasing effect of takeover activity i.e., if the firm is subject to a takeover, the supply elasticity of the firm increases. There is also a reverse effect of elasticity on Dutch auctions i.e., firms expecting higher price elasticity are those who chose the Dutch auction format to repurchase outstanding shares (Hodrick, 1999).

Despite criticism on the methods used in early studies of the matter (e.g. McWilliams and Siegel (1997) and McWilliams et al. (1999)), a large strand of literature emerged with findings suggesting that trades have price impact at the market microstructure level (e.g. Bouchaud et al. (2018) and section 2.3) and on the market macrostructure level (section 2.2).

The effects of trades on prices have been used to predict volatility. E.g., Greenwood and Thesmar (2011) construct a predictive measure for volatility based on the ownership structure of the stock. The idea behind, what they call ‘fragility’, is that if stock owners face correlated liquidity shocks the stock in question is more volatile.

Demand effects on prices by large institutions can explain some stylized facts in financial markets e.g., momentum and reversal patterns (Vayanos and Woolley, 2013).

Furthermore, Lou et al. (2019) documents that demand patterns during overnight and intraday periods differ, giving rise to different profitability of strategies during different periods. He attributes this effect to differing demands between the traders active during the day v during the night.

That heterogeneous demand exhibits influence on prices and risk assessments is a near fact today and is incorporated in asset pricing models e.g., Koijen and Yogo (2019). Further theoretical papers include price elasticities into asset pricing theories such as Gabaix and Koijen (2021) and Haddad et al. (2021). The latter goes a step further, arguing that market elasticities emerge in a competitive way where agents are rational optimizers, alike the findings of Tóth et al. (2012) on a microstructural level. In summary, elasticities are dynamic and subject to the interplay between market participants.

To conclude this brief outline, there is a wide range of evidence for the effects of demand on price generation in financial markets.

Chapter 2

Theory

In Summary: This chapter first discusses the aspects of money and second, outlines shreds of the evolution of the theory which led to the model proposed by Gabaix and Koijen (2021). It further puts the model in relation to other approaches.

Main Points:

- Private provision of money can be efficient.
- In efficient markets prices change without trade.
- Neither prices nor their volatility change only due to fundamentals
- Markets with costly information cannot be informational efficient.
- Information in prices is decreasing in the cost of information.
- Common knowledge about stochastic dividends does not induce agents to form homogeneous beliefs.
- There is evidence of a tendency of market participants to align their beliefs.
- The impact of trades on prices has been found to increase as a function of the size of the order.
  - The power is found to be smaller than one.

2.1 Overview

This section presents an overview of some theoretical aspects later touched upon in the thesis. The main topics are the aspects identified by abstract approaches to understanding money, and the formation of prices in markets in general. A short introduction to the similarities of money and memory, which will be used later in section 3.1, and a discussion of the feasibility of private money provision is presented. Thereafter, the theory of market efficiency is discussed, and the theory of dynamic market adaption. Then, some models for trading are presented and finally, the distinction between micro- and macrostructure literature is drawn.

2.1.1 Money

Before turning to price formation, some aspects of money are noted, which make money different from other goods.

Kocherlakota (1998) described the parallels between money and memory. In his seminal paper, he showed in several models that money can enable distributional outcomes similar to that archived if agents had access to the memory of past transactions. Marimon et al. (2012) showed in their model that private provision of money is possible and efficient (except for the first period, i.e. the introduction stage) if the private entity can commit to stable inflation and there is competition for the provision of money. They argue further that with negative inflation the 'Friedman Rule' monetary equilibrium can be reached and is also efficient under competition. An interesting further note is that currency is an experience good.

The first aspect is built into bitcoin, with its distributed ledger of transactions, and a commitment for stable inflation is tried to be archived by the algorithmic commitment to a given supply. In their model, however, a currency can be produced at nearly no cost. This holds not in bitcoin due to the proof-of-work mechanism explained in section 5.1.1. A further caveat to transferring their model to bitcoin is that there is no profit maximizer behind the issuance of bitcoin.

Senner and Sornette (2019) qualify the money-like properties of bitcoin by emphasizing that bitcoin lacks the possibility of creating it dynamically i.e., as a response to an investment opportunity. As the authors further argue this slows innovation and economic growth and prevents bitcoin from backing future production. Moreover, the idea of a fixed supply governing inflation is outdated according to Senner and Sornette.

2.1.2 Market Efficiency

Market efficiency as defined by Fama (1970) implies that prices reflect all available information. Combined with the assumptions that expected returns describe the market equilibrium in its entirety and that the most recent information is used by market participants to form their return expectations and with that the price, Fama (1970) shows that the price process must be a martingale.

Such an efficient price is perfectly elastic. The arrival of new information changes the price to its efficient value, where it stays independent of demand. A price that reflects the fundamental value would deter investors from trading, as several authors find (see 2.1.3). Every trade will be done at an efficient price, nobody can gain by trading. In other words, prices change due to informational changes and not due to trading (Bouchaud, 2021). Gabaix and Koijen (2021) test the elasticity of classical economic models and show that the implied elasticities are high.

A qualification of the strong assumptions implied by the 'Efficient Market Hypothesis' is the 'Adaptive Market Hypothesis'. In Lo (2004) and further Lo (2005), Lo develops what he calls 'Adaptive Market Hypothesis' to reconcile the deviations of market behavior from the predictions of the efficient market hypothesis. He shows cyclical first-order autocorrelations of the S&P 500 index as evidence that markets are not efficient all the time but are at times. The force that drives the prices away from fundamentals is, in this view, learning effects. Changing market behavior was also noted by Brogaard et al. (2021). The authors suggest market maturing as a reason for their finding of overtime decreasing noise levels. They further note an increase of influence from firm-specific information and attribute this raise to changes in regulation.

It has also been shown that efficiency differs between markets e.g., Urquhart (2017) finds indications for inefficiencies, in a Fama (1970) sense, in precious metals markets, Choi (1999) reject the random walk hypothesis for some currencies and weak efficiency, in a Fama (1970) sense, has also been rejected in the art market (David et al., 2013). The authors of the latter study point to different potential factors influencing the elasticity of the art market, of which some are also present in the bitcoin market i.e., inelastic supply and difficult financial valuation (see Frey and Eichenberger (1995) for the complete list of factors).

2.1.3 Models of Trading

In Jaffe and Winkler (1976) investors' ability to forecast changes in future value is what generates profits from trading. In the light of the Keynesian Old Maid from chapter 1, one may think that the value to be predicted is influenced in the same way by fads as it is by fundamentals.

Similarly, Rubinstein (1975) shows that in his model, informational efficiency leads to no trade in the absence of new information. As shown by Milgrom and Stokey (1982) there is no trade if the initial allocation is Pareto optimal. Furthermore, they note that price changes can drown out the private information of traders. Grossman and Stiglitz (1976) show the importance of different information levels of agents to the existence of markets in a model where information is costly, and participants chose to be informed. Finally, Hakansson et al. (1982) derive necessary and sufficient conditions for the social value of information for a variety of models.

Yet, investors seem to trade more than they ought to (Odean, 1999) and prices change not only on new information (Cutler et al., 1988), neither does price volatility (Engle et al., 1988).

A possible path for the explanation of trading in efficient markets is when informed traders trade with uninformed or noise traders. In models where informed traders trade with noise traders, noise traders fulfill an important liquidity-providing function but also make prices noisy (Black, 1986). The necessity for noise traders as liquidity providers creates dangers for financial market functioning by the creation of liquidity crises (Brunnermeier and Pedersen (2009), Dall'Amico et al. (2019) and others).

However, it is not clear what drives noise traders to trade, as they do not make profits on average.

Different models were established with the informed trader v noise trader set-up. Grossman and Stiglitz (1980) show in their model that markets with costly information cannot be informationally efficient i.e., that costless information is a necessary condition for informational efficiency. Verrecchia (1982) extends the model of Grossman and Stiglitz to information aggregation through prices.

The models of Grossman and Stiglitz (1980) and Verrecchia (1982) show that the informativeness of the price is increasing with decreasing marginal utility of information in the number of informed individuals. The number of informed individuals is increasing in the noise of the supply. Further, the information contained in prices is decreasing as the price of information and the noise in the supply of the asset increases.

A further step to a better understanding of price generation in markets are models, in which agents incorporate their effects on prices and act accordingly. Kyle (1985) introduced a model where a single informed trader takes the effect of his trades on prices into account. In his model increasing the number of noise traders increases the profits of the informed trader, who has all the information. This single informed trader can bring prices in line with his information.

Another interesting facet of the model presented in Kyle (1985), is that the price impact of trading is endogenous and that the model makes predictions about market liquidity.

Later, Kyle (1989) expanded the model with traders who keep prices inefficient enough to profit from their information.

The last two models mark a departure from the way price impact was hitherto perceived. Price impact has become a strategic choice. Liquidity provision has to trade off gains from uninformed traders and losses from informed traders. This leads informed traders to hide their intentions and to adjust volume, as do liquidity providers. These considerations lead to a wide range of literature known as 'market microstructure' literature.

Furthermore, having agents account for their price impact opens the scope for price manipulation via trades i.e., traders who trade with the sole aim to push prices in a certain direction.

2.1.4 Price Generation

Allen and Gale (1992) describe in their paper a mechanism of price manipulation and show that it is indeed possible to manipulate prices if the other agents think that there is a chance that the manipulator is an informed trader. However, their example does not constitute what Kyle and Viswanathan (2008) define as illegal trading. This is because the manipulator in the model of Allen and Gale (1992) does not necessarily affect liquidity in a destabilizing manner. Hence, the manipulator in Allen and Gale (1992) merely is more of a 'successful' speculator or a successful noise trader.

An empirical investigation of price manipulation, as defined by Taiwanese law, is done by Huang and Cheng (2015). The authors describe how price manipulation affects the efficiency of prices and depends on company fundamentals. They note that the effects of price manipulation depend on the trustworthiness of the corporation's government and reporting and that manipulated prices change price efficiency.

This example shows, that simply driving prices away from fundamentals cannot constitute manipulation, even if other traders assume you might be better informed than they are. If they then join the trades you are executing, the price might rise further and further constituting a financial bubble.

Bubbles

Bubbles and crashes should only emerge sporadically in a rational market because agents incorporate new information in their price expectations. Yet, as early as Keynes (1936), pundits acknowledged the presence of bubbles and crashes in financial markets. Especially so after the experience of the 1930 market crash and the following recession.

Friedman and Aoki (1992) show how bubbles and crashes can occur in a rational setting. Their mechanism works through an imbalance of information i.e., less informed agents move the price when trading with better-informed agents. These price movements then induce other traders to incorporate a false price signal into their expectation updates. However, their restrictive assumptions keep the bubbles bounded and finally convergent to the true value. The mechanism of undervaluing private information can be rationalized as Bikhchandani et al. (1992) show. They propose a model where agents disregard private information completely and imitate the actions of the preceding agents. This behavior creates a cascade of self-reinforcing false information propagation.

In experiments, Camerer and Weigelt (1991) show that the assumption of uninformed traders in a market, can lead to irrational price rises because uninformed traders misinterpret price signals. Interestingly in their experiments Camerer and Weigelt note that lasting bubbles predominantly emerge in early periods in their experiments, indicating the learning effects of a market or a maturing of the market. Learning effects were also reported by Smith et al. (1988) and additionally, they show that common knowledge of identical stochastic dividends does not induce agents to form identical beliefs about returns. The latter finding suggests that even in settings where one part of the return i.e., expected dividends, are known to all participants, uncertainty about the behavior of others induces enough volatility to create seemingly profitable opportunities to deviate from the collective believes.

More recently, Hommes et al. (2005) show in their experiments that agents tend to coordinate their predictions, and in doing so, the agents form self-fulfilling prophecies. Moreover, Hommes et al. (2005) show that the presence of traders who strictly trade on fundamentals dampens bubble-building tendencies in markets.

The findings of the above experiments show that irrational forces play a role in market interactions. A view popularized by Shiller et al. (1984). Later summarizing in Shiller (2014), he lays out evidence that behavioral factors play a role in markets and following trends can be a rational strategy. Indeed, Kozak et al. (2018) show that factor models constructed on rational factors may only incorporate risk-premia created by investor behavior i.e., their beliefs and tastes. This finding holds when the behavior is comprising enough to influence large parts of the market i.e., when rational arbitrageurs react to demand from behavior-driven agents. The main assumption for this effect to play a role is in absence of near arbitrage opportunities, which despite the possibility of restraints on arbitrage (Shleifer and Vishny, 1997), seems plausible. Huang et al. (2019) show further that trades initiated devoid of fundamentals lead to large-scale price effects in markets, underlining the argument of Kozak et al. (2018).

The thinking of how markets work shifted from the representative two agents to one which understands markets as complex systems. The behavior of such a system is driven by the interactions of the thousands of participants interacting with the system and with each other.

Sornette (2004) looks at markets through the lens of such complex systems, where interactions of expectations rationally fuel irrational behavior. In the same vein, Bouchaud (2013) presents different models which exhibit 'state transitions' i.e., regimes where models are unstable, even with smooth underlying behavior of agents. This view brings us again close to the Keynesian view, where market participants need to foresee the moves of their peers and sudden mood changes can have dire consequences. Indeed, during crises the contribution of market-wide information to return variance spikes but is low during normal times (Brogaard et al., 2021).

The modern theoretic literature concerning the price impact of trade flows can roughly be divided into two literature strands. The market macrostructure literature, where Gabaix and Koijen (2021) forms part of and the market microstructure literature on which Bouchaud (2021) base their arguments.

According to Bouchaud (2021), the model and the results in Gabaix and Koijen (2021) can be related naturally to the market microstructure literature.

The main difference between the two strands is how close they zoom in on trades i.e., the market microstructure focuses on individual trades in general on intra-day timescales, orders, and metaorders. A metaorder is an order which is split into several orders. The smaller orders are distributed over time and possibly space i.e., sent to different exchanges. The market macrostructure looks at flows i.e., aggregated trades between funds or larger entities on timescales about a quarter of a year.

Yet, both strains look at the same phenomenon, which is the price impact of trading. Furthermore, what is called liquidity in the market microstructural approach refers to what is called elasticity in the market macrostructure approach (Hasbrouck, 2007).

Despite having different approaches both strands generate similar results as Gabaix and Koijen (2021) and Bouchaud (2021) point out. Both strands detected several instances, where markets are led astray from efficient valuation because of trading e.g., Coval and Stafford (2007) find price pressure on common holdings of funds with extreme capital in- and outflows. Furthermore, both approaches combine the feature of funds and mandates e.g., Frazzini et al. (2018) note that trading algorithms perform rebalancing trades and Gabaix and Koijen (2021) base their model on the mandates of funds. In other words, both approaches try to measure the same thing on different scales. This makes it hard to exactly differentiate between the two strands. The better-informed reader may pardon any eventual misclassification.

Summarizing this section, it is noted first, that it can be possible and efficient for private agents to offer money. Behavioral effects play a non-negligible role in price generation mechanisms. It is, however, extremely difficult to distinguish between effects that are due to collective behavioral tendencies or changes in some sort of fundamental value. That trade will not happen in an efficient and rational setting has been shown in different models. Noise traders can explain, why trades happen frequently in financial markets. More complex models try to incorporate the effects trades have on prices and the information prices offer. Recent models include fragile mechanisms of expectations leading to state transitions from stable states to unstable states.

2.2 Market Macrostructure

Focusing on large-scale phenomena, the market macrostructure literature is not as narrowly defined as the microstructure literature. The market macrostructure approach mainly derives its conclusions from market-wide effects, frequently from interactions of financial funds and markets. The focal point of the market macrostructure approach is on large-scale trading, sometimes referred to as flows. The effects are generally identified through exogenous factors and measured as the price impact of those e.g., Li et al. (2021) exploit demand shocks on funds during Chinese IPOs to measure the price impact of those shocks. Similarly, Da et al. (2018) investigate the effects a financial advisory firm has on the stock market through recommendations on market timing made to its customers.

The view of the market macrostructure literature is driven by the idea of a supply and demand setting for prices. As such, the price elasticity of demand is a natural assumption for the market in general, yet arbitrage arguments have so far put doubt on its existence in financial markets. Recent literature questions the idea of fully efficient markets and leans towards a more dynamic view (Lo, 2004).

In this more dynamic view, behavioral effects shape market reactions in addition to rationality. The model of Gabaix and Koijen (2021) is an attempt to reconcile that all trades influence prices and because demand effects can be driven by other sources than pure rationality e.g., irrational choices, can influence markets. This line of research is relatively new, and identification of clear effects is difficult because of the simultaneity of demand and supply (Levin and Wright, 2002). Early examples concentrate on the effects investors induced on funds by in- or disinvesting by using an instrumental variable approach to extract the effects.

In what follows exemplary studies are described to give an impression of the evolution of the literature. The reader is referred to section 3.2 for more examples.

Edelen (1999) studied the effects of flows of money on prices to develop a better understanding of fund performance. Edelens argument is that, because funds are subject to demand shocks of investors, they need to rebalance their positions. Such trading for the purpose of rebalancing is equivalent to noise trading because at least some investors are facing idiosyncratic reasons for their cash movement. Funds, therefore, provide liquidity services, which are costly to investors. Hence the relative underperformance of funds.

This argument paved the way for investigations on how flows in and out of funds or other financial entities affect prices. Coval and Stafford (2007) showed that asset fire sales of investors lead funds to decrease their positions fast. This cascade reduces asset prices temporarily and can be profitably exploited. This is evidence for the model presented by Brunnermeier and Pedersen (2005), which outlines traders profiting from others' distress by driving prices further down as the distressed is in need to sell. Both models shine a light on the mechanisms with which the price influence of trading can be exploited for profits.

Frazzini and Lamont (2008) interpret cash flows into and out of funds as sentiment, with this interpretation the authors show that sentiment-driven rebalancing of funds destroys value for investors in the long term. The investors in their sample are return chasing i.e., funds that have overperformed in the past are the ones experiencing inflows. This behavior leads the funds with inflows to increase their positions, further driving up prices. In the long term, prices reverse, and investors suffer losses on their funds' holdings. They can relate the flows during the observed period to trading strategies, bringing forward the question of why individual investors shift their holdings in the first place.

Lou (2012) shows that, because flows to funds are predictable and flows into funds drive asset prices, stock returns can be partially predicted. Especially strong is the connection between flows from and to funds and stock momentum effects. His findings are later corroborated by Li (2021).

All these price effects also influence fund behavior as Edmans et al. (2012) show. Price effects can increase the possibility that a fund is acquired by another financial entity. This finding point to reverse causality effects at play in price generation mechanisms.

More recently, Da et al. (2018) find effects of financial advice on the Chilean stock markets and documented increases of volatility around dates on which a large advisory firm distributes their suggestions to their customers via e-mail. The customers make use of a Chilean specialty in pension fund management, allowing the holders of funds to switch between the providers and types of funds easily.

The elasticity effect seems also to be present in IPO markets, as Li et al. (2021) document. The authors note a substantial effect of exogenous demand shocks on the returns of the traded asset. They exploit partial freezing of funds during IPOs.

The above examples, however, do not explain persistent movements. The very idea of a period of stress implies that after some time markets are driven back to their equilibrium efficient prices. In Gabaix and Koijen (2021) the authors mention the possibility of persistent flows, which can alter the price of an asset over a sustained period. Persistent inflows to some funds have predictive power on factor returns (Dong et al., 2022).

Continuing inflows can therefore lay at the heart of financial bubbles. If flows are fueled by high enough returns i.e., in the form of price rises, a bubble can build into a self-perpetuating mechanism.

These studies reveal an intricate relation between a rational price generating mechanism, where changes in fundamentals drive demand and therefore change prices in an informed manner, and other mechanics, where prices are changed with no direct connection to fundamentals and hence are driven away from their fundamental values.

An intriguing fact presented above is that some of these changes can be predicted to some extent and have self-enforcing properties. In the microstructure literature, there is a differentiation between statistical and fundamental efficiency. I will outline this and other aspects of the market microstructure literature in section 2.3.

The main takeaway of this section is that the effects of flows on prices are present on different levels. Funds, which are driven by inflows and bounded by their mandate influence prices in manners, which can lead others to follow. The reasons for the movements of money in and out of the financial entities cannot be answered. Yet, there is evidence that they are not completely driven by fundamentals.

2.3 Market Microstructure

The market microstructure approach derives its results from the effects individual orders or metaorders have on liquidity and prices (Bouchaud et al., 2018). As such it focuses on the market participant activities and interplays. Despite the focus on the microscopic behavior and structures of markets, the results apply to a wide range in time and scope e.g., the power law of market impact. The power law of market impact states that, in a certain range of size of the order, price impact decays as a power law with the power of roughly $\frac{1}{2}$. This effect is found to be present in different markets and describes effects on different time scales (Almgren et al. (2005), Tóth et al. (2011), Tóth et al. (2016), Donier and Bonart (2015) and others).

Bouchaud (2021) compares the results of Gabaix and Koijen (2021) to similar results from the market microstructure literature. Bouchaud uses several studies to underline the argument, that market volatility originates in large parts from trading. In doing so, Bouchaud aims to lay the ground for the mechanism at the origin of the elasticity effect described by Gabaix and Koijen (2021).

Bouchaud et al. (2018) note that if trades move prices without informational content, one needs to differentiate between statistical and fundamental efficiency: If market participants try to profit from the price impact of others, they induce martingale like properties on the price path, without connection to a fundamental value. This leads to a distinction between fundamental efficiency i.e., prices are martingales because they reflect the fundamental value changing on new information, and statistical efficiency, where prices are martingales because traders pick off all information from price movements. After all, every predictable pattern is exploited by market participants, leaving the martingale-like history of price movements. They suggest that the latter efficiency might be more important in short periods and the former dominates in the long run.

Bouchaud (2021) points out that the reason why prices change can be divided into an efficient view and an order-driven view. In the former, prices change due to traders' forecasts of future price moves. Importantly in the former notion, is that prices would change in the absence of trades. In the latter view, prices change because there is an imbalance in the order book. Hence, prices can change in the absence of information.

As pointed out in section 2.1 before, the model presented in Kyle (1985) laid the ground for investigations on how trading impacts prices. A large body of literature has emerged around the topic of trade impact on prices on the microstructural level. See e.g., Bouchaud et al. (2018) and the references therein.

In-depth studies of traders' behavior features often in the market microstructure literature. Tóth et al. (2012) observe in their sample of a pool of traders, that traders use heterogeneous trading practices and that traders seem to react to other market participants' orders and the price change induced by them or by others.

A prominent result appearing in several studies is the aforementioned 'power-law' or 'square-root-law' of market impact (Tóth et al., 2011). This law relates the price impact of a 'metaorder' i.e., an order which is divided into several smaller ones, to the size of the metaorder, the market volatility, and the traded volume. The power law of market impact has been detected in several markets.[8] It relates the price impact of an order to the square root, or more general to a power smaller than one, of the ratio of the size of the trade and the market turnover times volatility.

It needs to be noted that such metaorders are executed within hours whereas Gabaix and Koijen (2021) measures the impact of quarterly changes. Furthermore, the specific form of the 'law' holds within 'normal' execution times, and volumes (Bouchaud et al., 2018).

In a model developed in Benzaquen and Bouchaud (2018), the permanent impact of trades is computed, and it is found that the impact becomes linear in the limit. This finding is in line with the result of Gabaix and Koijen (2021) and highlighted by Bouchaud (2021) as the point of convergence of the microstructural and the macrostructural literature.

Gomes and Waelbroeck (2015) ask the question of whether the market impact is a feature of

[8] The square root law has also been ascertained in bitcoin markets (Donier and Bonart, 2015)

informed trades only. To answer this, the authors differentiate between metaorders done for rebalancing purposes, necessary due to in- or outflows, which they call cash-flow metaorders. They find that metaorders for rebalancing purposes have no permanent impact, while during execution the effects are similar to the trades done because of changes in fundamentals. Underpinning the short term findings of Frazzini and Lamont (2008) presented in section 2.2. However, the impact of trades differs between traders (Bladon et al., 2012).

That microstructural effects influence the market's macrostructure is not a novel idea. E.g., a relatively simple model proposed by Gabaix et al. (2003) tries to explain the typical heavy-tailed return distribution with trades of large market participants, this model has been developed further in Gabaix et al. (2006). The model can replicate stylized facts of market returns, trading volume, and price impact using observed trade-size distributions.

Subsuming this section, the effects of individual trades and interactions between traders on the market are important factors to a better understanding of market behavior. Especially noteworthy is the effect orders have on prices, which does not increase linearly with the size but is dampened by a power law with a power smaller than one. An emerging strand of literature investigates the effects of those interactions.

Chapter 3

Literature

In Summary: This section outlines the current state of the literature regarding some of the key elements of bitcoin and price elasticity. The main focus lies on recent literature and its connection to chapter 2.

Main Points:

- Results for statistical properties of bitcoin prices are dependent on the period and the exchange under investigation.
- There is evidence for feedback loops between social media and other information-providing platforms to bitcoin prices.
- Evidence indicates that correlated flows lead to correlated price moves.

3.1 Bitcoin

In this section, literature concerning the monetary properties, the price behavior of bitcoin, and how the price correlates with different economic and technical variables are discussed. Noteworthy is the evidence regarding the reactivity of bitcoin to media outlets and the arguments brought up against the usefulness of bitcoin as a medium of exchange, store of value, and unit of account.

3.1.1 Money or Asset

First, the question needs to be answered whether bitcoin is perceived as a currency or a financial asset. While some authors argue that bitcoin has asset-like properties (Yermack, 2015). Glaser et al. (2014) find that especially new and inexperienced users treat bitcoin as a speculative asset. Ron and Shamir (2013) find that a large portion of bitcoins in circulation is held in 'dormant' wallets i.e., wallets without transactions.

Luther and Olson (2013) points out that the data structure of bitcoin, see section 5.1.1, which only stores the transaction and not balances has striking similarities to what Kocherlakota (1998) called memory. Dowd (2014) notes that, due to its distributed ledger, bitcoin cannot be interpreted as a credit system. I.e., each valid transaction in bitcoin is performed with available funds. Lack of credit leads to the elimination of trust between the two transacting parties, as is the case with a transaction in cash. The fact that bitcoins cannot be created in response to a need for funds, is why Senner and Sornette (2019) argue that bitcoin and currencies with similar properties will not replace fiat currencies.

Further drawbacks to the use of bitcoin as a medium of exchange have been brought up. An issue raised by Yermack (2015), Dowd (2014) and Dwyer (2015) is the deflationary pressure of a fixed supply. The scarcity is even aggravated by attrition (Dowd (2014) and Dwyer (2015)). Yermack (2015) highlights the problem for consumers to read prices in bitcoin, given that bitcoin becomes a widely used currency, due to the many leading zeros necessary for small purchases. Dowd (2014) brings up the example of diminished trade on the *Silkroad* platform during times of fast appreciation of the bitcoin against the dollar.

3.1.2 Bitcoin Price

The market behavior of bitcoin prices is very dynamic. Several studies find differing results depending on the period under investigation. It has been shown that, in its early years, bitcoin returns did not display random walk behavior (Urquhart, 2016). However, Urquhart (2016) also shows that after the bitcoin exchange rate rose to a substantial level i.e., after the first of August 2013, he could not reject the hypothesis of a random walk anymore, tested with an AVR test (Choi, 1999). Furthermore, Urquhart (2016) also fails to reject the hypothesis of no autocorrelation in his second sample period using the Ljung-Box test (Ljung and Box, 1978). Urquhart concludes that bitcoin is inefficient, in a Fama (1970) sense, yet shows signs that it is becoming efficient as the market matures. The efficiency increase can in part be explained by liquidity and market capitalization effects (Brauneis and Mestel, 2018). A boost in market efficiency was detected after the launch of bitcoin futures on CBOE and the CME (Köchling et al., 2019).

Likewise, Kristoufek (2015) notes the changing nature of the correlations between different explanatory variables and bitcoin prices over time. In an involved investigation of bitcoin market efficiency, Kristoufek (2018) shows that the efficiency of the bitcoin market is changing and more efficient in periods after a fast price decrease. Furthermore, the methodology employed by Kristoufek (2018) shows that the structure of inefficiency is changing over time. Changes in correlations and other statistics are present in other relatively mature markets (Lo, 2004).

Comparing different cryptographic currencies, Gandal and Halaburda (2016) find changing correlations between returns in different periods. They interpret this finding as evidence for shifting network effects i.e., reinforcement (positively correlated returns) or substitution (negatively correlated returns). The results are insignificant for the whole period and while controlling for *Google* trend data. The authors interpret these results as evidence that sentiments affect different crypto-assets in different ways. Gandal and Halaburda (2016) note, however, that the price of bitcoin increased in value in each of the subperiods, putting some doubt on the reliability of the results.

Behavioral factors can also have large influences on mature markets (Shiller, 2014) and therefore can be expected to play a role in crypto-asset markets. It has been shown that trends in keywords searched on *Google* can predict stock market returns (Preis et al., 2013). Similar behavior has been found for bitcoin returns see e.g., Cheah and Fry (2015) or Kjærland et al. (2018). Posts on platforms such as *Twitter* or dedicated blogs are also correlated with bitcoin returns (Mai et al., 2015). Even though it is unclear in what direction Granger causality points between *Twitter* posts and bitcoin returns (Kaminski, 2016).

Garcia et al. (2014) investigate the role of social interactions and point to feedback loops between prices, the number of users, and information acquisition and distribution in the bitcoin universe. In addition, Garcia et al. (2014) construct a lower bound for the fundamental value of bitcoin from the estimated energy costs of the mining process. This lower bound is interesting because it marks a boundary, below which mining becomes unprofitable.

Relatedly, Bouoiyour et al. (2014) finds different granger-causality structures at different time horizons for a proxy of attractiveness and the ratio of exchange volume to on-chain volume, which can be interpreted as further evidence for the feedback mechanisms presented in Garcia et al. (2014). Indeed, Kristoufek (2015) also finds evidence underlining the feedback loops. Granger causality is also present between different quantiles of volume and return distributions around median returns (Balcilar et al., 2017).

More recent studies focused on the introduction of bitcoin futures (December 2017) and its implication for bitcoin price discovery. The results are mixed, depending on the time horizon investigated. Kapar and Olmo (2019) find leading futures prices in daily data, whereas Baur and Dimpfl (2019) find leading spot prices on 5 min frequency. Entrop et al. (2020) note that price discovery differs, depending on liquidity, trading costs, and uncertainty based on intra-day trade and quote data. The introduction of futures on established exchanges might have boosted market integration, measured by a dynamic equi-correlation model (Bouri et al., 2021).

Given the models outlined in chapter 2.1, these findings are rather unsurprising. The fundamental value of bitcoin is uncertain at best. Hence, information about bitcoin should have a larger impact on the price as it would where the fundamental value is clear.

Bubbles

Cheah and Fry (2015) find evidence for price bubbles in the bitcoin market and Donier and Bouchaud

(2015) investigates the predictability of the bubbles via market liquidity. Later, Wheatley et al. (2019) puts forward a model which employs user activity to predict bubbles. Gerlach et al. (2019) present an overview of the larger price bubbles detected. Huber and Sornette (2022) shines a light on the benefits and the social aspects of bubbles. They argue that price bubbles are by design a part of bitcoin and helped to establish bitcoin publicly.

There is evidence for 'pump-and-dump' schemes in bitcoin markets (Hamrick et al., 2018). In line with the theoretic models outlined in chapter 2 and especially with the power law presented in 2.3 and shown to be present in bitcoin markets by Donier and Bonart (2015), Hamrick et al. (2018) find larger price impact of pump-and-dump attacks when volatility is high. Furthermore, the most important factor found in their study is market volume. This finding aligns with the power law of price impact presented earlier. The authors also find differing effects between exchanges. That there are different effects on prices at different exchanges is underlined by similar findings on price discovery mechanisms between exchanges (Brandvold et al. (2015) and Ji et al. (2021)).

Alternative factors apart from 'Irrational Exurberance' (Greenspan, 1996) or 'Social Dynamics' (Shiller et al., 1984), which could contribute to the volatility of bitcoin exchange rates is the algorithmic scarcity of bitcoin (Nakamoto, 2008). Bitcoin becomes especially scarce when demand is large because supply cannot be ramped up as it could be with any other commodity (Antonopoulos, 2017). That scarcity can have a positive impact on valuation and thus on prices is widely regarded as an economic and psychological fact (Lynn, 1991).

To wrap up this section it can be noted that even though bitcoin prices and information transmission is an active field of research many results are contradicting depending on the period investigated. Noteworthy are the facts that the monetary usefulness of bitcoin is disputed, the power law of price impact seems to be present and there is evidence for feedback loops between social-media platforms and bitcoin prices. Bitcoin prices are bubble prone and are frequently subject to pump-and-dump schemes.

3.2 Price Impact of Trading and Market Elasticity

This section describes recent advances in the fields of the price impact of trading and market elasticity. Many recent studies point to the effects of flows on price generation and volatility. The literature has identified correlated ownership as a source of correlated flows.

As mentioned in chapter 2, the price impact of trading and price elasticity of demand essentially mean the same thing.

A test of price impact on the microstructural level i.e., within-fund, was done by Frazzini et al. (2018). They test a wide range of different models on an extensive dataset. The authors highlight the importance of a concave trade impact function and further, the market environment the trades are conducted in.

The macrostructure literature's focus are flows between funds e.g., Ben-Rephael et al. (2011) study flows to funds at the Tel Aviv stock exchange and find strong mean reversion effects of price changes induced by flows. The effects of flows between funds are documented to be so pronounced, that they amount to a separate risk factor. See e.g., Huang et al. (2019), which show the large effects of noise traders exert on market prices, which they identify with flows to and from mutual funds. They construct a risk factor from exposure to fund trading, which in turn is heavily influenced by uninformed traders. Li (2021) documents the influence money flows have on the Fama-French (Fama and French, 1992) 'risk factors'. She notes that around 30% of the quarterly variance of these factors can be explained by flows to and from funds.

More recently, ETFs have become a focal point of researchers. Ben-David et al. (2018) shows that dependent on whether a stock is included in ETFs or not, the volatility in that stock increases relative to other similar stocks which are not parts of ETFs. They attribute their finding to an increase in trading in the stocks from the ETFs. Overall, they note that ETF inclusion might have negative effects on price discovery and poses a non-diversifiable risk to investors in the respective stocks.

Also looking at ETFs Brown et al. (2021) document that flows of ETFs themselves contain information about demand which does not originate in fundamentals. They argue that the mispricing brought by this demand has different effects over different time horizons.

The studies above indicate that the ownership of assets is important to their behavior. Ben-David et al. (2021a) study this possibility and find evidence that the ownership structure of equities influences their statistical properties. They note that equities held by larger institutions face larger volatilities and smaller returns during market drawdowns. They suggest that centralized risk management leads to these effects and notice the greater autocorrelation in returns in stocks that are held by the same entities. This larger autocorrelation stands in contrast to equities held by smaller institutions.

Another study looking at flow effects of funds is Ben-David et al. (2021b). The authors make use of a change in the rating mechanism of *Morningstar*, from which they find strong evidence for price impact caused by flows induced by *Morningstar*'s ratings.

Different funds also seem to trade differently e.g., Parker et al. (2020) note that target date funds (TDFs) are a large class of contrarian investors. Contrarian investing, they speculate, could curb market volatility, and connect the returns on bond and stock markets but also might reduce fundamental price efficiency. Overall, they add to evidence that flows of funds impact returns of stocks and bonds.

As suggested by Gabaix and Koijen (2021), the frequencies of flows matter. Dong et al. (2022) examine different frequencies of flows and note that low frequency ('persistent') flows have predictive power for factor returns. They argue that the reason for this effect is due to choices by active fund managers.

In conclusion, this section highlights the effects of flows to financial markets. Correlation within these flows leads to correlated price changes and with that affects the risk inherent to certain financial assets.

Chapter 4

Model from Gabaix and Koijen (2021)

In Summary: This section broadly describes the model introduced by Gabaix and Koijen (2021). The simulation of the model presented below forms part of chapter 7.1. The main purpose of this chapter is self-containment of the thesis and a reader already acquainted with the model can skip the following two sections and jump to chapter 5.

Main Points:

- The model relies on irrational agents.
- Flows change prices independent of fundamentals.
- Share buybacks are a type of flow.
- The discount rate of the model is affected by the funds' mandates. I.e., the discount rate increases with decreasing equity share and sensitivity to the equity premium.

An overview of the model described in Gabaix and Koijen (2021) with the notation therein is presented in the sections below. First some general remarks on the notation: Lowercase letters denote percentage changes in the two-period model and deviations from the baseline in the multi-period model. Δ denotes first differences, where the time index indicates the time index of the positive variable i.e., $\Delta x_{t+1} = x_{t+1} - x_t$.

The model of Gabaix and Koijen (2021) explains the volatility puzzle described by Shiller (1980) among others by the price impact of trading activity. In the model, a price change can be traced to a change in quantity demanded. Hence, the model predicts a long-term effect of trading activity on the price of an asset. While the effect is explained by trading, the model makes no statement about the reasons for changing demand.

In the first section, the model as described by Gabaix and Koijen (2021) is outlined and commented on. Two models are presented in the paper Gabaix and Koijen (2021), in effect. As in the original article, the 'two-period' model is presented first and thereafter follows the 'infinite horizon' model.

4.1 Two-Period Model

The two-period model of Gabaix and Koijen (2021) consists of a fixed supply of Q shares and B bonds, with price P. The price is endogenous to the model. The dividends paid by the shares are denoted by D. The equity premium in Gabaix and Koijen (2021) is defined as $\pi = \frac{D^e}{P} - 1 - r_f$, where $D^e = \mathbb{E}[D]$: the expected dividend and r_f the risk free rate. $\hat{\pi} = \pi - \bar{\pi}$ denotes the difference between the equity premium π and its average $\bar{\pi}$.

There is one representative consumer, who invests in the two assets via I institutions. W_i denotes institutions i's wealth and the superscript $\mathcal{E}$ denotes the wealth held in equities. In general, the subscript i describes variables assigned to institution $i \in I$. I.e., institutions i's wealth invested in equities can be described by $W_i^{\mathcal{E}} = \frac{PQ_i}{W_i}$.

Gabaix and Koijen (2021) assume that each institution's equity investments follow a mandate given by:

$$\frac{PQ_i}{W_i} = \theta_i e^{\kappa_i \hat{\pi}} \,. \tag{4.1}$$

and the rest is invested in risk-free bonds. κ_i indicates how the institution reacts to changes in expected returns, the larger κ_i the more risk-seeking is the institution. $\theta_i \geq 0$ is the institution's mandate i.e., the fraction of equity it is obliged to hold.

The index $i = 0$ denotes a special institution in Gabaix and Koijen (2021): the 'pure bond fund' ($\theta_0 = \kappa_0 = 0$). Gabaix and Koijen note that only because consumers are not fully rational in their model, do the mandates of the institutions matter. Fully rational consumers would take the mandates into account and undo the effects of the mandates in their optimization.

4.1.1 The Elasticity of Demand for Equity

In the 'two-period' model of Gabaix and Koijen (2021) bars are used to denote values at time $t = 0^-$ before any shock.[9] I.e., $\bar{W}_i$ and $\bar{Q}_i$ denote institution i's wealth and number of equities at time $t = 0^-$ respectively. The equity premium at time $t = 0^-$ is given by $\bar{\pi}$. $\delta = \frac{\bar{D}^e}{\bar{P}}$ denotes the dividend-price-ratio, with $\bar{D}^e = \mathbb{E}[\bar{D}]$.

The representative household invests ΔF_i dollars in each institution $i \in I$. ΔF_i represents the number of dollars taken from the pure bond fund and placed into the mixed fund, all at time $t = 0$. Gabaix and Koijen (2021) draw attention to the assumption that these extra dollars are taken from the pure bond fund. Thus, the fractional flow is given by $f_i = \frac{\Delta F_i}{W_i}$. $f_i > 0$ corresponds to an inflow and $f_i < 0$ to an outflow.

q_i, p and d_i denote the percentage deviations of demand for equity, price, and expected dividends from the initial values at $t = 0^-$:

$$q_i = \frac{Q_i}{\bar{Q}_i} - 1 \,, \qquad p = \frac{P}{\bar{P}} - 1 \,, \qquad d = \frac{D^e}{\bar{D}^e} - 1 \,. \tag{4.2}$$

The change in demand of institution $i \in I$ given f_i, d and p is denoted by q_i. In Gabaix and Koijen (2021) q_i is computed in:

9 This definition will change in the 'infinite-horizon' model where bars denote percentage deviations from a baseline.

Proposition 1 (Gabaix and Koijen, 2021): Demand for aggregate equities in the two-period model. The proof is repeated for completeness in appendix B.1.

$$q_i = -\zeta_i p + \kappa_i \delta d + f_i \ , \tag{4.3}$$

where ζ_i is the elasticity of equity demand of institution $i \in I$ and is given by:

$$\zeta_i = 1 - \theta_i + \kappa_i \delta \ . \tag{4.4}$$

From the percentage change of demand, q_i Gabaix and Koijen (2021) move one step ahead and compute the aggregated demand. Gabaix and Koijen (2021) aggregate the elasticity of demand for equity. They do that by defining the aggregate demand for stocks as:

$$Q = \sum_{i \in I} \bar{Q}_i (1 + q_i) \ . \tag{4.5}$$

Gabaix and Koijen (2021) further compute an equity weight, S_i, which labels the baseline share of equity the institution holds given total equity:

$$W_i^{\mathcal{E}} = Q_i P = \theta_i W_i e^{\kappa_i \hat{\pi}} \ , \tag{4.6}$$

$$S_i = \frac{\bar{W}_i^{\mathcal{E}}}{\sum_{j \in I} \bar{W}_j^{\mathcal{E}}} = \frac{\bar{Q}_i}{\sum_{j \in I} \bar{Q}_j} \ . \tag{4.7}$$

Comment: In Gabaix and Koijen (2021) (4.6) is given by $W_i^{\mathcal{E}} = Q_i P = \theta_i W_i$. Here $e^{\kappa_i \hat{\pi}}$ is introduced to make the definition consistent with equation (4.1).

With the definition of S_i Gabaix and Koijen (2021) construct the equity-holdings weighted mean for a given variable $x = (x_0, ..., x_I)$ as:

$$x_S = \sum_{i \in I} S_i x_i \ . \tag{4.8}$$

Gabaix and Koijen (2021) stress that there are two notions of equity share. The institution's equity share and the market-wide equity share. The authors differentiate the two in the following manner:

$$\text{Wealth weighted equity share} = \frac{\text{Total value of equities}}{\text{Total value of assets}}\,; \tag{4.9}$$
$$\theta_W = \frac{W^{\mathcal{E}}}{W^{\mathcal{E}} + W^B}\,, \tag{4.10}$$
$$= \frac{\sum_{i\in I} W_i \theta_i e^{\kappa_i \hat{\pi}}}{\sum_{i\in I} W_i}\,. \tag{4.11}$$

$$\text{Equity-holdings weighted equity share} = \frac{\text{Total value of equities weighted by fund variables}}{\text{Total value of equity}}\,; \tag{4.12}$$
$$\theta_S = \frac{\sum_{i\in I} W_i^{\mathcal{E}} \theta_i e^{\kappa_i \hat{\pi}}}{\sum_{i\in I} W_i^{\mathcal{E}}}\,, \tag{4.13}$$
$$= \frac{\sum_{i\in I} W_i \theta_i^2 e^{2\cdot\kappa_i \hat{\pi}}}{\sum_{i\in I} W_i \theta_i e^{\kappa_i \hat{\pi}}}\,. \tag{4.14}$$

Comment: Only equations (4.9), (4.10) and (4.13) are presented in Gabaix and Koijen (2021). Additionally, $e^{\kappa_i \hat{\pi}}$ is appended in equation (4.13) for consistency.

The second definition of the equity-holdings weighted equity share is the one used in the model, note Gabaix and Koijen (2021). Moreover, $\theta_S > \theta_W$ with θ_S constant over time and θ_W non-constant because the price changes will move the value of θ_W [10].

From the expressions (4.8), (4.5) and (4.7) Gabaix and Koijen compute the aggregate change of demand:

$$q = \frac{\Delta Q}{Q} = \frac{\sum_{i\in I} \bar{Q}_i q_i}{Q} = \sum_{i\in I} S_i q_i = q_S\,. \tag{4.15}$$

Furthermore, Gabaix and Koijen (2021) show the consistency between q_i and q_S in:

[10] To see that use equation (4.1) to replace $\theta_i e^{\kappa_i \hat{\pi}}$ in equations (4.14) and (4.11). Note that because $\theta_0 = 0$ the following transformation is not possible: $W_i = \frac{PQ_i}{\theta_i e^{\kappa_i \hat{\pi}}}$ for $i = 0$. Therefore, we end up with: $\theta_W = P\frac{\sum_{i\in I} Q_i}{\sum_{i\in I} W_i}$ and $\theta_S = \frac{\sum_{i\in I} Q_i \theta_i e^{\kappa_i \hat{\pi}}}{\sum_{i\in I} Q_i}$. In the latter expression, the price P drops out, whereas in the former we cannot drop P.

Proposition 2 (Gabaix and Koijen, 2021): Aggregate demand for aggregate equities in the two-period model. A repetition of the proof can be found in appendix B.2.

$$q_S = -\zeta_S p + \kappa_S \delta d + f_S \,, \tag{4.16}$$

where ζ_S is the elasticity of aggregate equity demand and is given by:

$$\zeta_S = 1 - \theta_S + \kappa_S \delta \,. \tag{4.17}$$

From the introduction, it is clear that flows play an important role in the model. After putting special emphasis on the distinction between the weighting schemes of the institution holdings, Gabaix and Koijen (2021) define the aggregate flow into equities in an equity-weighted manner as:

$$\begin{aligned} f_s &= \frac{\sum_{i \in I} \theta_i \Delta F_i}{W^{\mathcal{E}}} \,, && (4.18) \\ &= \sum_{i \in I} \frac{\bar{W}_i^{\mathcal{E}}}{W^{\mathcal{E}}} \frac{\Delta F_i}{\bar{W}_i} \,. && (4.19) \end{aligned}$$

The authors note that despite there always being a 'seller for every buyer', there is scope for a nonzero aggregate flow.

Comment: In the paper only (4.18) is presented.

4.1.2 The Impact of Flows

Gabaix and Koijen (2021) analyze the impact of flows in the following way:

They first set the elasticity $\zeta_S > 0$ and $q = 0$. The supply of equities is fixed in the 'two-period' model and hence, the equilibrium is static. Having a positive value for ζ_S implies that equity is not a Giffen good.

Using the above assumptions in equation (4.16), Gabaix and Koijen derive the following relation for the price change p:

$$q_S = -\zeta_S p + \kappa_S \delta d + f_S \ , \tag{4.20}$$

$$\Rightarrow$$

$$0 = -\zeta_S p + \kappa_S \delta d + f_S \ , \tag{4.21}$$

$$\Leftrightarrow$$

$$p = \frac{\kappa_S \delta}{\zeta_S} d + \frac{f_S}{\zeta_S} \ . \tag{4.22}$$

Gabaix and Koijen (2021) then further use a first-order Taylor approximation around f_S to simplify expression (4.22). Leading to:

$$p = \frac{f_S}{\zeta_S} \ . \tag{4.23}$$

Gabaix and Koijen (2021) note that the approximation is exact if all $\kappa_i = 0$ and furthermore, that if $d \neq 0$ in equation (4.22) there is an extra effect of a dividend change. Noting that $\frac{\kappa_S \delta}{\zeta_S} < 1$[11] Gabaix and Koijen (2021) argue that without flows, prices underreact to the changes in fundamentals in inelastic markets.

Gabaix and Koijen (2021) explain further that, share repurchases and issuances are a type of flow. They propose the notation:

$$f_C = \frac{\text{Net repurchases (in value)}}{\text{Total equity value}} = -\frac{\text{Net issuances (in value)}}{\text{Total equity value}} \ . \tag{4.24}$$

With that f can be decomposed in the following way:

$$f = f_S + f_C \ . \tag{4.25}$$

This discussion opens the scope for supply elasticity of firms (ζ_C). With ζ_C the equilibrium changes

[11] Indeed: $\frac{\kappa_S \delta}{\zeta_S} = \frac{\kappa_S \delta}{1-\theta_S+\kappa_S \delta} \leq 1$ as $\theta_S \in [0,1]$. Arguably, $\theta_S \in (0,1)$, thought theoretically possible a market with either only 'pure bond institutions' or 'pure equity institutions' is unlikely at best.

to:

$$f_S - \zeta_S p = -f_C + \zeta_C p \,, \tag{4.26}$$

$$\Leftrightarrow$$

$$p = \frac{f_s + f_C}{\zeta_S + \zeta_C} \,. \tag{4.27}$$

Yet, Gabaix and Koijen (2021) argue that the supply of shares is inelastic ($\zeta_C = 0$).

4.2 Infinite-Horizon Model

The main difference between the two-period model and the infinite horizon model is that the latter is dynamic, as emphasized by Gabaix and Koijen (2021). Gabaix and Koijen consider the case where there is a representative pure bond institution and a mixed institution in their main text. They leave a model with different funds in their appendix G.7.

In the infinite horizon model the mandate of the mixed institution is the following way:

$$\frac{P_t Q_t}{W_t} = \theta e^{\kappa \hat{\pi}_t + \nu_t} \,. \tag{4.28}$$

where ν_t denotes additional demand shocks and t is the time index.

Gabaix and Koijen (2021) linearize the model economy around baseline values with a balanced growth path with constant equity premium $\bar{\pi}$: $\bar{P}_t$, $\bar{D}_t$, $\bar{W}_t$ and $\bar{Q}_t$. Assuming that the baseline values grow with a common cumulative growth factor $\mathcal{G}_t$.

$\frac{\mathcal{G}_{t+1}}{\mathcal{G}_t}$ follows an i.i.d. growth process with mean g, i.e. $(\bar{P}_t,\ \bar{D}_t,\ \bar{W}_t) = \mathcal{G}_t(\bar{P}_0,\ \bar{D}_0,\ \bar{W}_0)$. The constant equity premium $\bar{\pi}$ follows $r_f + \bar{\pi} - g = (1+g)\delta$ with $\frac{\bar{P}_t \bar{Q}_t}{\bar{W}_t} = \theta$ and $\frac{\bar{D}_t}{\bar{P}_t} = \delta$.

Bond holdings of the mixed institution are given by the sum: $\bar{B}_0 + \bar{F}_t$, with B_0 the initial quantity of bonds held and F_t the cumulative dollar flow since $t = 0$. I.e. new bonds acquired by the mixed institution originate from flows. Gabaix and Koijen (2021) note that, the bond holding of the mixed institution should represent the fraction $1 - \theta e^{\kappa \hat{\pi}_t + \nu_t}$[12] of the institution's wealth, i.e. is

[12] $e^{\kappa \hat{\pi}_t + \nu_t}$ added for consistency reasons, given equation (4.28). The original article does not have the expression $e^{\kappa \hat{\pi}_t + \nu_t}$. The following derivations include the expression here, whereas in the original paper they are not included.

influenced by the mandate. Hence, $\bar{B}_0 + \bar{F}_t = \frac{1-\theta e^{\kappa\hat{\pi}_t+\nu_t}}{\theta e^{\kappa\hat{\pi}_t+\nu_t}}\bar{P}_t\bar{Q}$. This expression can be reformulated to: $\bar{F}_t = \frac{1-\theta e^{\kappa\hat{\pi}_t+\nu_t}}{\theta e^{\kappa\hat{\pi}_t+\nu_t}}(\bar{P}_t - \bar{P}_0)\bar{Q}$.[13]

The deviations from the baseline are denoted by $p_t = \frac{P_t}{\bar{P}_t} - 1$, $w_t = \frac{W_t}{\bar{W}_t} - 1$, $d_t = \frac{D_t}{\bar{D}_t} - 1$ and $q_t = \frac{Q_t}{\bar{Q}_t} - 1$. The flow f_t is defined by Gabaix and Koijen (2021) as scaled cumulative inflow in excess of the baseline:

$$f_t = \frac{F_t - \bar{F}_t}{\bar{W}_t} \,. \tag{4.29}$$

With $d_t^e = \mathbb{E}[d_{t+1}]$ Gabaix and Koijen denote the expected dividend deviation and with $\pi_t = \frac{\mathbb{E}[\Delta P_{t+1}+D_{t+1}]}{P_t} - r_f$ the expected excess return. Gabaix and Koijen (2021) use taylor expansion to derive an expression for $\hat{\pi}_t$:

$$\hat{\pi}_t = \delta(d_t^e - p_t) + \mathbb{E}[\Delta p_{t+1}] \,. \tag{4.30}$$

The derivation of this expression is repeated in appendix B.3.

Proposition 4 (Gabaix and Koijen, 2021): Demand for aggregate equities in the infinite-horizon model. The demand change for equities is given by:

$$q_t = -\zeta p_t + f_t + \nu_t + \kappa\delta d_t^e + \kappa\mathbb{E}[\Delta p_{t+1}] \,. \tag{4.31}$$

with $\zeta = 1 - \theta + \kappa\delta$ the aggregate elasticity of the demand for equities as in equation (4.16). The proof is repeated in appendix B.4

Gabaix and Koijen (2021) assume that the amount of equities is constant and hence set $q_t = 0$ in equilibrium. From those assumptions, they derive the equilibrium price of equities as:

Proposition 5 (Gabaix and Koijen, 2021): Equilibrium price in the infinite horizon model.

$$p_t = \mathbb{E}_t\left[\sum_{\tau=t}^{\infty} \frac{1}{(1+\rho)^{\tau-t+1}}\left(\rho\frac{f_\tau + \nu_\tau}{\zeta} + \delta d_\tau^e\right)\right] . \tag{4.32}$$

With:

$$\rho = \frac{\zeta}{\kappa} = \delta + \frac{1-\theta}{\kappa} \,. \tag{4.33}$$

[13] This expression follows from the identity: $B_0 = \frac{1-\theta e^{\kappa\hat{\pi}_t+\nu_t}}{\theta e^{\kappa\hat{\pi}_t+\nu_t}}\bar{P}_0\bar{Q}$.

denoting the 'macro market effective discount rate' and

$$\hat{\pi} = \frac{(1-\theta)p_t - f_t + \nu_t}{\kappa} \,. \tag{4.34}$$

the deviation of the equity premium from the average. The proof is repeated in appendix B.5.

Gabaix and Koijen (2021) make interesting observations from the results above: First, they note that the discount factor ρ is larger than the price-earnings ratio δ.[14] Second, the discount rate is affected by κ and θ i.e., by the aggregate mandate. Gabaix and Koijen (2021) emphasize: '*[...] the market is more myopic (higher ρ) when it is less sensitive to the equity premium (lower κ) and when the mixed fund has a lower equity share (lower θ)*' (p. 18).

Gabaix and Koijen (2021) explain the intuition of the effects of the two variables as a balance between the weight for the fixed mandate θ and the weight κ for the expectation term $\hat{\pi}$. Third, Gabaix and Koijen (2021) highlight that this myopia creates momentum, as fundamental news (modeled by dividends) are not directly incorporated into the price.

Comment: Because of the linearization used to derive equation 4.31 κ enters not as an exponent but as a linear term. This leads to the possibility of a price explosion if the representative fund is anti-cyclical (negative κ). Due to a discount factor ρ smaller than one, if $\kappa < 0$ and $\zeta > 0$. Note that $\zeta > 0$ in the notation used here means that the good is a 'normal' good i.e., falling demand given rising prices. If further scenarios are taken into account a price explosion can occur whenever: $\kappa > 0$ and $\zeta < 0$ i.e., the good in question has Giffen good properties, and the funds are risk-seeking.

4.2.1 The Impact of Flows

In what follows the effects of different types of flows identified by Gabaix and Koijen (2021) are outlined. They differentiate between permanent and mean reverting flows.

[14] Note the two possible definitions used, one with expectations and the other from the baseline. See appendix B.3.

Permanent Flow

In the 'infinite horizon' model of Gabaix and Koijen (2021), permanent flows into or out of equities have permanent price impacts. This results directly from equation(4.32) setting $\mathbb{E}_0[f_\tau] = f_0$:

$$\mathbb{E}_0[p_t] = \frac{1}{\zeta} f_0 \, . \tag{4.35}$$

For a derivation see appendix B.6. A permanent flow is accompanied by a decrease in the premium:

$$\mathbb{E}_0[\hat{\pi}_t] = -\delta \frac{f_0}{\zeta} \, . \tag{4.36}$$

Mean Reverting Flow

Gabaix and Koijen (2021) define a mean-reverting flow in such a way that the expected cumulative flow is given by: $\mathbb{E}_0[f_\tau] = (1-\phi_f)^\tau f_t$. From 4.32 we get $p_t = \frac{f_t}{\zeta+\kappa\phi_f}$ and thus:

$$\mathbb{E}_0[p_t] = \frac{(1-\phi_f)^t}{\zeta+\kappa\phi_f} f_0 \, . \tag{4.37}$$

The derivation can be found in the appendix B.7. Gabaix and Koijen (2021) note that the size of the price change is inversely related to the speed of mean-reversion and positively related to the change in equity premium. The equity premium for mean-reverting flows is given by:

$$\mathbb{E}_0[\hat{\pi}_t] = -\frac{\delta+\phi_f}{\zeta+\kappa\phi_f} (1-\phi_f)^t f_0 \, . \tag{4.38}$$

Chapter 5

Data

In Summary: This section describes data stored on the blockchain and the data used for the thesis. Because the data has to be transformed to estimate the parameters of the model of Gabaix and Koijen (2021) statistics of the data are presented in chapter 6. The two datasets are presented. The first, called 'block-level dataset', downloaded from the *GraphSense* python API (Haslhofer et al., 2021) and the second, referred to as 'daily dataset' provided by Stütz et al..

Main Points:

- Data on the blockchain is stored in so-called blocks.
- Blocks include transaction data between pseudonyms.
- Two data sets are used in the thesis:
  - Daily data: block-level data aggregated by day and by entity.
    - Transactions are aggregated on a daily and entity basis.
  - block-level data: The whole blockchain data.
    - Transactions are aggregated on a block basis.

The data is provided by *GraphSense* and accessed through their python API[15] (Haslhofer et al., 2021). The API provides a large set of different access points. Most important for the purposes in this thesis is block-level information. Besides block-level, the API allows for address-level and so-called entity-level data access. Entities are collections of addresses likely to be controlled by the same actor in the bitcoin network, which are identified using the methodology from Meiklejohn et al. (2013).

The publicly available bitcoin data consist of transactions stored on a public ledger. Another feature of the data stored on the blockchain is that because the available space for storage for transactions is limited, agents compete for the inclusion of their transactions into the public ledger and thus public validation via fees added to the transactions. The size of the fees can give a natural measure of congestion in the bitcoin network.

Those facts allow the test of several economic theories on transactions and their impact on economic variables.

In the following sections, the data structure of the blockchain is described in general and afterward follows the block-level data used for the main estimations. In a later section, the data provided by Stütz et al. is described.

5.1 Data Structure of the Blockchain

The starting point builds an outline of the data stored on the blockchain and thereafter the structure of the block-level data accessed is described.

5.1.1 General

The seminal white paper Nakamoto (2008) describes the mechanism of how a fully decentralized medium of exchange can prevent double spending of the assets traded. The mechanism is called proof-of-work and consists of the storage of transactions, which is shared between the participants in the network and communally enlarged and maintained. This storage, the blockchain, is designed similarly to a balance sheet or ledger. Hence, the name 'Distributed Ledger' for this technology.

15 The access to the API was provided by the Institute of Informatics at the University of Zürich

As delineated in Antonopoulos (2017), the transaction data itself follows an architecture similar to a balance sheet. Where the inputs form the asset side, and the outputs build the liability side. Each transaction sends at the same time the value to be transferred to the counterparty and the change sent back to the initializing party. Participants in a transaction are identified by an address.

An address is a between 26- and 35-character long identifier, generated by a bitcoin wallet using the public identifier or public key. The addresses are stored on the ledger of the blockchain and can be seen by the public, the address is known to the receiver in the respective transaction, such that he can send bitcoin to the address. To access the bitcoin sent to an address the private key needs to be known. The private key is generated simultaneously with the public key when a bitcoin wallet is created. There are three types of addresses and several methods to generate these. No further detail on the different addresses and their differences is provided here but note that a multitude of addresses can be controlled by one actor in the network. The interested reader is referred to Antonopoulos (2017) for further information on addresses, their generation, security, and their anonymity.

A block consists of at least one transaction (Nakamoto, 2008). The first transaction recorded on the block is also known as the coinbase transaction. This transaction distributes newly generated bitcoins (Antonopoulos, 2017). A block is generated by a so-called miner, identified by an address, which solved the computational problem[16] the first in the network.

Antonopoulos (2017) further notes that, the coinbase transaction generates new bitcoins. During the propagation of the information stored on the block through the network other nodes control whether the transaction fulfills the requirements given by the consensus rules of the network. A block accepted by all participants is seen as valid. Additionally, the miner includes other transactions in the block and by doing so the transactions included are validated.

Each valid block is then added to the chain of valid blocks. The link between the blocks is warranted by including hashes of the previous blocks into the hash of the newly generated blocks which forms part of the problem to be solved (Nakamoto, 2008). By including the hashes of previous blocks, the problem of the current block and with it the solution is made dependent on the history of preceding blocks. This mechanism leads to the property of near immutability of blocks below the

[16] The problem which is to be solved, is to create a 'hash' below a numeric threshold. For further information see Antonopoulos (2017)

new ones, as changing a block requires altering all the previous blocks accordingly. The produced chain of blocks is what gives blockchain its name.

5.1.2 Block-Level Data

The structure of the data stored on the blockchain is subdivided into blocks. Each block stores the transactions which occurred during the new block was mined (roughly 10 minutes) and which have been included by the miner. Included transactions in accepted blocks are validated through proof-of-work (Nakamoto, 2008).

For every transaction, there are inputs and outputs. Inputs are the bitcoin address or addresses of the sending entity and the number of bitcoins. Outputs are the receiving addresses and the number of bitcoins. Total input and total output do not sum up in general. The difference is called a fee and is added to the reward of the miner of the block. (Antonopoulos, 2017). Higher fees incentivize miners to include the transaction in the current block, speeding up transaction validation for the sender of bitcoin (Nakamoto, 2008).

Important to mention here is that the transaction inputs cannot be subdivided as Antonopoulos (2017) notes. Hence, the output mostly includes an address of the sender of the bitcoins. For the same reasons, transactions can include different sub-transactions performed from the same or different addresses. The addresses involved in the provision of inputs can be used to assess which addresses are likely controlled by the same entity but without certainty. There are caveats to this procedure Antonopoulos (2017) cites several exceptions: Multiple entities can collaborate to form one transaction and there are also addresses that can be controlled by more than one party. Finally, one entity can potentially be in control of an infimum of addresses.

Through the *GraphSense* (Haslhofer et al., 2021) API the entries of each block can be accessed. The appendix A.1 contains a detailed description of a sample API output.

5.1.3 Special Cases

Besides the above-described general case, there are other special entries in the ledger of the bitcoin network, which are important to mention. There exists the possibility to include short texts in the hashes. Such a text inclusion appears as a transaction without an output.

Another important special case is the possibility of transactions not directly stored on the blockchain. Such transactions include complicated contract architectures and can be performed with the security of no double spending as on-chain transactions. A famous example of such transactions is the lightning network (Poon and Dryja (2016) and Antonopoulos (2017)).

In summary, the lightning network functioning is like the central bank deposits for transactions of financial market participants, where transactions in a currency are equivalent to movements of value between the central bank deposit accounts of the financial market participants. In this comparison, the blockchain plays the role of the central bank and the retail banks are the entities operating on the blockchain, whereas the customers of retail banks operate on the lightning network. The main benefit of this arrangement is that the parties can economize on the fees, which would be necessary with on-chain transactions, and on transaction speed (Poon and Dryja, 2016).

From an economic perspective seeing the lightning network as the 'retail' sector of the financial network naturally leads to the question of how price changes affect the workings of the lightning network. This might be a promising path for future research. It has been shown that tightening effects in the interbank markets spill over to the wider financial markets (Nyborg and Östberg, 2014) and thus could be expected to do also in the bitcoin second layer markets. Especially, given the tendency of centralization found in the lightning network (Lin et al., 2020).

To conclude this section, it is noted that the blockchain consists of stored transactions. These transactions are connected by the computational problem to be solved by miners and hence lower blocks are made close to immutable. Because inclusion in the blockchain is costly and slow there exist alternatives, which leverage the benefits of the blockchain to off-chain transactions. A widely known example of this is the lightning network.

5.2 Daily Data

The daily transaction data is provided by Stütz et al..[17] They used this data for the final stake shift computations in Stütz et al. (2020).

The data contains daily aggregated transactions of bitcoin entities i.e., combined addresses expected to be controlled by the same agent. The data covers the period from January 03, 2009, until March 15, 2022, or from block 0 up to and including block 727370. Entities are defined as addresses identified to have more than one bitcoin address by the algorithm *GraphSense* employs.

The dataset contains information on the entity and the number of bitcoins transferred. It represents therefore a subsample of the full block-level data.

The price data used with the daily data was downloaded from *investing.com*, which provides daily price information in a close-open-high-low format and additionally the volume traded. For the estimation outlined in 6, the daily closing prices were used.

The data on the difficulty was downloaded from *blockchain.com*. The difficulty data is not in daily frequency but as roughly one observation every third day. To transform the data into a daily format, it is interpolated using cubic splines.

To compute the difficulty per bitcoin, the difficulty series is divided by the number of bitcoins mined during the period. The data on the mined bitcoins is provided by the Institute of Informatics at the University of Zürich. The data contains the block's timestamp and the number of coins mined at the respective block. The timestamp can be matched with the timestamps of the transaction data. To compute the created coins per day, the daily data is joined with the transaction data. This leaves the dates present in the transaction data matched to the coin supply data. Then, the blocks with no date are assigned to dates by imputing the last date matched up to the next block where the date could be assigned with the previously matched date. By summing over the blocks with the same date, the daily coins created are aggregated.

For this thesis, the data is transformed as outlined in the section 6.2.

[17] Special thanks to Rainer Stütz for recomputing the analysis done in their paper.

Chapter 6

Estimation

In Summary: This chapter describes the procedure for computing the estimations. In the first step, it is argued why on-chain data is used, besides the benefit of availability. Thereafter, the implementation is explained and justified. Then, the formal definitions of the transformations are laid out and finally, the results are displayed.

Main Points:

- On-chain data is used to perform the estimations.
- Rolling averages represent the baseline.
- Algorithmic supply allows for direct estimation of demand shocks.
- Both datasets contain large numbers of outliers.
- The coefficients suggest positive slopes of the price elasticity of demand.
- The results differ between the datasets.

In this chapter first, it is argued why on-chain data is a reasonable choice to perform the analyses. Second, the implementation of the model from Gabaix and Koijen (2021) is discussed. Following, the exact transformations performed on the data to estimate the parameters of the model are described. Finally, the results are presented for the daily data and the block-level data.

For the purpose of this thesis, on-chain data is used i.e., the data stored on the blockchain. Despite this data having drawbacks in terms of trading activity i.e., trading happens partially on exchanges without any connection to the blockchain, it is a reasonable choice. Since, bitcoin has no direct link to the USD, except for its production cost (Garcia et al., 2014), one could argue that using on-chain data only is equivalent to looking at chain activity and not on the impact of trading.

The choice of using on-chain transactions can be motivated by:

(i) The impact attractiveness and usability have on the bitcoin price, see section 3.1. Having many transactions on the blockchain increases the viability of the specific blockchain, in turn increasing expectations that it can be a long-lived store of value (Wheatley et al., 2019). Hence, on-chain activity is correlated with trading activity on exchanges (Ante, 2020).

(ii) The fact that transactions in bitcoin only 'truly' happen if they are done on-chain, this because after being verified on the ledger transactions become close to immutable, see 5.1.1 and Antonopoulos (2017).

(iii) Because of this immutability of on-chain transactions, transactions settled in bitcoin need to be done on-chain and therefore transactions between exchanges and other larger entities are made through the bitcoin network. Even lightning network payments will eventually materialize on-chain. This means, sooner or later every transaction will be recorded on the public ledger.

(iv) At least some of the manipulative trading happens off-chain (Gandal et al., 2018). The on-chain transactions are less volatile because they take longer to be settled than trading via an exchange, due to the 10-minute delay for validation. A longer settlement increases the volatility risk incurred during a pump-and-dump scheme. Therefore, on-chain transactions appear less attractive for speculative trading.

(v) Furthermore, on-chain transactions are costly to implement because of the fee on the one side and the additional setup of a wallet to interact with the network on the other side. This introduces additional costs for speculators who are in search of fast profits, increasing the reliability of on-chain data.

(vi) On-chain transactions are independent of intermediaries and the risk connected to using mediator services (Moore and Christin (2013) and Gandal et al. (2018)), making them more attractive for larger payments.

(vii) By looking at on-chain transactions only, there is no locality i.e., no overweighting of certain geographical regions. The existence of different exchanges with differing prices denominated in different currencies (Brandvold et al., 2015) might introduce bias to the estimation because some transactions might not be recorded. It makes therefore sense to circumvent the problem of selecting exchanges and inevitably omitting regions trades happen.

Employing on-chain transaction data also has its shortcomings. There are surely transactions done by agents which are never registered on-chain. Those transactions will be missed while looking at on-chain transactions only. Similarly, transactions done on the network might be different from those outside the network. I.e., less technically affine investors might only hold bitcoin in an account at an exchange and never perform on-chain transactions. It is indisputable that the price of bitcoin is formed on exchanges, as the blockchain per se does not have any link to the 'real' world. In an extreme scenario, where bitcoin is only used by a minority as a medium of exchange and by the majority only in accounts at exchanges, the on-chain transactions have little to no effect on the price of bitcoin in USD.

However, such a scenario is unlikely. Miners, at least, need to pay their electricity bills and merchants, accepting payments in bitcoin, will at some point need to pay their suppliers and other stakeholders. With the assumption that there is still some link to analog means of payments, at some point, on-chain transactions will need to translate into an exchange rate.

In summary, despite some detriments, using on-chain data is expected to give a realistic view of the price elasticity of demand of the bitcoin economy, as on-chain transactions are correlated to real-world transactions. It could, however, underestimate the true effects of transactions on prices. Because the correlation might be fogged by transactions made on exchanges only. Exchange-only transactions have an impact on bitcoin prices but do not manifest on-chain.

6.1 Implementation

This section reviews the notation and adaptations made for the implementation of the model of Gabaix and Koijen (2021) for bitcoin data.

As discussed in 4, the model of Gabaix and Koijen (2021) employs deviations from the in-equilibrium baseline. Bitcoin is still in its infancy and as a nascent technology, it has probably not reached an equilibrium state. To have a gauge for a probable baseline, here rolling averages are used. Rolling averages are chosen because of their simplicity and because they are model free. More involved methods, such as Kalman-filters or Loess have beside their complexity the drawback that they also imply a model as a prior.

Using rolling averages means that, the model estimated is close to what Campbell and Shiller (1988) estimated. They used a 30-year rolling average of real earnings in a data set ranging from 1891 until 1987 i.e., using roughly a third of the data to compute the mean. In recent times, some doubt has been put on the use of such ratios e.g., Campbell and Shiller (2001) and the references therein.

Gabaix and Koijen (2021) define the following variables: Q_i denoting the number of stocks an institution holds; P is the price of the commercial paper and W_i is the total wealth of the institution.

For this thesis, concerned with bitcoins, the number of bitcoins an entity holds is referred to by Q_i and the price of bitcoin by P.[18] A complication is that entities total wealth W_i is not observable on the blockchain. Therefore, the wealth W_i is approximated by what Gabaix and Koijen call the equity holdings of institution i: $W_i^{\mathcal{E}}$. $W_i^{\mathcal{E}}$ is represented naturally by the number of bitcoins held by entity i.

This approximations is feasible, as shown in equation (4.9) and following.

Relying on Garcia et al. (2014), the difficulty[19] of the verification mechanism is used as proxy for the dividend D. The difficulty is measured as an approximate number of hashes to be performed to validate the next block. As Garcia et al. (2014) note, the difficulty is closely related to the amount of energy needed to verify transactions on the blockchain. It is, therefore, related to a lower

[18] For simplicity, the time subscript is omitted. Hence, $P_t = P$ or $Q_{i,t} = Q_i$

[19] https://www.coinwarz.com/mining/bitcoin/difficulty-chart

bound under which bitcoins can only be produced at a loss. Because the difficulty is determined algorithmically bi-weekly, in the estimation the expectation is omitted. Implying the assumption that agents participating in bitcoin transactions or mining are aware of the difficulty and the expectations are fairly accurate. In this thesis, the D is computed as the number of approximated hashes per new bitcoin.

The deviations from the in-equilibrium baseline are defined in equation (4.2), where the in-equilibrium baseline is represented by the rolling averages of the quantities employed.

For the expectation of the mean price deviation difference $\mathbb{E}[\Delta p_{t+1}]$, several possible implementations are used. First, is linear extrapolation, here the expectation is approximated by linear regression of the last several days. Second, the technical trader expectation, which replaces the expectation by the difference of two rolling averages of different lengths, and finally, the martingale model, where the expectation is replaced by the deviation at the current time t.

These expectations are employed because it seems unreasonable that an agent knows the future price path exactly. For the sake of completeness, regressions using the one step ahead difference are also performed.

A special case is made for the flows f_s. The flows are directly computed via equation (4.19), where θ_i is set to one by assumption. The assumption is needed as the fraction of wealth invested in bitcoin θ_i is not observable in the data. Presumably, the value is quite low, however, setting it to one is the least influential assumption because any other assumption would influence the computation by reducing the sum and with it f_s. There are several ways to think of the size of θ_i in the model. One is that most investors venturing into the bitcoin economy hold a small fraction of their wealth in bitcoins i.e., θ_i close to zero. However, at least some of the agents holding bitcoin will have high fractions, probably close to total wealth invested in bitcoins e.g., large exchanges, young investors, or firm believers in the technology. As those entities are potentially also those interacting more on-chain, it can be argued that the assumption of $\theta_i = 1$ might not be far of. A clear drawback is that it might be the entities performing the largest transactions which hold the smallest amount of wealth in bitcoins. If this is the case, an overly inflated measure for f_i would result. Contrary, setting θ_i to a value close to zero might result in deflated estimates for f_i.

The definitions outlined above allow for the direct estimation of equation (4.31) repeated here:

$$q_t = -\zeta p_t + f_t + \nu_t + \kappa\delta d_t + \kappa\mathbb{E}[\Delta p_{t+1}] \quad \text{where} \quad \zeta = 1 - \theta + \kappa\delta \,. \tag{6.1}$$

The estimation of this equation allows for the identification of κ, δ, and θ. The identified θ is the aggregated θ and not the institution dependent θ_i, which remains unobservable in the data at hand.

κ can directly be read off the coefficient on the price change expectation. Having κ allows for the identification of δ by dividing the coefficient of the dividend proxy by κ and lastly, having both, κ and δ allows for the identification of θ through the equation: $\zeta = 1 - \theta + \kappa\delta$.

A clear benefit of bitcoin, as opposed to other commodities or cash, is that the supply shocks are negligible (Gronwald, 2019).

This section outlined the reasoning and the implementation of the model for bitcoin transaction data. It argues that rolling averages are a sensible choice for the baseline and the assumption of $\theta_i = 1$ is imperfect but the least influential. It is pointed out that due to the algorithmic supply, supply shocks are negligible.

6.2 Transformations

This section presents the formal computation of the variables used for the parameter estimations.

To compute the rolling averages the observations up to and excluding the present observation are used, to make sure that the information available at day t was available to all agents. This means, for a variable X and a timespan v the rolling average is computed as:

$$RA_{t-v,t}(X) = \frac{1}{v} \sum_{i=t-v-1}^{t-1} X_i \,. \tag{6.2}$$

Each deviation from the baseline for a variable X takes the form:

$$x_t = \frac{X_t}{RA_{t-v,t}(X)} - 1 \,. \tag{6.3}$$

Note, that the notation in Gabaix and Koijen (2021) the deviation from the baseline is denoted by lowercase letters. The same notation is used for the deviations from the rolling average in the model presented here.

The variables $q_{i,t}$, d_t and p_t follow the above pattern. For the time series of d_t, first, the difficulty is divided by the number of new bitcoins of that day and then the above transformations are applied.

f_t was treated specially, because of the complication of unobserved variables outlined in section 6.1 i.e., θ_i.

In the model presented here $f_{i,t}$ is computed according to:

$$f_{i,t} = \frac{F_{i,t} - \sum_{\tau - v - 1}^{t-1} F_{i,\tau}}{RA_{t-v,t}(W_i^{\mathcal{E}})} \, . \tag{6.4}$$

To arrive at the market aggregate q_t, the model follows closely Gabaix and Koijen (2021) and sums over the weighted entities within each period, given by equations (4.7) and (4.8). The weighting is given by:

$$S_i = \frac{RA_{t-v,t}(Q_i)}{\sum_{i \in I_t} RA_{t-v,t}(Q_i)} \, . \tag{6.5}$$

The expression in the divisor denotes the sum over all the institutions with bitcoins at the current point in time. With that weight, the aggregated q_t is computed as a weighted sum divided by the exponential of the logarithm of the growth rate of bitcoin generation (g_t^{BTC}) during period t:

$$q_t = \frac{\sum_{i \in I_t} S_i q_{i,t}}{\exp(g_t^{BTC})} \, . \tag{6.6}$$

Dividing through the growth rate accounts for large initial holdings, when bitcoin was not widely known, let alone used.

The procedure is similar for f_t. The difference is mainly that the $f_{i,t}$ constructed as described in equation (6.4) is already bitcoin weighted (equity weighted in Gabaix and Koijen (2021)). Hence, it is only needed to sum the within period flow deviation ($f_{i,t}$) up,

$$f_t = \sum_{i \in I_t} f_{i,t} \, . \tag{6.7}$$

This section presented the computations for the variables used in the estimation procedure in a formal way.

6.3 Estimation Results

In this section, the estimation results will be shown and outlined. First, the results from the smaller dataset i.e., the one from Stütz et al. are discussed, and thereafter the larger dataset i.e., the block-level data set.

For both datasets, the period starts in January 2012 because of the very noisy series encountered before this date.

6.3.1 Baseline Selection - Daily Data

The first task is the decision of a period length for the rolling mean. The question answered here is what constitutes a reasonable baseline.

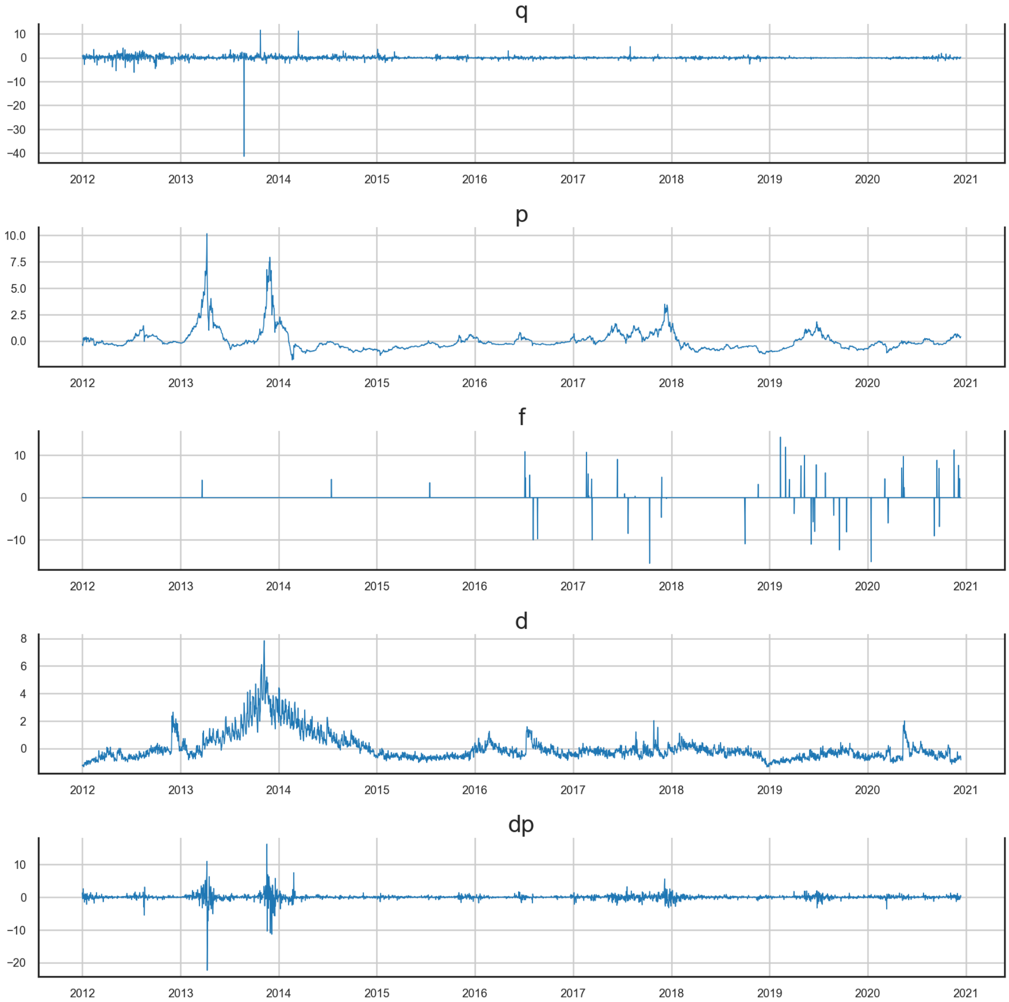
In this thesis, the baseline period is chosen such that the resulting series is arguably trend stationary and has no unit root. These conditions are necessary for a state in which disturbances let the model gravitate around an equilibrium state. They further result in more reliable estimates and are advantageous for the simulation, because the simulation will work around a steady state.

To examine which time series, fulfill the conditions the series are tested with the ADF-GLS test for unit root (Elliott et al., 1996) and the KPSS test of weak stationarity (Kwiatkowski et al., 1992), both tests are implemented routines in the *arch* library for python (Sheppard et al., 2022).

Because of the distortions introduced by the moving averages, the validity of the test should be taken with a grain of salt (Franses (1991) and Olekalns (1996)).

Before starting the tests, the possible sizes are restricted. The trade-off between having a long period over which the average is computed, and a shorter period is that the longer period takes up less noise but smooths over possibly informative variance. A shorter period takes up much more possibly informative variance but in doing so, it also takes up noise. It is argued in the scope of the thesis that, because bitcoin is very volatile very short periods i.e., weekly will take up too much

Figure 6.1 – Timeline of q, p, f, d and dp for the daily data set.



Notes: *All features are in percent deviations from their five-monthly rolling mean. All values have been scaled to unit variance and zero mean.*

noise, and very long periods i.e., several years, will smooth out too much information. The periods tested initially here are a month, half a year, and a year. From those results, it became apparent that the optimal lag length lies between a month and half a year. Hence, periods in between are tested in monthly brackets. Finally, five monthly rolling averages are taken as the baseline. The summary statistics for the KPSS and the ADF-GLS tests are shown in table 6.1 and in the appendix A.3. In the results, a pattern can be seen. Where for shorter periods for the averages, the variable q seems to have a unit root according to the KPSS test, in longer periods the null of trend stationarity cannot be rejected anymore. Similarly, for dp the ADF-GLS test cannot reject the null hypotheses of a unit root in short periods. In longer periods, however, the null is rejected in favor of trend stationarity. The same holds for the p series.

By eyeballing figure 6.1, it seems reasonable to assume that the series is stationary, yet highly persistent. An additional argument for stationarity is the construction of the series. By dividing through the rolling average, the series will, by construction, hover around zero.

Table 6.1 – Summary Statistics the ADF-GLS and the KPSS test.

	q	p	f	d	dp
KPSS	0.078	0.147	0.039	0.368	0.013
(p-value)	(0.285)	(0.052)	(0.739)	(0.000)	(0.996)
DFGLS	−5.583	−4.771	−11.371	−1.746	−3.355
(p-value)	(0.000)	(0.000)	(0.000)	(0.437)	(0.012)

Notes: *The statistic is presented with the p-value in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean before conducting the tests. The results have not been influenced by the scaling.*

The results of the ADF-GLS show that the null of weak stationarity is rejected at the 1% level for all time series except d and dp. It cannot be rejected at any sensible level for d and can be rejected at the 5% level for dp. The KPSS test does not reject the null of weak stationarity for all series at the 5% level, except the series d. Despite not being able to reject non-stationarity in the series d, the regression analyses are performed using the series d as is. The main reason is to keep interpretation close to the original model.

A further complication is posed by the fact that for f_t the aggregation is the sum over the inflows. Hence, a long period makes the values extremely large, some are in the order of 10^{15} and larger. This drawback could be due to the assumption that θ_i is equal to one, see 6.1. To omit numerical problems arising from an estimation combining such large values and small values, all the values are scaled to have unit variance and mean zero.

Summary statistics for the scaled five monthly data are shown in table 6.2. Summary statistics for the data sets with monthly, semi-annual, and annual periods can be found in the appendix A.2.

From the summary table, it becomes apparent that many of the values from the f series are

Table 6.2 – Summary Statistics for five monthly data.

	q	p	f	d	dp
count	3270	3270	3270	3270	3270
min	-42.459	-1.796	-15.516	-2.810	-22.316
25%	-0.199	-0.544	-0.008	-0.611	-0.160
50%	-0.038	-0.231	-0.008	-0.138	0.003
75%	0.173	0.245	-0.008	0.442	0.189
max	11.819	10.163	14.232	7.863	16.170

Notes: *All features are in percent deviations from their five monthly rolling mean. All values are scaled to unit variance and zero mean.*

scaled to the same value close to zero, leaving only some outliers. The problem is not alleviated by taking natural logarithms of the prices when computing the sum. Considering shorter periods could arguably change the magnitude of the f series. However, this would introduce more noise in the other observations and leave some series hardly stationary. Therefore, this problem has to be seen as an additional caveat to the data used.

Additionally, it can be inferred that the data is heavy-tailed. This could be a problem for OLS regression because OLS is sensitive to outliers. To have a robustness check for this issue, the regressions are repeated with quantile regressions around the median (Koenker and Bassett, 1978), referred to as median regressions in the following.

Furthermore, a regression using 'fenced' outliers is performed (Tukey, 1977). Fencing uses the interquartile range to determine the outliers and sets them equal to a maximal value, mostly the decision boundary of outlier v non-outlier. In the original description all values smaller than $Q_{25\%} - k(Q_{75\%} - Q_{25\%})$ are set to the value of the lower bound and all values larger than $Q_{75\%} + k(Q_{75\%} - Q_{25\%})$ are set to the value of the upper bound (Q_x denotes the x-quantile). k is a parameter recommended to be 1.5 or 3 for 'far off' values.

To be conservative, the value k is set to 5 and the quantiles used are the 20% and the 80% quantiles for the smaller and larger quantiles respectively in the fenced regressions. After the fencing, the dataset is scaled to unit variance and zero mean because of the wide range chosen between the upper and lower limit for the fencing values.

6.3.2 Regression Analysis - Daily Data

Both, OLS, and quantile regressions are conducted with the *statsmodels* library available for python (Seabold and Perktold, 2010). The OLS standard errors are autocorrelation and heteroskedasticity adjusted standard errors (Newey and West, 1987). The lag length for the standard errors has been chosen to be $0.75 \cdot N^{\frac{1}{3}}$ where $N = 3270$ is the number of observations rounded up to the next integer (Stock and Watson, 2014). This computation results in a lag length of 12 periods.

For the technical model, the periods for the rolling means are chosen to be 7 and 23 days. For the linear model, two weeks are selected to calculate the predictions i.e., the linear regression is fitted on the last 14 entries and then the prediction is calculated using the last available observation. 'Realized' denotes the regression with the shifted values for dp i.e., what an agent with perfect foresight would expect. Note that the 'realized' time series is one observation shorter than the others. Because the last observation cannot be foreseen, it is omitted. The results for the median regression and the half-yearly regression can be found in the appendix A.4.

Table 6.3 – OLS regression results.

	Linear	Technical	Martingale	Realised	Without
$Const.$	-0.0076	-0.0076	-0.0076	-0.0076	-0.0075
	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
p	0.0255	0.0245	0.0269	0.0220	0.0243
	(0.024)	(0.021)	(0.022)	(0.022)	(0.022)
d	-0.0041	0.0051	0.0043	0.0053	0.0045
	(0.049)	(0.048)	(0.048)	(0.048)	(0.048)
f	-0.0028	-0.0030	-0.0035	-0.0029	-0.0030
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
dp	-0.0144	-0.0709	-0.0296	-0.0236	–
	(0.054)	(0.035)**	(0.011)***	(0.014)*	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean. The asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.*

The regression results displayed in table A.9 show that the results for the elasticity are positive and stay roughly the same for the different models. The difference between the models is relatively small except for the coefficients of dp. From these results, the other parameters for the model can be calculated and are presented in table 6.4.

In comparison with results from the data using the semi-annual averages, the coefficients of the variables p and f are similar in size. The coefficients for d change the sign but stay insignificant. For dp the coefficients are similar, except for the linear model and the estimation without the expectation. The comparison between the models reveals that the estimation of the coefficients for the d variable is unstable.

Regarding the median regression, the coefficients are largely different. The sign on the coefficients for p and f do not change but they do for the other variables. The different sizes of the effects are a sign of the large influence of the outliers.

The fenced results are not fundamentally different from the baseline results. This could be due to the very conservative fences chosen or contrary to the assessments from the median regression, outliers are not so influential.

Table 6.4 – Parameters for the 5 monthly rolling-averages on the daily dataset.

	Linear	Technical	Martingale	Realised
$-\zeta$	0.0255	0.0245	0.0269	0.0220
θ	1.0214	1.0194	1.0312	1.0167
κ	−0.0144	−0.0709	−0.0296	−0.0236
δ	0.2847	−0.0719	−0.1453	−0.2246

Notes: *Parameters computed from the regression results of the five monthly dataset.*

The computed parameters describe the mandate of the funds and the elasticity of the market. For simplicity, the term 'fund' is replaced by 'agent' in the following, as it makes more sense to talk about the agents in the bitcoin economy than funds.

The elasticity parameter ζ implies a positive price elasticity of demand. Note the prefixed minus in front of the ζ due to the notation in Gabaix and Koijen (2021). A positive elasticity means that increasing price increases demand. A finding in line with the findings of Frazzini and Lamont (2008) and Ben-David et al. (2021b), who note that investors are return chasing.

A θ bigger than one implies that the agents are leveraged i.e., they invest more than their total wealth in bitcoin. In the table above, taking the linear model as an example the agents are leveraged by 2.14%. Whether this finding is influenced by the assumption made for the computation of f_i has to be seen. There the θ_i was set to one, but the link between the assumption and the indirect computation leading to the estimate for θ here is not straightforward and thus is left for future work.

κ smaller than zero indicates that agents are investing according to a contrarian strategy i.e., the agent invests more in bitcoin when it has a negative expected return.

The baseline dividend-price ratio δ is negative in some models. As the price is never negative, this would imply negative dividend flows from bitcoin.

6.3.3 Regression Analysis - block-level Data

The block-level data is constructed in the same way as the daily data is. The rolling mean is computed over 144 blocks. 144 blocks correspond to roughly one day, as the goal of block creation in the bitcoin blockchain is a new block every 10 minutes (Antonopoulos, 2017).

There are limitations to how many blocks can be included in the computation for the variables. The two main dimensions of the constraints are time and memory. The longer the period to compute the rolling averages the longer the computation takes, and the more memory will be used. Hence, the decision to use 144 blocks. The large number of observations did not allow for an in-depth investigation of the best possible period of the rolling mean for the baseline, as it was done for the daily dataset.

For the handling of the data *pyspark* is used. *Pyspark* allows for modifications on larger than memory datasets. The full size of the blockchain data in CSV format is 471.3 GB.

Like in the section 6.3.2 the dataset is scaled for the estimation. The regressions are done on a fenced and scaled dataset and on one which is only scaled. The standard errors used for the significances are heteroskedasticity and autocorrelation robust standard errors. The lag length is computed in the same way done for the daily data, which led to a lag length of 62 periods.

The dataset is as before truncated at the beginning. The starting block is block nr. 160029. The block with the number 160030 was minted on the first of January 2012 at 00:00, according to *blockchain.com.* [20]

Table A.4 in the appendix A.2 shows summary statistics for the scaled block-level dataset. The same problems entail the block-level dataset as are present in the summary statistics for the daily dataset. Many to most of the values are scaled to the same or close to the same values. This poses a numerical problem for the regression because values are close to identical to each other which in reality are not.

The summary statistics for the fenced dataset, presented in table 6.5, look more appropriate. Since a large value for k is chosen in the fencing, the values still encompass a wide range of values. Yet, the range is far smaller than for the non-fenced dataset. This highlight one big caveat of the data. Large outliers are frequent. This fact weakens the validity of the regression estimates. The regression results for the scaled block-level dataset can be found in the appendix A.4 in table A.10. The resulting coefficients for the scaled dataset are nearly all very close to zero. The same holds for the median regression displayed in appendix A.4 in table A.11. Both methods, OLS, and the more robust median regression led to values close to zero indicating a severe influence of the outliers in the dataset.

A caveat of the fenced data is that, despite taking a conservative range, the impact of the fencing is large. The effect of the fencing can be deduced from the summary statistics table A.4 and 6.5. The maxima and minima differ by up to a factor of 400. This seems in part to be a cause of one very large outlier present in the data. Figure 6.2 shows a comparison between the variable p in the scaled and fenced datasets where the large outlier is visible. The effect of scaling is however very extreme in other time series. The effect can be seen by comparing plots of the fenced variables with the scaled ones, e.g. variable q depicted in appendix A.5, figure A.1.

The regression results for the fenced dataset are displayed in table 6.6. The results are stable over the different models. Except for the coefficient on dp. This difference is rather unsurprising because the dp series is the one changed in the different models. Interestingly also with the block-level dataset, the coefficients on the price are all positive, as was the case for the results with the daily dataset. Further comparison with the results from the daily dataset reveals other differences. First, smaller coefficients in the results from the block-level data for the elasticity estimates. Second,

[20] `https://www.blockchain.com/btc/block/160030`

Table 6.5 – Summary Statistics for the fenced block-level data set.

	q	p	f	d	dp
count	559'353	559'353	559'353	559'353	559'353
mean	0.000	0.000	0.000	0.000	0.000
std	1.000	1.000	1.000	1.000	1.000
min	-3.860	-4.253	-3.354	-42.415	-4.953
25%	-0.214	-0.261	-0.459	-0.134	-0.277
50%	0.133	0.057	-0.422	-0.109	-0.023
75%	0.278	0.249	-0.122	-0.038	0.353
max	3.830	4.208	2.968	51.657	5.044

Notes: *All features are in percent deviations from the rolling mean using 144 blocks. All values are scaled to unit variance and zero mean. The values have been fenced before the scaling. I.e., the values have been truncated, where they exceed the 80% quantile by more than five times the distance between the 80% and the 20% quantile and where the values are less than the 20% quantile minus five times the distance between the 80% and 20% quantiles.*

larger coefficients on the variable d in absolute terms from the block-level data estimations. Third, smaller coefficients in absolute terms for the f variable, and finally smaller effects for the variable dp in the block-level dataset.

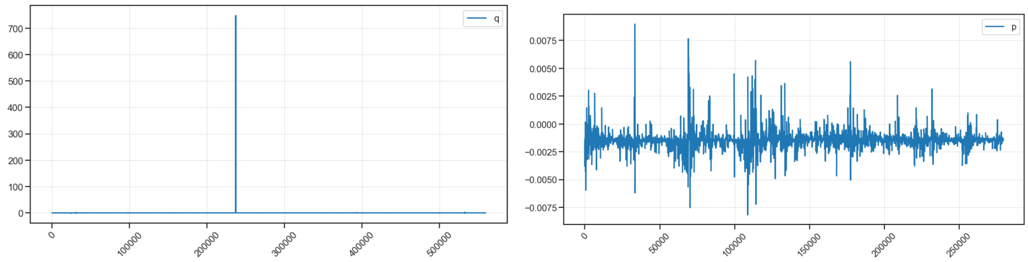
The signs are similar. They are the same for all except d which on the block-level data is negative for all models on the block-level dataset and positive for all but the linear model on the daily dataset.

Appendix A.4 contains in table A.12 the results from the median regression on the fenced dataset. A comparison of the results of the two different regression methods shows the same signs of the coefficients from variables p, d, and dp. Interestingly, the coefficients for the price are roughly half the size in the median regression and the coefficient for d are roughly double the size in the median regression. The effects estimated from dp decrease in size going from the linear model to the realized model (from left to right in table 6.6) in the OLS regressions. The effects decrease going through the same sequence of comparison in the median results.

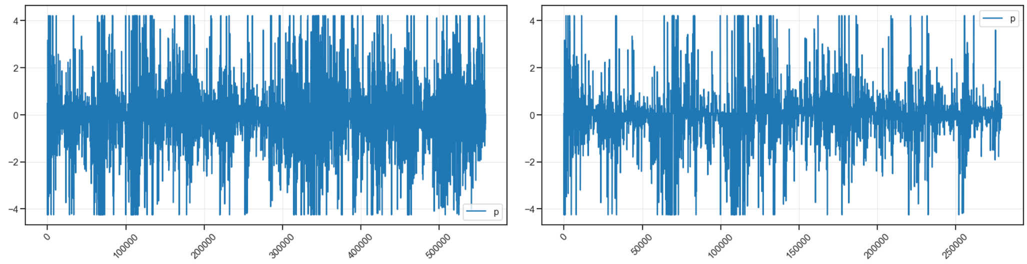
The results from the series f differ the most. This can be attributed to the fact that this series is the one most prone to outliers. Hence, the less robust method, OLS, will be more influenced by the outliers and thus the differing coefficients.

Figure 6.2 – Timeline of p for the scaled and the fenced block-level dataset.

(a) Timeline of p from the scaled block-level dataset.



(b) Timeline of p from the fenced block-level dataset.



Notes: *The figures above (a) show the scaled variable p from the block-level dataset. For the whole dataset on the left and up to block 1'894'092 on the right. The figures below (b) show the fenced variable p from the block-level dataset. For the whole dataset on the left and up to block 279'676 on the right. All values have been scaled to unit variance and zero mean.*

Overall, the similarities between the coefficients of the median and the OLS regressions are a promising sign for the validity of the estimates.

With the results shown in table 6.6, the model parameters are computed in the same way as was done for the daily dataset. Table 6.7 shows the results.

The parameters from the block-level dataset differ from the ones computed from the estimations on the daily dataset. First, the values for δ are far larger than the same values from the block-level dataset. The values found for θ are all smaller than one and are similar to the original value of 0.875. The values for κ and ζ are far smaller, in absolute terms than the ones from the daily dataset.

Similarities are primarily to be found in the signs of the values for the price elasticity of demand (positive) and the kappa values (negative).

Two interesting facets of the parameters from the block-level data are that the values for θ are smaller than one and that the values for δ are huge in comparison to the other values. Values smaller

Table 6.6 – Fenced OLS regression results.

	Linear	Technical	Martingale	Realised	Without
Constant	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p	0.0084	0.0084	0.0087	0.0090	0.0096
	(0.004)*	(0.005)*	(0.005)*	(0.005)**	(0.005)**
d	−0.1514	−0.1520	−0.1502	−0.1495	−0.1486
	(0.237)	(0.236)	(0.237)	(0.237)	(0.237)
f	−0.0003	−0.0002	−0.0003	−0.0003	−0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
dp	−0.0042	−0.0131	−0.0013	−0.0008	–
	(0.003)	(0.003)	(0.005)	(0.005)	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their rolling mean using 144 blocks. All values have been scaled to unit variance and zero mean. The values have been truncated, where they exceed the 80% quantile by more than five times the distance between the 80% and the 20% quantile and where the values are less than the 20% quantile minus five times the distance between the 80% and 20% quantiles. The asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.*

Table 6.7 – Parameters for the fenced block-level dataset.

	Linear	Technical	Martingale	Realised
$-\zeta$	0.0084	0.0084	0.0087	0.0090
θ	0.8570	0.8564	0.8567	0.8595
κ	−0.0042	−0.0131	−0.0013	−0.0008
δ	36.0476	11.6031	115.5385	186.8750

Notes: *Parameters computed from the regression results of the fenced block-level dataset. Due to a division through zero, the value for d in the martingale model cannot be determined within the precision used here.*

than one for θ indicate that the agents do not leverage their bitcoin investments. The opposite was the case for the daily dataset.

The extremely large values for δ, which denotes the average dividend-price ratio could indicate that the return of bitcoin entails more than the simple price return. What the cause could be for the large implied baseline dividend-price ratio will need further investigation.

To sum up the results, it can be said that they differ greatly between the two datasets. This observation comes unsurprisingly given the different ways the datasets are constructed. Within the datasets, the results for the daily data does not differ that much between the fenced and the scaled dataset. The median regressions, however, differ to a greater extent. Indicating the large influence outliers have on the estimations.

For the block-level dataset, the coefficients from the regressions on the fenced data seem promising. The results from the scaled block-level dataset are disappointing. With all coefficients extremely close to zero, they put doubt on the usefulness of the model as it is constructed and estimated in this thesis. Comparing both regressions to their median regression counterpart, it seems that outliers are roughly in line with the relations found in the rest of the data, indicated by the similarities of the signs.

In both datasets the coefficients for the price elasticity of demand are positive. This is true for all estimated regressions except for the regressions performed on the scaled block-level dataset, where the coefficients are so close to zero, that they fall below the precision reported herein. The results of positive price elasticity of demand pair well with the findings of Frazzini and Lamont (2008) and Ben-David et al. (2021b). They report that investors are return chasing. For bitcoin, this means that inflows beget inflows. Further underlining the findings of Hamrick et al. (2018), that bitcoin and other cryptocurrencies are prone to pump and dump schemes. I.e., increasing prices are creating more demand for bitcoin.

According to the model of Gabaix and Koijen (2021), it seems likely that the typical investor in bitcoin invest with a contrarian strategy and that bitcoin investors predominantly found in the daily dataset are slightly leveraged, whereas bitcoin investors dominating the block-level dataset seem to have only a fraction of their savings in bitcoin. However, the results for the fraction invested are to be doubted.

Chapter 7

Simulation

In Summary: The simulations have been performed with the model of Gabaix and Koijen (2021). First, the simulations using the original model are shown. Thereafter, the estimated parameters from chapter 6 are used for the simulations. At first with the results from the daily dataset and later with the results from the block-level data.

Main Points:

- The simulations overestimate the observed moments for the bitcoin prices.
- Block-level simulations seem to be closer to the observed moments.
- Two simulations imply a negative bitcoin premium.

7.1 Gabaix and Koijen (2021) Simulation

This section presents an overview of the model proposed by Gabaix and Koijen (2021) in the main part of their paper. This section follows closely the implementation in Gabaix and Koijen (2021) and a later step uses the estimated parameters from section 6.3 to investigate what the model predicts for the bitcoin market. The moments resulting from the simulations are then compared to the realized moments from the bitcoin market.

The model in Gabaix and Koijen (2021) is stated as endowment economy. The endowment follows a log-normal growth rate, which is split into a log-normally growing dividend stream and a residual. The investment universe consists of two funds. One is a pure bond fund, investing only in bonds, and the other is a mixed fund, which is invested in bonds and stocks according to a mandate.

Importantly, the agent in the model is not fully rational. A fully rational agent would not adhere to the imposed mandate but would see through the mandates and invest as there would be no mandates and just bonds and stocks to hold.

To omit the fully rational behavior the investor is split between a consumption-choosing rational part and an equity-choosing irrational part. The equity-choosing part is influenced by an exogenous factor denoted by b_t in Gabaix and Koijen (2021). This factor influences the flows of the equity-choosing part, additionally to narrow framing (Barberis et al., 2006). Thus, influencing prices non-rationally. b_t is modeled as AR(1) process. Gabaix and Koijen stress that this assumption is a simplification and the model could be calibrated with more involved behavioral assumptions for the flows.

Gabaix and Koijen solve their model analytically and calibrate it to annualized parameters of the US market. The parameters have been estimated by Gabaix and Koijen with the GIV estimator (Gabaix and Koijen, 2020). They note that the peculiarities of the model are mainly the inelasticity of the market, that flows influence prices, and with the prices the risks.

For the repetition of the simulation with the estimated parameters from bitcoin, the same US variables are used for simplicity, and only the estimated variables as presented in tables 6.4, and 6.7 are changed.

7.1.1 Replication of the Calibration (Gabaix and Koijen (2021))

This section follows closely the steps described in Gabaix and Koijen (2021) for the calibration. The inputs used are displayed in table 7.1.

Table 7.1 – Input parameters for calibration of the Simulation in Gabiax and Koijen (2021).

γ	g	σ_y	r_f	σ_D	σ_f	ϕ_b	ζ^M	κ	θ
2.000	0.020	0.008	0.010	0.050	0.028	0.040	0.200	1.000	0.875

Notes: *The parameters used as inputs for the calibration described in Gabaix and Koijen (2021) p. 109-111*

From the input parameters the expected price dividend ratio and the variance of the price dividend ratio can be directly computed and result in:

$$\text{Expected price-dividend ratio: } 33.1330$$
$$\text{Variance of the expected price-dividend ratio: } 0.2500\,.$$

The other parameters are calculated as described in Gabaix and Koijen (2021). The moments of interest are simulated with $1'000$ repetitions. The simulation results are given by:

$$\text{Mean equity premium: } 0.0438$$
$$\text{Standard deviation of excess stock returns: } 0.1419$$
$$\text{Mean price-dividend ratio: } 32.5914$$
$$\text{Standard deviation log. price dividend ratio: } 0.4501\,.$$

A constant risk-free rate of 1% is assumed throughout the simulations. The correlation between flow shocks and dividend shocks is assumed to be zero. The model is simulated with twelve months over 72 years i.e., a time increment of $\frac{1}{12}$.

7.1.2 Simulation with Bitcoin Parameters

For the simulation using the bitcoin parameters, the parameters γ, g, σ_y, σ_D, r_f, σ_f and ϕ_b are unchanged. Hence, the assumptions for risk-aversion, endowment growth, endowment volatility, dividend volatility, risk-free rate, volatility of flows, and the mean-reversion speed of flows are the same as in the original model. The first five make sense to leave unchanged as one could assume that the agents acting in the respective economies i.e., bitcoin and stocks and bonds, are the same and also face the same shocks and risk-free rate. The flow parameters, however, could differ between the market for bonds and stocks, and that for bitcoins. Though, a sensible estimation of the parameters is beyond the scope of the thesis and left for future work. For simplicity, it is hereafter assumed that the flows are similar enough to justify the same parameters.

Five-Monthly Data

Table 7.2 repeats the inputs used for the simulation. Parameters γ, g, σ_y, σ_D, r_f, σ_f and ϕ_b are unchanged and therefore omitted. In contrast to the original calibration, in the bitcoin data, δ is implied by the estimates from the data and not computed from the other inputs. Hence, it is added to the table. Because many of the parameters are negative, the computations involving logarithms result in NaNs in some models. As they involve dividends, which bitcoin does not pay, they are of questionable value anyway.

Table 7.2 – Parameters for calibration of the Simulation in Gabaix and Koijen (2021).

	ζ^M	κ	θ	δ
Linear	-0.0026	-0.0006	1.0032	0.2847
Technical	-0.0028	-0.0021	1.0022	-0.0709
Martingale	-0.0024	-0.0008	1.0018	-0.1453
Realized	-0.0247	-0.0082	1.0188	-0.2246

Notes: *The parameters are estimated from the daily bitcoin data using five-monthly averages. The parameters are used as inputs for the calibrated simulation described in Gabaix and Koijen (2021) p. 109-111*

All moments of interest are simulated with $1'000$ repetitions, as it was done in Gabaix and Koijen

(2021). The predictive regressions have not been repeated as they too include the dividends, which cannot be determined from the bitcoin market. A further difference is that in the bitcoin models, only ten years are simulated with a time increment of $\frac{1}{365}$ to adjust the simulation to the difference in the period of the estimated variables.

A naïve computation of the prices used for the estimation gives the following values for the observed values:

Observed Values: Values for the moment of interest computed from the prices used for the estimation of the parameters in the daily dataset:

Mean bitcoin premium: -0.0059

Standard deviation of excess bitcoin returns: 0.0748

A constant risk-free rate of 1% is assumed for the computation. The results of the simulations are displayed in table 7.3.

Table 7.3 – Simulation results for the daily dataset using five-monthly averages.

	Linear	Technical	Martingale	Realised
Mean bitcoin premium:	231.7749	200.0217	272.2914	2.5860
St. d. of excess bitcoin returns:	10.4677	9.7201	11.3402	1.1018

Notes: *The regression results from the simulation proposed in Gabaix and Koijen (2021) with the parameters estimated from the respective model.*

All simulated results heavily overestimated the average of the bitcoin premium and its standard deviation.

Reasons for this behavior can be found in the computation of the '*slope of log price deviation to flow*' (Gabaix and Koijen (2021) p. 19). This factor is computed as:

$$b_f^p = \frac{1}{\zeta + \kappa\phi_f} \,. \tag{7.1}$$

Hence, small values for ζ and κ given ϕ_b is kept the same lead to very large numbers for b_f^p. This value lays at the heart of the model and influences not only the variance of the stock or bitcoin market but also the bitcoin premium computations.

To omit this problem, the '*mean reversion rate of cumulative flow and log D/P*' would need to increase proportionally, to offset the effect of the small values in ζ and κ. However, because κ is negative the mean reversion rate should also be negative, and it should be very large. A back-of-the-envelope calculation posits a mean reversion rate for the linear model at around 236.67%, to get a value for b_f^p equal to five as is in the paper Gabaix and Koijen (2021).

Whether this value for b_f^p would be sensible for the bitcoin data is beyond the scope of this thesis.

block-level Data

The results for the block-level data are less extreme, but still overstate the true moments greatly. Table 7.4 displays the parameters used for the simulations. The time increment used is $\frac{1}{52'560}$, this because it corresponds to the estimations ($144 \cdot 365 = 52'560$). The simulation is then computed over ten years.

The results for the block-level data are less extreme but still overstate the true moments greatly. Table 7.4 displays the parameters used for the simulations. The time increment used is $\frac{1}{52'560}$, this because it corresponds to the estimations ($144 \cdot 365 = 52'560$). The simulation is then computed over ten years.

Table 7.4 – Parameters for calibration of the Simulation in Gabaix and Koijen (2021).

	ζ^M	κ	θ	δ
Linear	-0.0084	-0.0042	0.8570	36.0476
Technical	-0.0084	-0.0131	0.8564	11.6031
Martingale	-0.0087	-0.0013	0.8567	115.5385
Realized	-0.0090	-0.0008	0.8595	186.8750

Notes: *The parameters are estimated from the block-level bitcoin data using averages over 144 blocks. The parameters are used as inputs for the calibrated simulation described in Gabaix and Koijen (2021) p. 109-111*

Table 7.5 – Simulation results for the fenced block-level dataset using rolling averages over 144 blocks.

	Linear	Technical	Martingale	Realised
Mean bitcoin premium:	14.2942	19.6677	−3.8101	−18.9868
St. d. of excess bitcoin returns:	3.3255	3.3255	3.2109	3.1038

Notes: *The regression results from the simulation proposed in Gabaix and Koijen (2021) with the parameters estimated from the respective model.*

Table 7.5 shows the results of the simulations for the fenced block-level data. A striking fact is that the large values for δ lead to negative premiums. I.e., it appears to be the case that bitcoin investors are willing to pay for the risk they take by buying bitcoin. All the simulated standard deviations are similar. These similarities originate in the similar values for ζ.

The negative premium on bitcoin seems in to be in line with the observed value, which is also negative. As previous studies note, in further work, it might be interesting to investigate results for different periods.

Concluding the simulation results: Because the estimated parameters in the daily dataset are very close to zero the generated moments are far off what is observed in the data. The results are closer to the observed moments in the simulations using the results from the block-level data. They are still far off. Interesting is the fact that large values for the mean dividend-price ratio lead the bitcoin premium to become negative. The negative premium could imply that investors are willing to pay for the risk taken up when buying bitcoin. That the daily data does not feature a negative premium might hint at differences between the observed cohorts.

It can be argued that the assumption of the same mean reversion coefficients for the flows into bitcoin as into equities is the main reason for the failure of the model to generate moments close to the observed moments.

Chapter 8

Conclusion

In Summary: This chapter summarizes the results of the thesis, criticizes it, and shows where future work could lead.

Main Points:

- The results from the estimations and the simulations put doubt on the explaining power of the model as it is implemented in the thesis.
- Handling the large amount of data posed the main obstacle for the estimations.
- A large corpus of literature had to be read to gain a grasp of the problem.
- Numerically solving an adapted model was not possible within the time constraints for the thesis.

8.1 Results

Does the model of Gabaix and Koijen (2021) explain bitcoin price fluctuations ?

The research question is answered negatively with the methods and the implementation used in this thesis. The answer consists of two parts. The first part concerns the estimations and the second part the simulation study. Both results put doubt on whether the model tells the full story of the origins of bitcoin price fluctuations.

Starting with the estimations: The low values and significances put doubt on the veracity of the model. Although it can be questioned whether the impact of taking rolling averages as the baseline is the culprit for the meager results or if the data employed understates the effects on prices, given that it is on-chain data. Nevertheless, the results underline the hypothesis that the bitcoin market may be inelastic, and further indicate that bitcoin investors are return-chasing.

The regressions indicate that, given the validity of the model and its implementation, agents in the bitcoin economy invest contrarian and some might be leveraged. The bitcoin market has a positive price elasticity of demand close to zero i.e., positively inelastic. These findings indicate that bitcoin investors stabilize the bitcoin exchange rate. They buy bitcoin if it deteriorates in price and sell bitcoin if the price rises. Yet, because some might be leveraged, it may be the case that large downward movements impede the possibilities of agents to buy and therefore stabilize the price path. Such a scenario would lead to heavy downturns in the bitcoin market. As the stabilizing effects of the contrarian investment strategy and the positive elasticity break down. In any case, the results for the fraction invested in bitcoin are dependent on the cohort observed and the assumptions for the data transformations and need qualification.

In short, the findings from the regressions indicate that bitcoin is stabilized steadily for as long as contrarian agents are able to buy it on downward movements.

The simulations put further doubt on the explaining power of the model. The resulting moments are not close to the observed moments.

The simulations show that because the values estimated from the data are very close to zero, model internal variables controlling the resulting moments become very large. Leading to overly large moments in the simulations.

A general reference to the simulation results is that the mean reversion coefficient of bitcoin flows has not been estimated and that the results might depend on the employed period length of the averages.

In summary, the results indicate that the model might not be able to explain the return volatility of bitcoin prices. The regression results indicate that the transformed data is still extremely noisy and the estimations uncertain. The simulations performed on the grounds of the estimates led to results that do not strengthen the case for the simulation. Doubts on this conclusion persist because a model parameter governing the simulation results was not estimated.

8.1.1 Encountered Difficulties

A big problem was posed by long computing times on the two large datasets. A simple error in the code easily puts you back up to three days. Furthermore, it was challenging to plot the data. Hence, one is flying blind most of the time when working with the datasets. The long computing times and the troubles in having an overview had the consequence, that most estimations are first shots at difficult problems. Besides that, installing and setting up *pyspark* was a hurdle on its own.

The differences between the daily and the block-level dataset were surprising at first. For example, the differences between the fenced and the unfenced regressions are very prominent in the block-level dataset and small in the daily dataset. Likely, the differences would also be stark when the logarithms of the transactions would have been taken. This was not done because, in the daily dataset the series became less stationary, which was interpreted as a strong caveat and a sign that the benefits of doing so in the block-level dataset are small.

To gain an understanding of the theories and assumptions involved, a large body of literature had to be read. The question of price elasticity and price impact covers several dimensions as outlined in the first three chapters of the thesis. The width of the existing literature made it difficult to keep the overview and not drift too deeply into specific strains of literature and keep the topic close to the original paper Gabaix and Koijen (2021).

The setup of the model to solve the problem numerically posed severe obstacles. Starting with the belief that, as it was solved analytically with some simplifications, it should not be much of a hassle to solve it numerically, it had to be scrapped in the end.

The main reason might be that because of the rolling averages selected for the baseline, the model became very dependent on the past values of prices and quantities and with that to the initial conditions given. Furthermore, because of the deterministic nature of the price process in the model, bitcoin became essentially a risk-free asset for a representative agent. Because if there is one sole agent, he knows the in- and outflows exactly. In the model of Gabaix and Koijen (2021), this problem is circumnavigated with the introduction of the behavioral disturbance and the separation of the agent into a rational and an irrational part. Essentially making the model one of cooperating heterogeneous agents.

Due to the sensibility of the model to the baseline values i.e., the derivatives were dependent on the ratios of past average bitcoin holdings and prices. Not even a simpler model with one asset was solvable.

It was further unclear at the beginning that the behavioral disturbance is helping to solve the model. The initial take was that an easier version omitting as much noise as possible would be the easiest to solve.

The main problems posed in the thesis were size related. The size of the dataset and the size of the literature concerned with price generation. Further, numerically solving a simplified model was not possible.

8.2 Critique

A large question mark can be put on the validity of the rolling averages as the baseline. Using this baseline makes the data mean reverting, thus this transformation could be the main driver of the results interpreted in 8.1. I.e., given that computing all values in percentage deviations from its rolling averages, how surprising can the finding of mean-reversion be?

Yet, this problem possibly has deeper roots. Given that the model proposed is completely construed around deviations from a baseline, the question of what this baseline constitutes is natural. In Gabaix and Koijen (2021) this problem is solved, by making assumptions on the processes generating endowments and flows. With these assumptions on the processes rational means can be computed, which serve as the baseline. Given the author's inability to solve a simple adaption of the model numerically without these assumptions, it remains to be seen whether it could have been solved with other methods.

Another point of critique is the use of on-chain data. As explained in the chapter 2 and 3, price driving mechanisms are at play in the interaction between exchanges, which display the prices, and the agents interacting with the exchanges. In the bitcoin economy, this distinction between 'over-the-counter' or on-chain transactions with only an indirect link to the exchange rate and the transactions performed in parts off-chain on the exchanges whit a direct link to the exchange rate is especially severe.

As it is argued in the thesis (6), there is reason to believe that on-chain transactions are connected to the bitcoin exchange rate. However, as more people use bitcoin as an asset off-chain and not as a medium of exchange on-chain, these connections could become weaker. The shift towards more centralization of the bitcoin network could indicate a loosening of the relation. Moreover, the introduction of bitcoin futures, which are traded entirely off-chain and are settled financially without the involvement of bitcoin itself (CME Group Inc., 2020), can enhance the dissolvement of the link between on-chain transactions and the exchange rate of bitcoin.

That the estimations are made based on the model might obscure possible other effects. E.g., that the demand series is computed as prescribed by the model is heavily altering the original data. These modifications make sense in the scope of this thesis, which aims to test the validity of the model. It could be beneficial to perform estimations without modifications. In the same vein, it is not fully clear whether a large number of outliers originates from the data or the transformations. Especially the divisions are prone to producing extremely large values if the denominator is small.

Given the market microstructure literature presented in 2.3 it would make sense to adjust the transaction with a power law. The effects on the transformed data and the estimations could be large and further distort the results. Therefore, this would need to be done in conjunction with a model-free estimation, to assess the impact of these transformations.

Too little attention has been put to the transition from 'macro' to 'micro' implied by the shift from the daily to the block-level dataset. A less model-based approach, in the sense of **?**, to the estimations done on the block-level dataset could have produced better results. To bring together the macrostructural and the microstructural view is, however, clearly beyond the scope of this thesis.

A further point of critique is the handling of the outliers, fencing seems like a viable solution, however, it severely alters the data used.

To decision to handle the full sample as one observation and imply the same data generating process might be an invalid assumption. Given the differing results for different periods detailed in the first three chapters, it might be possible that the data generating process has changed. E.g., after the introduction of bitcoin futures, price generation could be expected to be distorted from what it was previously.

The determining values for the periods used in the rolling means for the technical model and the period used to compute the estimations in the linear model are arbitrary. Other values could lead to different estimates of κ and therefore alter the results of the simulations.

8.3 Outlook

The data used is very rich in information and large in scope. Furthermore, the algorithmic supply makes bitcoin or similar currencies perfectly suited for the estimation of demand impact on prices.

In future work, it would be interesting to see if less model-driven approaches i.e., without the rolling averages, differ from the results shown in this thesis. As was pointed out in the section 8.2, it might be beneficial to pair the data with volume data from exchanges and other sources, to diminish the effects of the on-chain data-only approach.

An in-depth investigation of the origins of the large values for δ might be interesting too. Possibly, a behavioral effect lays at the origin of this. To evaluate this hypothesis a further look into similarly build models as the one from Gabaix and Koijen (2021) is needed.

The estimation of the missing parameter could be tackled by first identifying a suitable model for the process of the flows. Several models could be potential candidates e.g., AR(n), ARCH, GARCH, or other more involved models. The decision of which model to take would best be done via cross-validation with a suitable error measure.

For the numerical computation of the model, there would be the need to circumvent the dependence on past values. A possibility is to replace the rolling averages with their theoretical counterparts i.e., variance, mean, and covariance. This approach has the obvious drawback of bringing back the assumptions it was meant to omit. Another viable way could be the implementation of a two-step process in agent's optimizations as proposed in Haddad et al. (2021). However, an in-depth look at the model would be needed first.

The synopsis of the outlook is that the data is plentiful, and the topic is interesting and an active field of research. It would be appealing to continue working in this direction.

8.4 Closing Words

Given the results presented in this thesis, does it makes sense to say that the ones who buy early in order to try to sell to others later at higher prices? The idea which led to the uptake of the question for the thesis.

It seems not. Contrarian investing agents are the opposite of what would have been expected in the light of the Keynesian Beauty contest or the dollar auction. The opposite seems to be the case, agents act against the movements instead of enhancing them. The roots of this behavior remain in the dark, however.

As was expected, the noise surrounding the estimates is large. The reasons for this are manifold and some are outlined in chapter 2. Others surely are covered in noise.

A fascinating aspect is that a good without clear fundamental value has contrarian investing agents.

Appendices

Appendix A

Output

A.1 Sample API- Output

Below a sample block output from the graphsense API (Haslhofer et al., 2021) is shown.

The first entry ‘coinbase’ indicates whether the transaction is a Coinbase transaction. ‘height’ denotes the block number, or the position of the block relative to the genesis block (Antonopoulos, 2017).

The keyword ‘inputs’ is followed by a list of information about the transaction inputs. The first ‘input’ list is empty because it is a coinbase transaction, which is the first in every block and does not originate from a specific address (Nakamoto, 2008).

The ‘output’ keyword contains also a list of transaction information. This list, as is the list containing the input information, is divided in the ‘address’, the ‘fiat value’, denoted in euro and us dollar and the ‘value’ denoted in bitcoin.

Each transaction is followed by a summary of the total value transferred. The fee paid to the miner can be calculated from the difference between the total input and the total output (Nakamoto, 2008).

Additionally, the timestamp indicating the approximate time the block was mined and the fiat values at the time are given by the API. The timestamp is given by the machine of the miner and is only approximately correct (Antonopoulos, 2017).

Each transaction ends with the transaction hash ('tx_hash') and the type of the transaction type ('tx_type').


```
[{'coinbase': True,
'height': 71000,
'inputs': [],
'outputs': [{'address': ['19ozhWSeWPgcPrAPvXmZvxfiFFgPCmGs8r'],
'value': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 5000000000}}],
'timestamp': 1280419020,
'total_input': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 0},
'total_output': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 5000000000},
'tx_hash': '3ce6ba71b976dec9f4d22a57575bf7de51048bb218b4f6dd691310088cde1ab0',
'tx_type': 'utxo'}, {'coinbase': False,
'height': 71000,
'inputs': [{'address': ['1MChrKgpmeDFRkkZzXstozzC2b8NLaedKU'],
'value': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 3000000000}}],
'outputs': [{'address': ['1LtXTCCqSMHquWsLZSL8xd11hdBUxckVGG'],
'value': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 3000000000}}],
'timestamp': 1280419020,
'total_input': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 3000000000},
'total_output': {'fiat_values': [{'code': 'eur', 'value': 0.0},
{'code': 'usd', 'value': 0.0}],
'value': 3000000000},
```

'tx_hash': '1c474d87ab4ddd47c2e5393286e2bb0decf36bb8badd016f9c822a98f799a2a4',
'tx_type': 'utxo'}]

A.2 Summary Statistics

Table A.1 – Summary Statistics for monthly data.

	q	p	f	d	dp
count	3270	3270	3270	3270	3270
min	-21.800	-4.672	-12.148	-2.407	-15.872
25%	-0.269	-0.483	-0.017	-0.604	-0.275
50%	-0.086	-0.152	-0.017	-0.167	0.014
75%	0.217	0.336	-0.017	0.377	0.314
max	11.897	9.230	33.758	6.738	14.740

Notes: *All features are in percent deviations from their monthly rolling mean. All values are scaled to unit variance and zero mean.*

Table A.2 – Summary Statistics for semi annual data.

	q	p	f	d	dp
count	3270	3270	3270	3270	3270
min	-43.063	-1.609	-15.516	-1.276	-22.843
25%	-0.191	-0.574	-0.008	-0.594	-0.148
50%	-0.033	-0.228	-0.008	-0.293	0.003
75%	0.175	0.223	-0.008	0.139	0.173
max	11.867	10.243	14.232	7.570	15.479

Notes: *All features are in percent deviations from their semi annual rolling mean. All values are scaled to unit variance and zero mean.*

Table A.3 – Summary Statistics for annual data.

	q	p	f	d	dp
count	3270	3270	3270	3270	3270
min	-41.792	-1.096	-15.516	-0.950	-23.251
25%	-0.185	-0.630	-0.008	-0.592	-0.108
50%	-0.029	-0.222	-0.008	-0.315	0.001
75%	0.187	0.207	-0.008	0.056	0.120
max	12.571	9.599	14.232	7.118	15.189

Notes: *All features are in percent deviations from their annual rolling mean. All values are scaled to unit variance and zero mean.*

Table A.4 – Summary Statistics for the scaled block-level data set.

	q	p	f	d	dp
count	559’354	559’354	559’354	559’354	559’354
mean	0.000	0.000	0.000	0.000	0.000
std	1.000	1.000	1.000	1.000	1.000
min	-1.170	-0.024	-124.0131	-42.415	-527.237
25%	-0.002	-0.002	-0.001	-0.134	-0.000
50%	-0.001	-0.001	-0.001	-0.109	0.000
75%	-0.001	-0.001	-0.001	-0.038	0.000
max	747.887	747.213	735.913	51.657	529.576

Notes: *All features are in percent deviations from the rolling mean using 144 blocks. All values are scaled to unit variance and zero mean.*

A.3 Stationarity Tests

Table A.5 – Summary Statistics: DFGLS and the KPSS test (Monthly to Quarterly).

	Monthly		Bi-Monthly		Quarterly	
	KPSS	DFGLS	KPSS	DFGLS	KPSS	DFGLS
q	0.349 (0.001)	−3.911 (0.002)	0.199 (0.015)	−4.372 (0.000)	0.134 (0.070)	−4.662 (0.000)
p	0.087 (0.227)	−4.134 (0.001)	0.104 (0.145)	−4.418 (0.000)	0.122 (0.093)	−5.065 (0.000)
f	0.048 (0.599)	−13.234 (0.000)	0.036 (0.787)	−55.908 (0.000)	0.049 (0.588)	−57.097 (0.000)
d	0.227 (0.008)	−7.425 (0.000)	0.286 (0.002)	−4.270 (0.000)	0.325 (0.001)	−2.861 (0.050)
dp	0.0105 (0.998)	−2.384 (0.149)	0.007 (0.998)	−2.290 (0.180)	0.008 (0.997)	−2.345 (0.161)

Notes: *The statistic is presented with the p-value in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean before conducting the tests. The results have not been influenced by the scaling.*

Table A.6 – Summary Statistics: DFGLS and the KPSS test (Trimesterly to Annually).

	Trimesterly		Semi-Annually		Annually	
	KPSS	DFGLS	KPSS	DFGLS	KPSS	DFGLS
q	0.101 (0.159)	−5.072 (0.000)	0.058 (0.471)	−5.890 (0.000)	0.018 (0.985)	−5.928 (0.000)
p	0.136 (0.067)	−5.283 (0.000)	0.160 (0.038)	−4.181 (0.001)	0.216 (0.010)	−3.644 (0.005)
f	0.039 (0.739)	−11.371 (0.000)	0.039 (0.739)	−11.371 (0.000)	0.039 (0.739)	−11.371 (0.000)
d	0.346 (0.001)	−2.017 (0.293)	0.387 (0.000)	−1.617 (0.513)	0.434 (0.000)	−1.402 (0.638)
dp	0.010 (0.997)	−2.627 (0.088)	0.015 (0.995)	−4.438 (0.000)	0.018 (0.987)	−5.843 (0.000)

Notes: *The statistic is presented with the p-value in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean before conducting the tests. The results have not been influenced by the scaling.*

A.4 Regression Results

Table A.7 – Median regression results.

	Linear	Technical	Martingale	Realised	Without
Const.	−0.0277	−0.0277	−0.0294	−0.0294	−0.0285
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
p	0.0087	0.0087	0.0061	0.0061	0.0058
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
d	0.0417	0.0417	0.0419	0.0419	0.0427
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***
f	−0.0011	−0.0011	−0.0010	−0.0010	−0.0011
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
dp	0.0043	0.0043	−0.0103	−0.0103	–
	(0.005)	(0.005)	(0.005)**	(0.005)**	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean. The standard errors are not adjusted and should not be trusted.*

Table A.8 – OLS regression results for the semi-annual data.

	Linear	Technical	Martingale	Realised	Without
$Const.$	−0.0072	−0.0072	−0.0072	−0.0073	−0.0072
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
p	0.0238	0.0236	0.0257	0.0215	0.0232
	(0.022)	(0.020)	(0.021)	(0.021)	(0.021)
d	0.0033	0.0041	0.0032	0.0042	0.0035
	(0.049)	(0.048)	(0.048)	(0.049)	(0.048)
f	−0.0023	−0.0024	−0.0028	−0.0023	−0.0023
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
dp	−0.0074	−0.0797	−0.0289	−0.0172	–
	(0.051)	(0.033)**	(0.011)**	(0.013)	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean. The asterisks (*, **, ***) indicate significance at the 10%, 5% and 1% level. Standard errors are compted using autocorrelation robust standard errors. The d time series is differenced because of non-stationarity*

Table A.9 – Fenced OLS regression results.

	Linear	Technical	Martingale	Realised	Without
Const.	0.0000	0.0000	0.0000	−0.0000	−0.0000
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
p	0.0261	0.0252	0.0276	0.0226	0.0250
	(0.024)	(0.022)	(0.023)	(0.023)	(0.023)
d	0.0042	0.0052	0.0044	0.0055	0.0046
	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)
f	−0.0029	−0.0031	−0.0036	−0.0030	−0.0030
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
dp	−0.0050	−0.0233	−0.0304	−0.0242	–
	(0.019)	(0.011)**	(0.012)***	(0.014)*	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their five monthly rolling mean. All values have been scaled to unit variance and zero mean. The values have been truncated, where they exceed the 80% quantile by more than five times the distance between the 80% and the 20% quantile and also where the values are less than the 20% quantile minus five times the distance between the 80% and 20% quantiles. The asterisks (*, **, ***) indicate significance at the 10%, 5% and 1% level.*

Table A.10 – OLS regression results for the scaled block-level data.

	Linear	Technical	Martingale	Realised	Without
Constant	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p	0.0000	−0.0000	0.0000	−0.0000	−0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
d	−0.0144	−0.0144	−0.0144	−0.0144	−0.0144
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
f	−0.0000	−0.0000	0.0000	−0.0000	−0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
dp	−0.0000	−0.0000	0.0000	−0.0000	–
	(0.000)	(0.000)	(0.000)	(0.000)	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their rolling mean using 144 blocks. All values have been scaled to unit variance and zero mean. The asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.*

Table A.11 – Median regression results for the scaled block-level data.

	Linear	Technical	Martingale	Realised	Without
Constant	−0.0012	−0.0012	−0.0012	−0.0012	−0.0012
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p	−0.0000	−0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)***	(0.000)***	(0.000)***
d	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
f	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
dp	0.0000	0.0000	−0.0000	0.0000	–
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their rolling mean using 144 blocks. All values have been scaled to unit variance and zero mean. The asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.*

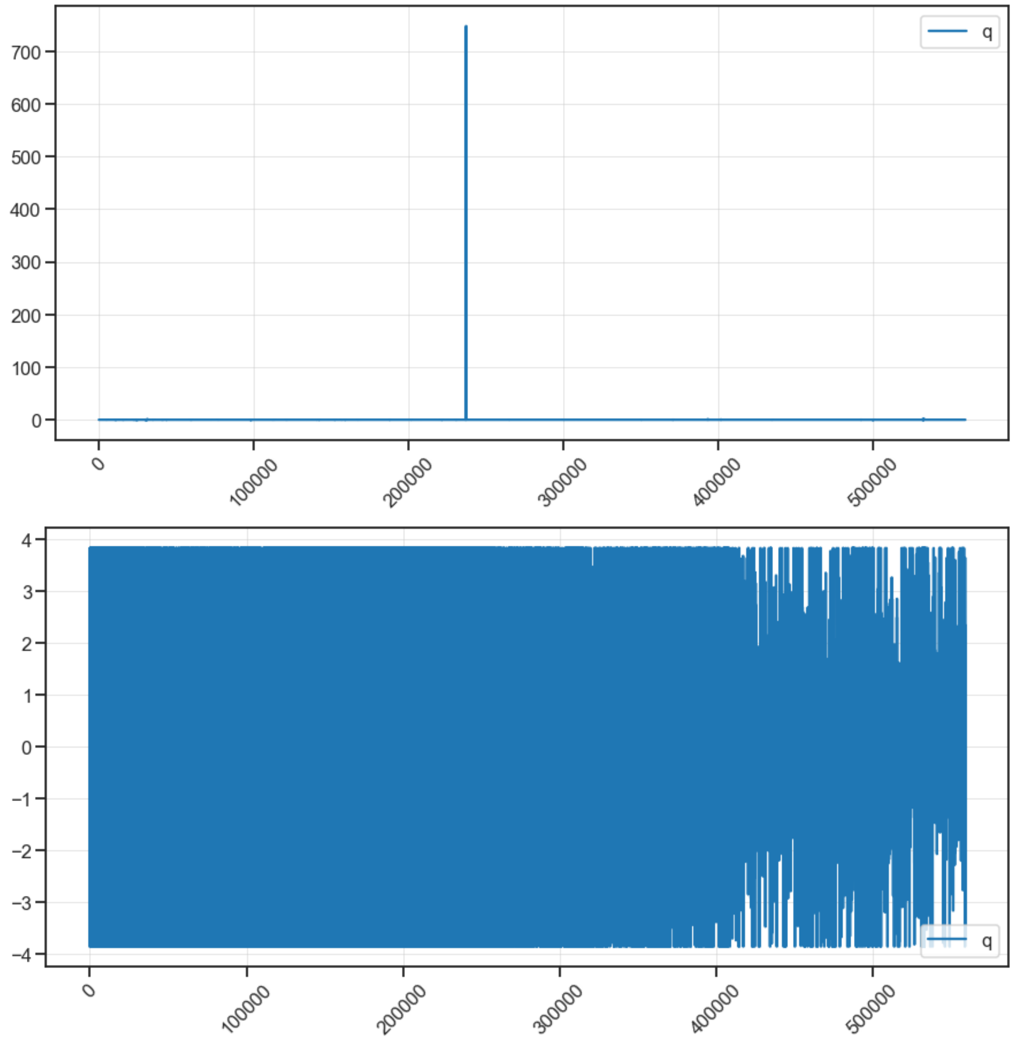
Table A.12 – Fenced median regression results.

	Linear	Technical	Martingale	Realised	Without
Constant	0.1323	0.1323	0.1324	0.1323	0.1323
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p	0.0046	0.0046	0.0020	0.0018	0.0055
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
d	−0.2765	−0.2765	−0.2725	−0.2727	−0.2722
	(0.020)***	(0.020)***	(0.020)***	(0.020)***	(0.020)***
f	0.0043	0.0043	0.0044	0.0044	0.0043
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
dp	−0.0027	−0.0027	−0.0045	−0.0047	–
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	–

Notes: *The coefficients are presented with the standard errors in brackets. All features are in percent deviations from their rolling mean using 144 blocks. All values have been scaled to unit variance and zero mean. The values have been truncated, where they exceed the 80% quantile by more than five times the distance between the 80% and the 20% quantile and also where the values are less than the 20% quantile minus five times the distance between the 80% and 20% quantiles. The asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.*

A.5 Figures

Figure A.1 – Timeline of q for the scaled and the fenced block-level dataset.



Notes: *The figure above shows the scaled variable q from the block-level dataset. The figure below shows the variable q from the fenced dataset. All values have been scaled to unit variance and zero mean.*

Appendix B

Proofs from Gabaix and Koijen (2021)

B.1 Proof of Proposition 1 (Gabaix and Koijen (2021))

Institutions i's wealth at time $t = 0^-$ is given by: $\bar{W}_i = \bar{P}\bar{Q}_i + \bar{B}$. The holdings can be rewritten according to equation (4.1):

$$\bar{P}\bar{Q}_i = \theta_i \bar{W}_i, \qquad \bar{B}_i = (1-\theta_i)\bar{W}_i. \tag{B.1}$$

Because at $t = 0^-$ we have $\pi = \bar{\pi}$ the term $e^{\kappa_i \hat{\pi}}$ drops out.

At time $t = 0$ after a flow ΔF_i and a corresponding price change to the equilibrium price P, the wealth of a particular institution $W_i = P\bar{Q}_i + \bar{B}_i + \Delta F_i$. Under the assumption that the prices of bonds are fix, Gabaix and Koijen (2021) write $\Delta W_i = W_i - \bar{W}_i = \bar{Q}_i \Delta P + \Delta F_i$. Following from that notation the value of assets held by the institution changes by a fraction of:

$$w_i = \frac{\Delta W_i}{\bar{W}_i} \tag{B.2}$$

$$= \frac{\bar{Q}_i \Delta P}{\bar{W}_i} + \frac{\Delta F_i}{\bar{W}_i} \tag{B.3}$$

$$= \frac{\bar{Q}_i \bar{P}}{\bar{W}_i} \cdot \frac{\Delta P}{\bar{P}} + \frac{\Delta F_i}{\bar{W}_i} \tag{B.4}$$

$$= \theta_i \cdot p + f_i \tag{B.5}$$

From (B.2) to (B.3) the definition was used and from (B.3) to (B.4) the first fraction is multiplied by $\frac{\bar{P}}{P}$ and separated thereafter. From (B.3) to (B.4) definitions are used.

Using the definition in equation (4.1) Gabaix and Koijen make the following transformations:

$$
\begin{aligned}
Q_i &= \frac{\theta_i e^{\kappa_i \hat{\pi}} W_i}{P} && \text{(B.6)}\\
&= \frac{\theta_i e^{\kappa_i \hat{\pi}} \bar{W}_i (1+w_i)}{\bar{P}(1+p)} && \text{(B.7)}\\
&= \bar{Q}_i e^{\kappa_i \hat{\pi}} \frac{1+w_i}{1+p} && \text{(B.8)}
\end{aligned}
$$

Using this expression and inserting it in the definition of q_i Gabaix and Koijen derive while keeping $\kappa_i = 0$:

$$
\begin{aligned}
q_i &= \frac{Q_i}{\bar{Q}_i} - 1 && \text{(B.9)}\\
&= e^{\kappa_i \hat{\pi}} \frac{1+w_i}{1+p} - 1 && \text{(B.10)}\\
&= \frac{e^{\kappa_i \hat{\pi}}(1+w_i) - 1 - p}{1+p} && \text{(B.11)}\\
&= \frac{e^{\kappa_i \hat{\pi}} - 1 + e^{\kappa_i \hat{\pi}} w_i - p}{1+p} && \text{(B.12)}\\
&= \frac{e^{\kappa_i \hat{\pi}} - 1 + e^{\kappa_i \hat{\pi}}(\theta_i p + f_i) - p}{1+p} && \text{(B.13)}\\
&= \frac{e^{\kappa_i \hat{\pi}} - 1 + p(\theta_i e^{\kappa_i \hat{\pi}} - 1) + f_i e^{\kappa_i \hat{\pi}}}{1+p} && \text{(B.14)}\\
&= \frac{e^{\kappa_i \hat{\pi}} - 1 - \zeta_i p + f_i e^{\kappa_i \hat{\pi}}}{1+p} && \text{(B.15)}\\
&\overset{\kappa_i=0}{\Rightarrow} \frac{f_i - \zeta_i p}{1+p} && \text{(B.16)}
\end{aligned}
$$

With $\zeta_i = 1 - \theta_i e^{\kappa_i \hat{\pi}}$ or, equivalent for $\kappa_i = 0$, $\zeta_i = 1 - \theta_i$.

To derive the equation in 4.1.1 first Gabaix and Koijen (2021) transform the dividend-price ratios and then take the natural logarithm in equation (4.1): Starting by taking logs and differences from the baseline in the dividend price ratio Gabaix and Koijen derive the following relation:

$$
\Delta ln\Big(\frac{D^e}{P}\Big) = \Delta ln(D^e) - \Delta ln(P) \approx d - p\ . \tag{B.17}
$$

By definition $\delta = \frac{D^e}{P} = 1 + r_f + \pi$ Gabaix and Koijen (2021) derive further:

$$\Delta ln\Big(\frac{D^e}{P}\Big) = ln\Big(\frac{D^e}{P}\Big) - ln\Big(\frac{\bar{D}^e}{\bar{P}}\Big) \tag{B.18}$$
$$= ln(1 + r_f + \pi) - ln(1 + r_f + \bar{\pi}) = ln\Big(\frac{1 + r_f + \pi}{1 + r_f + \bar{\pi}}\Big) \tag{B.19}$$
$$= ln\Big(\frac{1 + r_f + \pi + \bar{\pi} - \bar{\pi}}{1 + r_f + \bar{\pi}}\Big) \tag{B.20}$$
$$= ln\Big(1 + \frac{\pi - \bar{\pi}}{1 + r_f + \bar{\pi}}\Big) = ln\Big(1 + \frac{\Delta\pi}{1 + r_f + \bar{\pi}}\Big) \tag{B.21}$$
$$\approx \frac{\Delta\pi}{1 + r_f + \bar{\pi}} = \frac{\hat{\pi}}{\delta} \tag{B.22}$$

By combining the results from (B.17) and (B.22) Gabaix and Koijen get a final expression for the equity premium:

$$\hat{\pi} \approx \delta(d - p)\ . \tag{B.23}$$

This equation brings the difference of the equity premium directly in to a relation with the change in prices and dividends.

$$\frac{PQ_i}{W_i} = \theta_i e^{\kappa_i \hat{\pi}} \Leftrightarrow Q_i = \frac{\theta_i e^{\kappa_i \hat{\pi}} W_i}{P} \tag{B.24}$$
$$ln(Q_i) = ln(W_i) + ln(\theta) + \kappa_i \hat{\pi} - ln(P) \tag{B.25}$$

From equation (B.25) Gabaix and Koijen take the difference from the baseline and arrive at:

$$\Delta ln(Q_i) = \Delta ln(W_i) + \Delta ln(\theta) + \kappa_i \hat{\pi} - \Delta ln(P) \tag{B.26}$$

Via first order taylor expansion Gabaix and Koijen (2021) resulting in $\Delta ln(Q_i) \approx q_i$, $\Delta ln(W_i) \approx w_i$, $\Delta ln(P) \approx p$ and the relation in (B.23) they arrive at:

$$q_i \approx -\underbrace{(1 - \theta_i \kappa_i + \delta)}_{\zeta_i} p + f_i + \kappa_i \delta d \tag{B.27}$$

■

B.2 Proof of Proposition 2 (Gabaix and Koijen (2021))

Proposition 2 follows directly from proposition 1 by taking the equity-holdings weighted mean over both sides:

$$q_i \approx -\underbrace{(1-\theta_i+\kappa_i\delta)}_{\zeta_i}p + f_i + \kappa_i\delta d \Rightarrow \tag{B.28}$$

$$\sum_{i\in I} S_i q_i \approx \sum_{i\in I} S_i\big(-\underbrace{(1-\theta_i+\kappa_i\delta)}_{\zeta_i}p + f_i + \kappa_i\delta d\big) \tag{B.29}$$

$$q_S \approx -\underbrace{\sum_{i\in I} S_i(1-\theta_i+\kappa_i\delta)}_{\sum_{i\in I} S_i\zeta_i}p + \sum_{i\in I} S_i f_i + \sum_{i\in I} S_i\kappa_i\delta d \tag{B.30}$$

$$q_S \approx -\underbrace{(1-\theta_S+\kappa_S\delta)}_{\zeta_S}p + f_S + \kappa_S\delta d \tag{B.31}$$

■

B.3 Derivation of $\hat{\pi}$ in the Infinite Horizon Model

The derivation starts with the identity $\hat{\pi} = \pi - \bar{\pi}$:

$$\begin{aligned}
1 + r_f + \bar{\pi} + \hat{\pi}_t &= 1 + r_f + \pi_t && \text{(B.32)}\\
&= \frac{\mathbb{E}_t[P_{t+1} + D_{t+1}]}{P_t} && \text{(B.33)}\\
&= \frac{\mathbb{E}_t[\bar{P}_{t+1}(1+p_{t+1}) + \bar{D}_{t+1}(1+d_{t+1})]}{\bar{P}_t(1+p_t)} && \text{(B.34)}\\
&= \mathbb{E}_t\Big[\frac{\bar{P}_{t+1}}{\bar{P}_t}\frac{(1+p_{t+1})}{1+p_t} + \frac{\bar{D}_{t+1}}{\bar{D}_t}\frac{\bar{D}_t}{\bar{P}_t}\frac{(1+d_{t+1})}{1+p_t}\Big] && \text{(B.35)}\\
&\approx \mathbb{E}_t\Big[\frac{\bar{P}_{t+1}}{\bar{P}_t}(1+p_{t+1}-p_t) + \frac{\bar{D}_{t+1}}{\bar{D}_t}\frac{\bar{D}_t}{\bar{P}_t}(1+d_{t+1}-p_t)\Big] && \text{(B.36)}\\
&= \mathbb{E}_t\big[(1+g)(1+p_{t+1}-p_t) + (1+g)\delta^\star(1+d_{t+1}-p_t)\big] && \text{(B.37)}\\
&= (1+g)(1+\delta^\star) + (1+g)\mathbb{E}_t\big[(p_{t+1}-p_t) + \delta^\star(d_{t+1}-p_t)\big] && \text{(B.38)}\\
&= (1+g)(1+\delta^\star) + (1+g)\mathbb{E}_t\big[\delta^\star(d_{t+1}-p_t) + \Delta p_{t+1}\big] && \text{(B.39)}
\end{aligned}$$

From that, by collecting the terms Gabaix and Koijen (2021) denote:

$$\underbrace{1 + r_f + \bar{\pi}}_{\text{Zero Order}} + \underbrace{\hat{\pi}_t}_{\text{First Order}} = \underbrace{(1+g)(1+\delta^\star)}_{\text{Zero Order}} + \underbrace{(1+g)\mathbb{E}_t\big[\delta^\star(d_{t+1} - p_t) + \Delta p_{t+1}\big]}_{\text{First Order}} \tag{B.40}$$

Gabaix and Koijen (2021) note that the zero order terms correspond to the Gordon growth formula $r_f + \bar{\pi} - g = (1+g)\delta^\star = \frac{\mathbb{E}_t[D_{t+1}]}{P_t}$. To arrive at the expression in (4.30) we need to rewrite the first order term of equation (B.40).

$$\hat{\pi}_t = (1+g)\mathbb{E}_t\big[\delta^\star(d_{t+1} - p_t) + \Delta p_{t+1}\big] \tag{B.41}$$

$$= (1+g)\delta^\star\mathbb{E}_t[d_{t+1} - p_t] + (1+g)\mathbb{E}_t[\Delta p_{t+1}] \tag{B.42}$$

In the next step Gabaix and Koijen (2021) define $\delta = \frac{\mathbb{E}_t[D_{t+1}]}{P_t}$and therefore that $(1+g)\delta^\star = \delta$

$$= \delta\big(\mathbb{E}_t[d_{t+1}] - p_t\big) + (1+g)\mathbb{E}_t[\Delta p_{t+1}] \tag{B.43}$$

Where from $g = 0$ follows finally that:

$$= \delta(d_t^e - p_t) + \mathbb{E}_t[\Delta p_{t+1}] \tag{B.44}$$

■

B.4 Proof of Proposition 4 (Gabaix and Koijen (2021))

Gabaix and Koijen (2021) start the proof by noting that, after dividend and coupon payments: $W_t = P_tQ + F_t$ and similarly for the baseline $\bar{W}_t = \bar{P}_tQ + \bar{F}_t$. By defining $\tilde{F}_t = F_t - \bar{F}_t$ and computing $W_t - \bar{W}_t = (P_t - \bar{P}_t)Q + \tilde{F}_t = \bar{P}_tQp_t + \tilde{F}_t = \bar{W}_tw_t$. By dividing through $\bar{W}_t$ and defining $f_t = \frac{\tilde{F}_t}{\bar{W}_t}$ arrive at an expression for w_t:

$$w_t = \theta p_t + f_t \tag{B.45}$$

Using the definition in equation (4.28) and the counterpart for the baselline economy ($\bar{Q}_t\bar{P}_t = \bar{W}_t\theta$) Gabaix and Koijen (2021) compute:

$$\frac{Q_tP_t}{\bar{Q}_t\bar{P}_t} = \frac{W_t}{\bar{W}_t}e^{\kappa\hat{\pi}_t+\nu_t} \tag{B.46}$$

$$\Leftrightarrow$$

$$(1+q_t)(1+p_t) = (1+w_t)e^{\kappa\hat{\pi}_t+\nu_t} \tag{B.47}$$

$$\Rightarrow$$

$$q_t + p_t = w_t + \kappa\hat{\pi}_t\nu_t \tag{B.48}$$

$$\Leftrightarrow$$

$$q_t = -(1-\theta)p_t + \kappa\hat{\pi}_t + f_t + \nu_t \tag{B.49}$$

Where from equation (B.47) to (B.48) the equation was linearized. Moving on with the result from equation (4.30) Gabaix and Koijen (2021) arrive at the desired result:

$$q_t = -(1-\theta+\kappa\delta)p_t + \kappa\delta d_t^e + \kappa\mathbb{E}_t[\Delta p_{t+1}] + f_t + \nu_t \tag{B.50}$$

■

B.5 Proof of Proposition 5 (Gabaix and Koijen (2021))

The proof of proposition 5 starts by rewriting the expression of proposition 4 (4.31):

$$\begin{aligned} q_t &= -\zeta p_t + f_t + \nu_t + \kappa\delta d_t^e + \kappa\mathbb{E}[\Delta p_{t+1}] && \text{(B.51)} \\ &= \kappa(\mathbb{E}_t[\Delta p_{t+1}] - \tfrac{\zeta}{\kappa}p_t + \delta d_t^e) + f_t + \nu_t && \text{(B.52)} \\ &= \kappa(\mathbb{E}_t[\Delta p_{t+1}] - \rho p_t + \delta d_t^e) + f_t + \nu_t && \text{(B.53)} \\ & && \text{(B.54)} \end{aligned}$$

Setting $q_t = 0$ and dividing through κ: [21]

$$0 = \kappa(\mathbb{E}_t[\Delta p_{t+1}] - \rho p_t + \delta d_t^e) + f_t + \nu_t \tag{B.55}$$

$$= \mathbb{E}_t[\Delta p_{t+1}] - \rho p_t + \delta d_t^e + \frac{f_t + \nu_t}{\kappa} \tag{B.56}$$

$$\tag{B.57}$$

Rearranging:

$$p_t = \left(\frac{1}{1+\rho}\right)\left(\mathbb{E}_t[p_{t+1}] + \delta d_t^e + \frac{f_t + \nu_t}{\kappa}\right) \tag{B.58}$$

$$= \left(\frac{1}{1+\rho}\right)\left(\mathbb{E}_t[(\tfrac{1}{1+\rho})(\mathbb{E}_{t+1}[p_{t+2}] + \delta d_{t+1}^e + \tfrac{f_{t+1}+\nu_{t+1}}{\kappa})] + \delta d_t^e + \frac{f_t + \nu_t}{\kappa}\right) \tag{B.59}$$

$$= \mathbb{E}_t\left[\mathbb{E}_{t+1}\left[\left(\tfrac{1}{1+\rho}\right)^2 p_{t+2} + \left(\tfrac{1}{1+\rho}\right)\delta d_t^e + \left(\tfrac{1}{1+\rho}\right)^2 \delta d_{t+1}^e + \left(\tfrac{1}{1+\rho}\right)\tfrac{f_t+\nu_t}{\kappa} + \left(\tfrac{1}{1+\rho}\right)^2 \tfrac{f_{t+1}+\nu_{t+1}}{\kappa}\right)\right]\right] \tag{B.60}$$

$$\tag{B.61}$$

Solving forward leads to:

$$p_t = \mathbb{E}_t\left[\sum_{\tau=t}^{\infty} \frac{\delta d_\tau^e + \frac{f_\tau + \nu_\tau}{\kappa}}{(1+\rho)^{\tau-t+1}}\right] + \underbrace{\lim_{\tau\to\infty} \mathbb{E}_\tau\left[\frac{p_{\tau+1}}{(1+\rho)^{\tau+1}}\right]}_{\to 0} \tag{B.62}$$

$$= \mathbb{E}_t\left[\sum_{\tau=t}^{\infty} \frac{\delta d_\tau^e + \frac{f_\tau + \nu_\tau}{\kappa}}{(1+\rho)^{\tau-t+1}}\right] \tag{B.63}$$

For the equity premium set $q_t = 0$ in equation (B.49):

$$q_t = -(1-\theta)p_t + \kappa\hat{\pi}_t + f_t + \nu_t \tag{B.64}$$

$$\Leftrightarrow$$

$$0 = -(1-\theta)p_t + \kappa\hat{\pi}_t + f_t + \nu_t \tag{B.65}$$

$$\Leftrightarrow$$

$$\hat{\pi} = \frac{(1-\theta)p_t - f_t - \nu_t)}{\kappa} \tag{B.66}$$

[21] Comment: By dividing through κ while q_t the equation is loosing solutions

■

B.6 Derivation of the Impact of Permanent Flow

In equilibrium the expected dividend deviation from the baseline is zero. Hence, $\mathbb{E}_t[d^e_\tau] = 0$ and $\nu_\tau = 0 \quad \forall\tau$. Then from equation (4.32) follows:

$$\mathbb{E}_0[p_t] = \mathbb{E}_0\left[\mathbb{E}_t\Big[\sum_{\tau=t}^{\infty}\frac{1}{(1+\rho)^{\tau-t+1}}\rho\frac{f_\tau}{\zeta}\Big]\right] \tag{B.67}$$

$$= \sum_{\tau=0}^{\infty}\frac{1}{(1+\rho)^{\tau+1}}\rho\frac{\mathbb{E}_0[f_\tau]}{\zeta} \tag{B.68}$$

$$= \rho\frac{f_0}{\zeta}\sum_{\tau=0}^{\infty}\frac{1}{(1+\rho)^{\tau+1}} \tag{B.69}$$

$$= \frac{f_0}{\zeta}\frac{\rho}{1+\rho}\sum_{\tau=0}^{\infty}\frac{1}{(1+\rho)^{\tau}} \tag{B.70}$$

$$= \frac{f_0}{\zeta}\frac{\rho}{1+\rho}\left(\frac{1}{1-\frac{1}{1+\rho}}\right) \tag{B.71}$$

$$= \frac{f_0}{\zeta}\frac{\rho}{1+\rho}\Big(\frac{1+\rho}{\rho}\Big) \tag{B.72}$$

$$\mathbb{E}_0[p_t] = \frac{1}{\zeta}f_0 \tag{B.73}$$

■

B.7 Derivation of the Impact of a Mean-Reverting Flow

In equilibrium the expected deviation of fundamentals from the price is zero. Hence, $\mathbb{E}_t[d^e_\tau] = 0$ and $\nu_\tau = 0 \quad \forall\tau$. Then from equation (B.63)follows:

$$\mathbb{E}_0[p_t] = \mathbb{E}_0\left[\mathbb{E}_t\Big[\sum_{\tau=t}^{\infty}\frac{1}{(1+\rho)^{\tau-t+1}}\frac{f_\tau}{\kappa}\Big]\right] \tag{B.74}$$

$$= \mathbb{E}_0\left[\sum_{\tau=t}^{\infty}\frac{1}{(1+\rho)^{\tau-t+1}}\frac{(1-\phi_f)^{\tau+t}\mathbb{E}_t[f_\tau]}{\kappa}\right] \tag{B.75}$$

$$= \mathbb{E}_0\left[\sum_{\tau=t}^{\infty}\frac{1}{(1+\rho)^{\tau-t+1}}\frac{(1-\phi_f)^{\tau+t}\mathbb{E}_t[f_\tau]}{\kappa}\right] \tag{B.76}$$

$$= \mathbb{E}_0\left[\frac{1}{\kappa}\frac{(1-\phi_f)^t}{1+\rho}\sum_{\tau=0}^{\infty}\left(\frac{1-\phi_f}{1+\rho}\right)^{\tau}\mathbb{E}_t[f_\tau]\right] \tag{B.77}$$

$$= \frac{f_0}{\kappa}\frac{(1-\phi_f)^t}{1+\rho}\left(\frac{1}{1-\frac{1-\phi_f}{1+\rho}}\right) \tag{B.78}$$

$$= \frac{f_0}{\kappa}\frac{(1-\phi_f)^t}{1+\rho}\left(\frac{1+\rho}{\rho+\phi_f}\right) \tag{B.79}$$

$$= \frac{f_0}{\kappa}\left(\frac{(1-\phi_f)^t}{\rho+\phi_f}\right) \tag{B.80}$$

$$\mathbb{E}_0[p_t] = \frac{(1-\phi_f)^t}{\zeta+\kappa\phi_f}f_0 \tag{B.81}$$

■

Bibliography

F. Allen and D. Gale. Stock-Price Manipulation. *The Review of Financial Studies*, 5(3):503–529, July 1992. ISSN 0893-9454. doi: 10.1093/rfs/5.3.503. URL https://doi.org/10.1093/rfs/5.3.503.

R. Almgren, C. Thum, E. Hauptmann, and H. Li. Direct estimation of equity market impact. *Risk*, 18(7):58–62, 2005. Publisher: Citeseer.

L. Ante. Bitcoin Transactions, Information Asymmetry and Trading Volume, June 2020. URL https://papers.ssrn.com/abstract=3618896.

A. M. Antonopoulos. *Mastering Bitcoin: Programming the Open Blockchain.* "O'Reilly Media, Inc.", June 2017. ISBN 978-1-4919-5436-2. Google-Books-ID: MpwnDwAAQBAJ.

L. S. Bagwell. Dutch Auction Repurchases: An Analysis of Shareholder Heterogeneity. *The Journal of Finance*, 47(1):71–105, 1992. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1992.tb03979.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1992.tb03979.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1992.tb03979.x.

M. Balcilar, E. Bouri, R. Gupta, and D. Roubaud. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64:74–81, Aug. 2017. ISSN 0264-9993. doi: 10.1016/j.econmod.2017.03.019. URL https://www.sciencedirect.com/science/article/pii/S0264999317304558.

N. Barberis, M. Huang, and R. H. Thaler. Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing. *American Economic Review*, 96(4):1069–

1090, Sept. 2006. ISSN 0002-8282. doi: 10.1257/aer.96.4.1069. URL https://www.aeaweb.org/articles?id=10.1257/aer.96.4.1069.

D. G. Baur and T. Dimpfl. Price discovery in bitcoin spot or futures? *Journal of Futures Markets*, 39(7):803–817, 2019. ISSN 1096-9934. doi: 10.1002/fut.22004. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/fut.22004. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/fut.22004.

M. Bedford Taylor. Bitcoin and the age of Bespoke Silicon. In *2013 International Conference on Compilers, Architecture and Synthesis for Embedded Systems (CASES)*, pages 1–10, Sept. 2013. doi: 10.1109/CASES.2013.6662520.

I. Ben-David, F. Franzoni, and R. Moussawi. Do ETFs Increase Volatility? *The Journal of Finance*, 73(6):2471–2535, 2018. ISSN 1540-6261. doi: 10.1111/jofi.12727. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12727. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12727.

I. Ben-David, F. Franzoni, R. Moussawi, and J. Sedunov. The Granular Nature of Large Institutional Investors. *Management Science*, 67(11):6629–6659, Nov. 2021a. ISSN 0025-1909. doi: 10.1287/mnsc.2020.3808. URL https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2020.3808. Publisher: INFORMS.

I. Ben-David, J. Li, A. Rossi, and Y. Song. Ratings-Driven Demand and Systematic Price Fluctuations. SSRN Scholarly Paper 3728056, Social Science Research Network, Rochester, NY, Sept. 2021b. URL https://papers.ssrn.com/abstract=3728056.

A. Ben-Rephael, S. Kandel, and A. Wohl. The Price Pressure of Aggregate Mutual Fund Flows. *Journal of Financial and Quantitative Analysis*, 46(2):585–603, Apr. 2011. ISSN 1756-6916, 0022-1090. doi: 10.1017/S0022109010000797. URL https://www.cambridge.org/core/journals/journal-of-financial-and-quantitative-analysis/article/price-pressure-of-aggregate-mutual-fund-flows/A5EB407ADC6FC5B16714458A21E86F1F. Publisher: Cambridge University Press.

M. Benzaquen and J.-P. Bouchaud. Market impact with multi-timescale liquidity. *Quantitative Finance*, 18(11):1781–1790, Nov. 2018. ISSN 1469-7688. doi: 10.1080/14697688.2018.1444279. URL https://doi.org/10.1080/14697688.2018.1444279. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2018.1444279.

R. Böhme, N. Christin, B. Edelman, and T. Moore. Bitcoin: Economics, Technology, and Governance. *Journal of Economic Perspectives*, 29(2):213–238, May 2015. ISSN 0895-3309. doi: 10.1257/jep.29.2.213. URL https://www.aeaweb.org/articles?id=10.1257/jep.29.2.213.

S. Bikhchandani, D. Hirshleifer, and I. Welch. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100(5):992–1026, Oct. 1992. ISSN 0022-3808. doi: 10.1086/261849. URL https://www.journals.uchicago.edu/doi/abs/10.1086/261849. Publisher: The University of Chicago Press.

F. Black. Noise. *The Journal of Finance*, 41(3):528–543, 1986. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1986.tb04513.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1986.tb04513.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1986.tb04513.x.

A. J. Bladon, E. Moro, and T. Galla. Agent-specific impact of single trades in financial markets. *Physical Review E*, 85(3):036103, Mar. 2012. doi: 10.1103/PhysRevE.85.036103. URL https://link.aps.org/doi/10.1103/PhysRevE.85.036103. Publisher: American Physical Society.

F. Bolici and S. D. Rosa. Mt.Gox Is Dead, Long Live Bitcoin! In T. Torre, A. M. Braccini, and R. Spinelli, editors, *Empowering Organizations*, pages 285–296, Cham, 2016. Springer International Publishing. ISBN 978-3-319-23784-8. doi: 10.1007/978-3-319-23784-8_22.

J.-P. Bouchaud. Crises and Collective Socio-Economic Phenomena: Simple Models and Challenges. *Journal of Statistical Physics*, 151(3):567–606, May 2013. ISSN 1572-9613. doi: 10.1007/s10955-012-0687-3. URL https://doi.org/10.1007/s10955-012-0687-3.

J.-P. Bouchaud. The Inelastic Market Hypothesis: A Microstructural Interpretation. SSRN Scholarly Paper ID 3896981, Social Science Research Network, Rochester, NY, July 2021. URL https://papers.ssrn.com/abstract=3896981.

J.-P. Bouchaud, J. Bonart, J. Donier, and M. Gould. *Trades, Quotes and Prices: Financial Markets Under the Microscope*. Cambridge University Press, Mar. 2018. ISBN 978-1-107-15605-0. Google-Books-ID: u45LDwAAQBAJ.

J. Bouoiyour, R. Selmi, and A. Tiwari. Is Bitcoin business income or speculative bubble? Unconditional vs. conditional frequency domain analysis, Sept. 2014. URL https://mpra.ub.uni-muenchen.de/59595/.

E. Bouri, R. Gupta, A. K. Tiwari, and D. Roubaud. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23:87–95, Nov. 2017a. ISSN 1544-6123. doi: 10.1016/j.frl.2017.02.009. URL https://www.sciencedirect.com/science/article/pii/S1544612317300363.

E. Bouri, P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20:192–198, Feb. 2017b. ISSN 1544-6123. doi: 10.1016/j.frl.2016.09.025. URL https://www.sciencedirect.com/science/article/pii/S1544612316301817.

E. Bouri, X. V. Vo, and T. Saeed. Return equicorrelation in the cryptocurrency market: Analysis and determinants. *Finance Research Letters*, 38:101497, Jan. 2021. ISSN 1544-6123. doi: 10.1016/j.frl.2020.101497. URL https://www.sciencedirect.com/science/article/pii/S1544612320300891.

M. Brandvold, P. Molnár, K. Vagstad, and O. C. Andreas Valstad. Price discovery on Bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money*, 36:18–35, May 2015. ISSN 1042-4431. doi: 10.1016/j.intfin.2015.02.010. URL https://www.sciencedirect.com/science/article/pii/S104244311500027X.

A. Brauneis and R. Mestel. Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*, 165:58–61, Apr. 2018. ISSN 0165-1765. doi: 10.1016/j.econlet.2018.02.001. URL https://www.sciencedirect.com/science/article/pii/S0165176518300417.

J. Brogaard, H. Nguyen, T. J. Putniņš, and E. Wu. What Moves Stock Prices? The Role of

News, Noise, and Information. SSRN Scholarly Paper 3105862, Social Science Research Network, Rochester, NY, Oct. 2021. URL https://papers.ssrn.com/abstract=3105862.

D. C. Brown, S. W. Davies, and M. C. Ringgenberg. ETF Arbitrage, Non-Fundamental Demand, and Return Predictability*. *Review of Finance*, 25(4):937–972, July 2021. ISSN 1572-3097. doi: 10.1093/rof/rfaa027. URL https://doi.org/10.1093/rof/rfaa027.

M. K. Brunnermeier and L. H. Pedersen. Predatory Trading. *The Journal of Finance*, 60(4):1825–1863, 2005. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2005.00781.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2005.00781.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2005.00781.x.

M. K. Brunnermeier and L. H. Pedersen. Market Liquidity and Funding Liquidity. *The Review of Financial Studies*, 22(6):2201–2238, June 2009. ISSN 0893-9454. doi: 10.1093/rfs/hhn098. URL https://doi.org/10.1093/rfs/hhn098.

C. Camerer and K. Weigelt. Information mirages in experimental asset markets. *Journal of Business*, pages 463–493, 1991. Publisher: JSTOR.

J. Y. Campbell and R. J. Shiller. Stock Prices, Earnings, and Expected Dividends. *The Journal of Finance*, 43(3):661–676, 1988. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1988.tb04598.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1988.tb04598.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1988.tb04598.x.

J. Y. Campbell and R. J. Shiller. Valuation ratios and the long-run stock market outlook: An update, 2001.

E.-T. Cheah and J. Fry. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130:32–36, May 2015. ISSN 0165-1765. doi: 10.1016/j.econlet.2015.02.029. URL https://www.sciencedirect.com/science/article/pii/S0165176515000890.

I. Choi. Testing the random walk hypothesis for real exchange rates. *Journal of Applied Econometrics*, 14(3):293–308, 1999. ISSN 1099-1255. doi: 10.1002/(SICI)1099-1255(199905/06)14:

3⟨293::AID-JAE503⟩3.0.CO;2-5. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/%28SICI%291099-1255%28199905/06%2914%3A3%3C293%3A%3AAID-JAE503%3E3.0.CO%3B2-5. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/%28SICI%291099-1255%28199905/06%2914%3A3%3C293%3A%3AAID-JAE503%3E3.0.CO%3B2-5.

P. Ciaian, M. Rajcaniova, and d. Kancs. The digital agenda of virtual currencies: Can BitCoin become a global currency? *Information Systems and e-Business Management*, 14(4):883–919, Nov. 2016a. ISSN 1617-9854. doi: 10.1007/s10257-016-0304-0. URL https://doi.org/10.1007/s10257-016-0304-0.

P. Ciaian, M. Rajcaniova, and d. Kancs. The economics of BitCoin price formation. *Applied Economics*, 48(19):1799–1815, Apr. 2016b. ISSN 0003-6846. doi: 10.1080/00036846.2015.1109038. URL https://doi.org/10.1080/00036846.2015.1109038. Publisher: Routledge _eprint: https://doi.org/10.1080/00036846.2015.1109038.

CME Group Inc. FAQ: CME Bitcoin Futures – CME Group - CME Group, 2020. URL https://www.cmegroup.com/content/cmegroup/en/education/bitcoin/cme-bitcoin-futures-frequently-asked-questions.html.

C. Conrad, A. Custovic, and E. Ghysels. Long- and Short-Term Cryptocurrency Volatility Components: A GARCH-MIDAS Analysis. *Journal of Risk and Financial Management*, 11(2):23, June 2018. ISSN 1911-8074. doi: 10.3390/jrfm11020023. URL https://www.mdpi.com/1911-8074/11/2/23. Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.

J. Coval and E. Stafford. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512, Nov. 2007. ISSN 0304-405X. doi: 10.1016/j.jfineco.2006.09.007. URL https://www.sciencedirect.com/science/article/pii/S0304405X07001158.

D. M. Cutler, J. M. Poterba, and L. H. Summers. What Moves Stock Prices? Working Paper 2538, National Bureau of Economic Research, Mar. 1988. URL https://www.nber.org/papers/w2538. Series: Working Paper Series.

Z. Da, B. Larrain, C. Sialm, and J. Tessada. Destabilizing Financial Advice: Evidence from Pension

Fund Reallocations. *The Review of Financial Studies*, 31(10):3720–3755, Oct. 2018. ISSN 0893-9454. doi: 10.1093/rfs/hhy011. URL https://doi.org/10.1093/rfs/hhy011.

L. Dall'Amico, A. Fosset, J.-P. Bouchaud, and M. Benzaquen. How does latent liquidity get revealed in the limit order book? *Journal of Statistical Mechanics: Theory and Experiment*, 2019(1): 013404, Jan. 2019. ISSN 1742-5468. doi: 10.1088/1742-5468/aaf10e. URL https://doi.org/10.1088/1742-5468/aaf10e. Publisher: IOP Publishing.

G. David, K. Oosterlinck, and A. Szafarz. Art market inefficiency. *Economics Letters*, 121(1): 23–25, Oct. 2013. ISSN 0165-1765. doi: 10.1016/j.econlet.2013.06.033. URL https://www.sciencedirect.com/science/article/pii/S0165176513003157.

X. Dong, N. Kang, and J. Peress. Fast and Slow Arbitrage: The Predictive Power of Capital Flows for Factor Returns. SSRN Scholarly Paper 3675163, Social Science Research Network, Rochester, NY, Mar. 2022. URL https://papers.ssrn.com/abstract=3675163.

J. Donier and J. Bonart. A Million Metaorder Analysis of Market Impact on the Bitcoin. *Market Microstructure and Liquidity*, 01(02):1550008, Dec. 2015. ISSN 2382-6266. doi: 10.1142/S2382626615500082. URL https://www.worldscientific.com/doi/abs/10.1142/S2382626615500082. Publisher: World Scientific Publishing Co.

J. Donier and J.-P. Bouchaud. Why do markets crash? Bitcoin data offers unprecedented insights. *PloS one*, 10(10):e0139356, 2015. Publisher: Public Library of Science San Francisco, CA USA.

K. Dowd. New Private Monies: A Bit-Part Player? SSRN Scholarly Paper ID 2535299, Social Science Research Network, Rochester, NY, June 2014. URL https://papers.ssrn.com/abstract=2535299.

G. P. Dwyer. The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17:81–91, Apr. 2015. ISSN 1572-3089. doi: 10.1016/j.jfs.2014.11.006. URL https://www.sciencedirect.com/science/article/pii/S1572308914001259.

A. H. Dyhrberg. Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research*

Letters, 16:85–92, Feb. 2016. ISSN 1544-6123. doi: 10.1016/j.frl.2015.10.008. URL https://www.sciencedirect.com/science/article/pii/S1544612315001038.

R. M. Edelen. Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics*, 53(3):439–466, Sept. 1999. ISSN 0304-405X. doi: 10.1016/S0304-405X(99)00028-8. URL https://www.sciencedirect.com/science/article/pii/S0304405X99000288.

A. Edmans, I. Goldstein, and W. Jiang. The Real Effects of Financial Markets: The Impact of Prices on Takeovers. *The Journal of Finance*, 67(3):933–971, 2012. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2012.01738.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2012.01738.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2012.01738.x.

G. Elliott, T. J. Rothenberg, and J. H. Stock. Efficient Tests for an Autoregressive Unit Root. *Econometrica*, 64(4):813–836, 1996. URL https://ideas.repec.org/a/ecm/emetrp/v64y1996i4p813-36.html. Publisher: Econometric Society.

R. F. Engle, T. Ito, and W.-L. Lin. Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market. Working Paper 2609, National Bureau of Economic Research, June 1988. URL https://www.nber.org/papers/w2609. Series: Working Paper Series.

O. Entrop, B. Frijns, and M. Seruset. The determinants of price discovery on bitcoin markets. *Journal of Futures Markets*, 40(5):816–837, 2020. ISSN 1096-9934. doi: 10.1002/fut.22101. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/fut.22101. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/fut.22101.

E. F. Fama. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2):383–417, 1970. ISSN 0022-1082. doi: 10.2307/2325486. URL https://www.jstor.org/stable/2325486. Publisher: [American Finance Association, Wiley].

E. F. Fama and K. R. French. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 47(2):427–465, 1992. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1992.tb04398.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1992.tb04398.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1992.tb04398.x.

L. Fang, E. Bouri, R. Gupta, and D. Roubaud. Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *International Review of Financial Analysis*, 61:29–36, Jan. 2019. ISSN 1057-5219. doi: 10.1016/j.irfa.2018.12.010. URL `https://www.sciencedirect.com/science/article/pii/S1057521918306495`.

P. H. Franses. Moving average filters and unit roots. *Economics Letters*, 37(4):399–403, Dec. 1991. ISSN 0165-1765. doi: 10.1016/0165-1765(91)90077-X. URL `https://www.sciencedirect.com/science/article/pii/016517659190077X`.

A. Frazzini and O. A. Lamont. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, 88(2):299–322, May 2008. ISSN 0304-405X. doi: 10.1016/j.jfineco.2007.07.001. URL `https://www.sciencedirect.com/science/article/pii/S0304405X08000184`.

A. Frazzini, R. Israel, and T. J. Moskowitz. Trading Costs. SSRN Scholarly Paper ID 3229719, Social Science Research Network, Rochester, NY, Apr. 2018. URL `https://papers.ssrn.com/abstract=3229719`.

B. S. Frey and R. Eichenberger. On the rate of return in the art market: Survey and evaluation. *European Economic Review*, 39(3):528–537, Apr. 1995. ISSN 0014-2921. doi: 10.1016/0014-2921(94)00059-9. URL `https://www.sciencedirect.com/science/article/pii/0014292194000599`.

D. Friedman and M. Aoki. Inefficient Information Aggregation as a Source of Asset Price Bubbles. *Bulletin of Economic Research*, 44(4):251–279, 1992. ISSN 1467-8586. doi: 10.1111/j.1467-8586.1992.tb00547.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8586.1992.tb00547.x`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-8586.1992.tb00547.x.

M. Friedman. *The Optimum Quantity Of Money*. Transaction Publishers, Jan. 2005. ISBN 978-1-4128-3809-2. Google-Books-ID: DZ9OTS6LbEcC.

X. Gabaix and R. S. J. Koijen. Granular Instrumental Variables, Dec. 2020. URL `https://www.nber.org/papers/w28204`.

X. Gabaix and R. S. J. Koijen. In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis. Working Paper 28967, National Bureau of Economic Research, June 2021. URL `https://www.nber.org/papers/w28967`. Series: Working Paper Series.

X. Gabaix, P. Gopikrishnan, V. Plerou, and H. E. Stanley. A theory of power-law distributions in financial market fluctuations. *Nature*, 423(6937):267–270, May 2003. ISSN 1476-4687. doi: 10.1038/nature01624. URL `https://www.nature.com/articles/nature01624`. Number: 6937 Publisher: Nature Publishing Group.

X. Gabaix, P. Gopikrishnan, V. Plerou, and H. E. Stanley. Institutional Investors and Stock Market Volatility. *The Quarterly Journal of Economics*, 121(2):461–504, May 2006. ISSN 0033-5533. doi: 10.1162/qjec.2006.121.2.461. URL `https://doi.org/10.1162/qjec.2006.121.2.461`.

N. Gandal and H. Halaburda. Can We Predict the Winner in a Market with Network Effects? Competition in Cryptocurrency Market. *Games*, 7(3):16, Sept. 2016. ISSN 2073-4336. doi: 10.3390/g7030016. URL `https://www.mdpi.com/2073-4336/7/3/16`. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

N. Gandal, J. Hamrick, T. Moore, and T. Oberman. Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, 95:86–96, May 2018. ISSN 0304-3932. doi: 10.1016/j.jmoneco.2017.12.004. URL `https://www.sciencedirect.com/science/article/pii/S0304393217301666`.

D. Garcia, C. J. Tessone, P. Mavrodiev, and N. Perony. The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy. *Journal of The Royal Society Interface*, 11 (99):20140623, Oct. 2014. doi: 10.1098/rsif.2014.0623. URL `https://royalsocietypublishing.org/doi/full/10.1098/rsif.2014.0623`. Publisher: Royal Society.

J. C. Gerlach, G. Demos, and D. Sornette. Dissection of Bitcoin's multiscale bubble history from January 2012 to February 2018. *Royal Society Open Science*, 6(7):180643, June 2019. doi: 10.1098/rsos.180643. URL `https://royalsocietypublishing.org/doi/full/10.1098/rsos.180643`. Publisher: Royal Society.

F. Glaser, K. Zimmermann, M. Haferkorn, M. C. Weber, and M. Siering. Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions. SSRN Scholarly Paper ID 2425247, Social Science Research Network, Rochester, NY, Apr. 2014. URL https://papers.ssrn.com/abstract=2425247.

C. Gomes and H. Waelbroeck. Is market impact a measure of the information value of trades? Market response to liquidity vs. informed metaorders. *Quantitative Finance*, 15(5):773–793, May 2015. ISSN 1469-7688. doi: 10.1080/14697688.2014.963140. URL https://doi.org/10.1080/14697688.2014.963140. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2014.963140.

A. Greenspan. *The Challenge of Central Banking in a Democratic Society: Remarks by Alan Greenspan, Chairman, Board of Governors of the Federal Reserve System at the Annual Dinner and Francis Boyer Lecture of the American Enterprise Institute for Public Policy Research, Washington, DC, December 5, 1996.* Board of Governors of the Federal Reserve System, 1996.

R. Greenwood and D. Thesmar. Stock price fragility. *Journal of Financial Economics*, 102(3): 471–490, Dec. 2011. ISSN 0304-405X. doi: 10.1016/j.jfineco.2011.06.003. URL https://www.sciencedirect.com/science/article/pii/S0304405X11001474.

M. Gronwald. Is Bitcoin a Commodity? On price jumps, demand shocks, and certainty of supply. *Journal of International Money and Finance*, 97:86–92, Oct. 2019. ISSN 0261-5606. doi: 10.1016/j.jimonfin.2019.06.006. URL https://www.sciencedirect.com/science/article/pii/S0261560619303547.

S. J. Grossman and J. E. Stiglitz. Information and Competitive Price Systems. *The American Economic Review*, 66(2):246–253, 1976. ISSN 0002-8282. URL https://www.jstor.org/stable/1817229. Publisher: American Economic Association.

S. J. Grossman and J. E. Stiglitz. On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, 70(3):393–408, 1980. ISSN 0002-8282. URL https://www.jstor.org/stable/1805228. Publisher: American Economic Association.

V. Haddad, P. Huebner, and E. Loualiche. How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing. SSRN Scholarly Paper 3821263, Social Science Research Network, Rochester, NY, Apr. 2021. URL https://papers.ssrn.com/abstract=3821263.

N. H. Hakansson, J. G. Kunkel, and J. A. Ohlson. Sufficient and Necessary Conditions for Information to have Social Value in Pure Exchange. *The Journal of Finance*, 37(5):1169–1181, 1982. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1982.tb03610.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1982.tb03610.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1982.tb03610.x.

J. T. Hamrick, F. Rouhi, A. Mukherjee, A. Feder, N. Gandal, T. Moore, and M. Vasek. The Economics of Cryptocurrency Pump and Dump Schemes. SSRN Scholarly Paper ID 3310307, Social Science Research Network, Rochester, NY, Dec. 2018. URL https://papers.ssrn.com/abstract=3310307.

J. Hasbrouck. *Empirical Market Microstructure: The Institutions, Economics, and Econometrics of Securities Trading*. Oxford University Press, Jan. 2007. ISBN 978-0-19-804130-6. Google-Books-ID: aaReNv846eMC.

B. Haslhofer, R. Stütz, M. Romiti, and R. King. GraphSense: A General-Purpose Cryptoasset Analytics Platform. *arXiv:2102.13613 [cs]*, Feb. 2021. URL http://arxiv.org/abs/2102.13613. arXiv: 2102.13613.

L. S. Hodrick. Does stock price elasticity affect corporate financial decisions? *Journal of Financial Economics*, 52(2):225–256, May 1999. ISSN 0304-405X. doi: 10.1016/S0304-405X(99)00009-4. URL https://www.sciencedirect.com/science/article/pii/S0304405X99000094.

C. Hommes, J. Sonnemans, J. Tuinstra, and H. van de Velden. Coordination of Expectations in Asset Pricing Experiments. *The Review of Financial Studies*, 18(3):955–980, Oct. 2005. ISSN 0893-9454. doi: 10.1093/rfs/hhi003. URL https://doi.org/10.1093/rfs/hhi003.

S. Huang, Y. Song, and H. Xiang. Noise Trading and Asset Pricing Factors. SSRN Scholarly Paper 3359356, Social Science Research Network, Rochester, NY, Nov. 2019. URL https://papers.ssrn.com/abstract=3359356.

Y. C. Huang and Y. J. Cheng. Stock manipulation and its effects: pump and dump versus stabilization. *Review of Quantitative Finance and Accounting*, 44(4):791–815, May 2015. ISSN 1573-7179. doi: 10.1007/s11156-013-0419-z. URL https://doi.org/10.1007/s11156-013-0419-z.

T. A. Huber and D. Sornette. Boom, Bust, and Bitcoin: Bitcoin-Bubbles as Innovation Accelerators. *Journal of Economic Issues*, 56(1):113–136, Jan. 2022. ISSN 0021-3624. doi: 10.1080/00213624.2022.2020023. URL https://doi.org/10.1080/00213624.2022.2020023. Publisher: Routledge _eprint: https://doi.org/10.1080/00213624.2022.2020023.

J. F. Jaffe and R. L. Winkler. Optimal Speculation Against an Efficient Market. *The Journal of Finance*, 31(1):49–61, 1976. ISSN 0022-1082. doi: 10.2307/2326394. URL https://www.jstor.org/stable/2326394. Publisher: [American Finance Association, Wiley].

Q. Ji, E. Bouri, L. Kristoufek, and B. Lucey. Realised volatility connectedness among Bitcoin exchange markets. *Finance Research Letters*, 38:101391, Jan. 2021. ISSN 1544-6123. doi: 10.1016/j.frl.2019.101391. URL https://www.sciencedirect.com/science/article/pii/S1544612319310773.

J. Kaminski. Nowcasting the Bitcoin Market with Twitter Signals. *arXiv:1406.7577 [cs]*, Jan. 2016. URL http://arxiv.org/abs/1406.7577. arXiv: 1406.7577.

B. Kapar and J. Olmo. An analysis of price discovery between Bitcoin futures and spot markets. *Economics Letters*, 174:62–64, Jan. 2019. ISSN 0165-1765. doi: 10.1016/j.econlet.2018.10.031. URL https://www.sciencedirect.com/science/article/pii/S0165176518304440.

G. Köchling, J. Müller, and P. N. Posch. Does the introduction of futures improve the efficiency of Bitcoin? *Finance Research Letters*, 30:367–370, Sept. 2019. ISSN 1544-6123. doi: 10.1016/j.frl.2018.11.006. URL https://www.sciencedirect.com/science/article/pii/S1544612318304124.

J. M. Keynes. General Theory of Employment, Interest and Money, 1936.

F. Kjærland, M. Meland, A. Oust, and V. Øyen. How can Bitcoin Price Fluctuations be Explained? *323-332*, 2018. ISSN 2146-4138. URL https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2500190. Accepted: 2018-06-04T12:42:31Z Publisher: EconJournals.

N. R. Kocherlakota. Money Is Memory. *Journal of Economic Theory*, 81(2):232–251, Aug. 1998. ISSN 0022-0531. doi: 10.1006/jeth.1997.2357. URL `https://www.sciencedirect.com/science/article/pii/S0022053197923577`.

R. Koenker and G. Bassett. Regression Quantiles. *Econometrica*, 46(1):33–50, 1978. ISSN 0012-9682. doi: 10.2307/1913643. URL `https://www.jstor.org/stable/1913643`. Publisher: [Wiley, Econometric Society].

R. S. J. Koijen and M. Yogo. A Demand System Approach to Asset Pricing. *Journal of Political Economy*, 127(4):1475–1515, Aug. 2019. ISSN 0022-3808. doi: 10.1086/701683. URL `https://www.journals.uchicago.edu/doi/full/10.1086/701683`. Publisher: The University of Chicago Press.

S. Kozak, S. Nagel, and S. Santosh. Interpreting Factor Models. *The Journal of Finance*, 73(3):1183–1223, 2018. ISSN 1540-6261. doi: 10.1111/jofi.12612. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12612`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12612.

L. Kristoufek. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLOS ONE*, 10(4):e0123923, Apr. 2015. ISSN 1932-6203. doi: 10.1371/journal.pone.0123923. URL `https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0123923`. Publisher: Public Library of Science.

L. Kristoufek. On Bitcoin markets (in)efficiency and its evolution. *Physica A: Statistical Mechanics and its Applications*, 503:257–262, Aug. 2018. ISSN 0378-4371. doi: 10.1016/j.physa.2018.02.161. URL `https://www.sciencedirect.com/science/article/pii/S0378437118302413`.

D. Kwiatkowski, P. C. B. Phillips, P. Schmidt, and Y. Shin. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54(1):159–178, Oct. 1992. ISSN 0304-4076. doi: 10.1016/0304-4076(92)90104-Y. URL `https://www.sciencedirect.com/science/article/pii/030440769290104Y`.

A. S. Kyle. Continuous Auctions and Insider Trading. *Econometrica*, 53(6):1315–1335, 1985. ISSN

0012-9682. doi: 10.2307/1913210. URL https://www.jstor.org/stable/1913210. Publisher: [Wiley, Econometric Society].

A. S. Kyle. Informed Speculation with Imperfect Competition. *The Review of Economic Studies*, 56(3):317–355, July 1989. ISSN 0034-6527. doi: 10.2307/2297551. URL https://doi.org/10.2307/2297551.

A. S. Kyle and S. Viswanathan. How to Define Illegal Price Manipulation. *American Economic Review*, 98(2):274–279, May 2008. ISSN 0002-8282. doi: 10.1257/aer.98.2.274. URL https://www.aeaweb.org/articles?id=10.1257/aer.98.2.274.

E. J. Levin and R. E. Wright. Estimating the price elasticity of demand in the London stock market. *The European Journal of Finance*, 8(2):222–237, June 2002. ISSN 1351-847X. doi: 10.1080/13518470110071218. URL https://doi.org/10.1080/13518470110071218. Publisher: Routledge _eprint: https://doi.org/10.1080/13518470110071218.

J. Li. What Drives the Size and Value Factors? SSRN Scholarly Paper 2909960, Social Science Research Network, Rochester, NY, June 2021. URL https://papers.ssrn.com/abstract=2909960.

J. J. Li, N. D. Pearson, and Q. Zhang. Impact of Demand Shocks on the Stock Market: Evidence from Chinese IPOs. SSRN Scholarly Paper ID 3731219, Social Science Research Network, Rochester, NY, Dec. 2021. URL https://papers.ssrn.com/abstract=3731219.

J.-H. Lin, K. Primicerio, T. Squartini, C. Decker, and C. J. Tessone. Lightning network: a second path towards centralisation of the Bitcoin economy. *New Journal of Physics*, 22(8):083022, Aug. 2020. ISSN 1367-2630. doi: 10.1088/1367-2630/aba062. URL https://doi.org/10.1088/1367-2630/aba062. Publisher: IOP Publishing.

G. M. Ljung and G. E. P. Box. On a measure of lack of fit in time series models. *Biometrika*, 65(2): 297–303, Aug. 1978. ISSN 0006-3444. doi: 10.1093/biomet/65.2.297. URL https://doi.org/10.1093/biomet/65.2.297.

A. W. Lo. The Adaptive Markets Hypothesis. *The Journal of Portfolio Management*, 30(5): 15–29, Aug. 2004. ISSN 0095-4918, 2168-8656. doi: 10.3905/jpm.2004.442611. URL https:

//jpm.pm-research.com/content/30/5/15. Publisher: Institutional Investor Journals Umbrella Section: Primary Article.

A. W. Lo. Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis. SSRN Scholarly Paper ID 1702447, Social Science Research Network, Rochester, NY, 2005. URL https://papers.ssrn.com/abstract=1702447.

C. Loderer, J. W. Cooney, and L. D. Van Drunen. The Price Elasticity of Demand for Common Stock. *The Journal of Finance*, 46(2):621–651, 1991. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1991.tb02677.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1991.tb02677.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1991.tb02677.x.

D. Lou. A Flow-Based Explanation for Return Predictability. *The Review of Financial Studies*, 25 (12):3457–3489, Dec. 2012. ISSN 0893-9454. doi: 10.1093/rfs/hhs103. URL https://doi.org/10.1093/rfs/hhs103.

D. Lou, C. Polk, and S. Skouras. A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, 134(1):192–213, Oct. 2019. ISSN 0304-405X. doi: 10.1016/j.jfineco.2019.03.011. URL https://www.sciencedirect.com/science/article/pii/S0304405X19300650.

W. J. Luther and J. Olson. Bitcoin is Memory. SSRN Scholarly Paper ID 2275730, Social Science Research Network, Rochester, NY, June 2013. URL https://papers.ssrn.com/abstract=2275730.

A. W. Lynch and R. R. Mendenhall. New Evidence on Stock Price Effects Associated with Changes in the S&P 500 Index. *The Journal of Business*, 70(3):351–383, 1997. ISSN 0021-9398. doi: 10.1086/209722. URL https://www.jstor.org/stable/10.1086/209722. Publisher: The University of Chicago Press.

M. Lynn. Scarcity effects on value: A quantitative review of the commodity theory literature. *Psychology & Marketing*, 8(1):43–57, 1991. ISSN 1520-6793. doi: 10.1002/mar.4220080105. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/mar.4220080105. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/mar.4220080105.

F. Mai, Q. Bai, J. Shan, X. S. Wang, and R. H. Chiang. The impacts of social media on Bitcoin performance. 2015.

R. Marimon, J. P. Nicolini, and P. Teles. Money is an experience good: Competition and trust in the private provision of money. *Journal of Monetary Economics*, 59(8):815–825, Dec. 2012. ISSN 0304-3932. doi: 10.1016/j.jmoneco.2012.10.006. URL `https://www.sciencedirect.com/science/article/pii/S0304393212001110`.

A. McWilliams and D. Siegel. Event Studies In Management Research: Theoretical And Empirical Issues. *Academy of Management Journal*, 40(3):626–657, June 1997. ISSN 0001-4273. doi: 10.5465/257056. URL `https://journals.aom.org/doi/abs/10.5465/257056`. Publisher: Academy of Management.

A. McWilliams, D. Siegel, and S. H. Teoh. Issues in the Use of the Event Study Methodology: A Critical Analysis of Corporate Social Responsibility Studies. *Organizational Research Methods*, 2(4):340–365, Oct. 1999. ISSN 1094-4281. doi: 10.1177/109442819924002. URL `https://doi.org/10.1177/109442819924002`. Publisher: SAGE Publications Inc.

S. Meiklejohn, M. Pomarole, G. Jordan, K. Levchenko, D. McCoy, G. M. Voelker, and S. Savage. A fistful of bitcoins: characterizing payments among men with no names. In *Proceedings of the 2013 conference on Internet measurement conference*, IMC '13, pages 127–140, New York, NY, USA, Oct. 2013. Association for Computing Machinery. ISBN 978-1-4503-1953-9. doi: 10.1145/2504730.2504747. URL `https://doi.org/10.1145/2504730.2504747`.

P. Milgrom and N. Stokey. Information, trade and common knowledge. *Journal of Economic Theory*, 26(1):17–27, Feb. 1982. ISSN 0022-0531. doi: 10.1016/0022-0531(82)90046-1. URL `https://www.sciencedirect.com/science/article/pii/0022053182900461`.

T. Moore and N. Christin. Beware the Middleman: Empirical Analysis of Bitcoin-Exchange Risk. In A.-R. Sadeghi, editor, *Financial Cryptography and Data Security*, pages 25–33, Berlin, Heidelberg, 2013. Springer. ISBN 978-3-642-39884-1. doi: 10.1007/978-3-642-39884-1_3.

M. Möser and R. Böhme. Join me on a market for anonymity. In *Workshop on Privacy in the Electronic Society*, 2016.

S. Nakamoto. Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, page 21260, 2008.

W. K. Newey and K. D. West. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708, 1987. ISSN 0012-9682. doi: 10.2307/1913610. URL https://www.jstor.org/stable/1913610. Publisher: [Wiley, Econometric Society].

K. G. Nyborg and P. Östberg. Money and liquidity in financial markets. *Journal of Financial Economics*, 112(1):30–52, Apr. 2014. ISSN 0304-405X. doi: 10.1016/j.jfineco.2013.12.003. URL https://www.sciencedirect.com/science/article/pii/S0304405X13003036.

T. Odean. Do Investors Trade Too Much? *American Economic Review*, 89(5):1279–1298, Dec. 1999. ISSN 0002-8282. doi: 10.1257/aer.89.5.1279. URL https://www.aeaweb.org/articles?id=10.1257/aer.89.5.1279.

N. Olekalns. Does seasonal adjustment distort tests of stationarity? Some small-sample evidence. *Applied Financial Economics*, 6(6):531–534, Dec. 1996. ISSN 0960-3107. doi: 10.1080/096031096333980. URL https://doi.org/10.1080/096031096333980. Publisher: Routledge _eprint: https://doi.org/10.1080/096031096333980.

J. A. Parker, A. Schoar, and Y. Sun. Retail Financial Innovation and Stock Market Dynamics: The Case of Target Date Funds. Working Paper 28028, National Bureau of Economic Research, Oct. 2020. URL https://www.nber.org/papers/w28028. Series: Working Paper Series.

A. Phillip, J. S. K. Chan, and S. Peiris. A new look at Cryptocurrencies. *Economics Letters*, 163:6–9, Feb. 2018. ISSN 0165-1765. doi: 10.1016/j.econlet.2017.11.020. URL https://www.sciencedirect.com/science/article/pii/S0165176517304731.

J. Poon and T. Dryja. The Bitcoin Lightning Network:. page 59, Jan. 2016.

T. Preis, H. S. Moat, and H. E. Stanley. Quantifying Trading Behavior in Financial Markets Using Google Trends. *Scientific Reports*, 3(1):1684, Apr. 2013. ISSN 2045-2322. doi: 10.1038/srep01684.

URL https://www.nature.com/articles/srep01684. Number: 1 Publisher: Nature Publishing Group.

D. Ron and A. Shamir. Quantitative Analysis of the Full Bitcoin Transaction Graph. In A.-R. Sadeghi, editor, *Financial Cryptography and Data Security*, pages 6–24, Berlin, Heidelberg, 2013. Springer. ISBN 978-3-642-39884-1. doi: 10.1007/978-3-642-39884-1_2.

D. Ron and A. Shamir. How Did Dread Pirate Roberts Acquire and Protect his Bitcoin Wealth? In R. Böhme, M. Brenner, T. Moore, and M. Smith, editors, *Financial Cryptography and Data Security*, pages 3–15, Berlin, Heidelberg, 2014. Springer. ISBN 978-3-662-44774-1. doi: 10.1007/978-3-662-44774-1_1.

M. Rubinstein. Securities Market Efficiency in an Arrow-Debreu Economy. *The American Economic Review*, 65(5):812–824, 1975. ISSN 0002-8282. URL https://www.jstor.org/stable/1806622. Publisher: American Economic Association.

S. Seabold and J. Perktold. Statsmodels: Econometric and Statistical Modeling with Python. pages 92–96, Austin, Texas, 2010. doi: 10.25080/Majora-92bf1922-011. URL https://conference.scipy.org/proceedings/scipy2010/seabold.html.

G. Selgin. Synthetic commodity money. *Journal of Financial Stability*, 17:92–99, Apr. 2015. ISSN 1572-3089. doi: 10.1016/j.jfs.2014.07.002. URL https://www.sciencedirect.com/science/article/pii/S1572308914000722.

R. Senner and D. Sornette. The Holy Grail of Crypto Currencies: Ready to Replace Fiat Money? *Journal of Economic Issues*, 53(4):966–1000, Oct. 2019. ISSN 0021-3624. doi: 10.1080/00213624.2019.1664235. URL https://doi.org/10.1080/00213624.2019.1664235. Publisher: Routledge _eprint: https://doi.org/10.1080/00213624.2019.1664235.

K. Sheppard, S. Khrapov, G. Lipták, mikedeltalima, R. Capellini, alejandro cermeno, Hugle, esvhd, S. bot, A. Fortin, JPN, M. Judell, W. Li, A. Adams, jbrockmendel, M. Rabba, M. E. Rose, N. Tretyak, T. Rochette, U. N. O. Leo, X. RENE-CORAIL, X. Du, and syncoding. bashtage/arch: Release 5.2.0, Mar. 2022. URL https://zenodo.org/record/6400724/export/hx.

R. J. Shiller. Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? Working Paper 456, National Bureau of Economic Research, Feb. 1980. URL `https://www.nber.org/papers/w0456`. Series: Working Paper Series.

R. J. Shiller. Speculative Asset Prices. *American Economic Review*, 104(6):1486–1517, June 2014. ISSN 0002-8282. doi: 10.1257/aer.104.6.1486. URL `https://www.aeaweb.org/articles?id=10.1257/aer.104.6.1486`.

R. J. Shiller, S. Fischer, and B. M. Friedman. Stock Prices and Social Dynamics. *Brookings Papers on Economic Activity*, 1984(2):457–510, 1984. ISSN 0007-2303. doi: 10.2307/2534436. URL `https://www.jstor.org/stable/2534436`. Publisher: Brookings Institution Press.

A. Shleifer. Do Demand Curves for Stocks Slope Down? *The Journal of Finance*, 41(3):579–590, 1986. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1986.tb04518.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1986.tb04518.x`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1986.tb04518.x.

A. Shleifer and R. W. Vishny. The Limits of Arbitrage. *The Journal of Finance*, 52(1):35–55, 1997. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1997.tb03807.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1997.tb03807.x`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1997.tb03807.x.

M. Shubik. The Dollar Auction game: a paradox in noncooperative behavior and escalation. *Journal of Conflict Resolution*, 15(1):109–111, Mar. 1971. ISSN 0022-0027. doi: 10.1177/002200277101500111. URL `https://doi.org/10.1177/002200277101500111`. Publisher: SAGE Publications Inc.

V. L. Smith, G. L. Suchanek, and A. W. Williams. Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets. *Econometrica*, 56(5):1119–1151, 1988. ISSN 0012-9682. doi: 10.2307/1911361. URL `https://www.jstor.org/stable/1911361`. Publisher: [Wiley, Econometric Society].

D. Sornette. A complex system view of why stock markets crash. *New Thesis*, 1(1):5–18, 2004.

J. H. Stock and M. W. Watson. *Introduction to Econometrics.* Pearson, Sept. 2014. ISBN 978-1-292-07131-2. Google-Books-ID: _57soAEACAAJ.

R. Stütz, P. Gaži, B. Haslhofer, and J. Illum. Stake Shift in Major Cryptocurrencies: An Empirical Study. *arXiv:2001.04187 [cs]*, 12059:97–113, 2020. doi: 10.1007/978-3-030-51280-4_7. URL http://arxiv.org/abs/2001.04187. arXiv: 2001.04187.

B. Tóth, Y. Lempérière, C. Deremble, J. de Lataillade, J. Kockelkoren, and J.-P. Bouchaud. Anomalous Price Impact and the Critical Nature of Liquidity in Financial Markets. *Physical Review X*, 1(2):021006, Oct. 2011. doi: 10.1103/PhysRevX.1.021006. URL https://link.aps.org/doi/10.1103/PhysRevX.1.021006. Publisher: American Physical Society.

B. Tóth, Z. Eisler, F. Lillo, J. Kockelkoren, J.-P. Bouchaud, and J. Farmer. How does the market react to your order flow? *Quantitative Finance*, 12(7):1015–1024, July 2012. ISSN 1469-7688. doi: 10.1080/14697688.2012.690886. URL https://doi.org/10.1080/14697688.2012.690886. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2012.690886.

B. Tóth, Z. Eisler, and J.-P. Bouchaud. The Square-Root Impace Law Also Holds for Option Markets. *Wilmott*, 2016(85):70–73, 2016. ISSN 1541-8286. doi: 10.1002/wilm.10537. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/wilm.10537. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wilm.10537.

J. W. Tukey. *Exploratory data analysis*, volume 2. Reading, MA, 1977.

A. Urquhart. The inefficiency of Bitcoin. *Economics Letters*, 148:80–82, Nov. 2016. ISSN 0165-1765. doi: 10.1016/j.econlet.2016.09.019. URL https://www.sciencedirect.com/science/article/pii/S0165176516303640.

A. Urquhart. How predictable are precious metal returns? *The European Journal of Finance*, 23(14):1390–1413, Nov. 2017. ISSN 1351-847X. doi: 10.1080/1351847X.2016.1204334. URL https://doi.org/10.1080/1351847X.2016.1204334. Publisher: Routledge _eprint: https://doi.org/10.1080/1351847X.2016.1204334.

D. Vayanos and P. Woolley. An Institutional Theory of Momentum and Reversal. *The Review of Financial Studies*, 26(5):1087–1145, May 2013. ISSN 0893-9454. doi: 10.1093/rfs/hht014. URL `https://doi.org/10.1093/rfs/hht014`.

R. E. Verrecchia. Information Acquisition in a Noisy Rational Expectations Economy. *Econometrica*, 50(6):1415–1430, 1982. ISSN 0012-9682. doi: 10.2307/1913389. URL `https://www.jstor.org/stable/1913389`. Publisher: [Wiley, Econometric Society].

T. Walther, T. Klein, and E. Bouri. Exogenous drivers of Bitcoin and Cryptocurrency volatility – A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money*, 63:101133, Nov. 2019. ISSN 1042-4431. doi: 10.1016/j.intfin.2019.101133. URL `https://www.sciencedirect.com/science/article/pii/S1042443119302446`.

S. Wheatley, D. Sornette, T. Huber, M. Reppen, and R. N. Gantner. Are Bitcoin bubbles predictable? Combining a generalized Metcalfe's Law and the Log-Periodic Power Law Singularity model. *Royal Society Open Science*, 6(6):180538, May 2019. doi: 10.1098/rsos.180538. URL `https://royalsocietypublishing.org/doi/full/10.1098/rsos.180538`. Publisher: Royal Society.

D. Yermack. Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal. In D. Lee Kuo Chuen, editor, *Handbook of Digital Currency*, pages 31–43. Academic Press, San Diego, Jan. 2015. ISBN 978-0-12-802117-0. doi: 10.1016/B978-0-12-802117-0.00002-3. URL `https://www.sciencedirect.com/science/article/pii/B9780128021170000023`.

Eidesstattliche Erklärung

Der/Die Verfasser/in erklärt an Eides statt, dass er/sie die vorliegende Arbeit selbständig, ohne fremde Hilfe und ohne Benutzung anderer als die angegebenen Hilfsmittel angefertigt hat. Die aus fremden Quellen (einschliesslich elektronischer Quellen) direkt oder indirekt übernommenen Gedanken sind ausnahmslos als solche kenntlich gemacht. Die Arbeit ist in gleicher oder ähnlicher Form oder auszugsweise im Rahmen einer anderen Prüfung noch nicht vorgelegt worden.

31.7.2022

Ort, Datum

Unterschrift des/der Verfassers/in