Digital Finance

Determinants of Liquidity in Cryptocurrency Markets

--Manuscript Draft--

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Abstract:	This research identified predictors of cryptocurrency liquidity and explored whether cryptocurrency is a true cash equivalent. Liquidity is important because cryptocurrencies aim to be cash substitutes, and thus totally liquid. Greater liquidity is correlated with more profitable trading, better price discovery; and more profitable market operation. The research tested five hypotheses concerning liquidity and its predictors, for a set of cryptocurrencies that represent ~90% of volume and market capitalization, thus are generalizable. Price was strongly supported as a predictor of liquidity, while volume was not. Fungibility, in the sense of ‘mutual interchangeability of particular pairs of cryptocurrencies, was not found to be a good predictor of liquidity, leading us to question whether cryptocurrencies can truly be considered ’cash equivalents.’ I also tested whether price and volume embedded in own-price elasticity was a predictor of liquidity, and rejected this hypotheses. Finally, an analysis involving step-wise regression unambiguously selected a combination (3) daily volume, and (4) own-price elasticity. Explanatory power was slightly better than other predictors, but lacking a structural model incorporating these predictors, the results here are suggestive of future research studies, and potential blockchain; electronic markets; liquidity_
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Author Comments:	PLEASE NOTE THAT A FORMATED PDF VERSION OF THESE RESPONSES WERE UPLOADED WITH THE REVISED MANUSCRIPT. THESE SHOULD BE EASIER TO READ THAN THIS TEXT VERSION. Resonse to Reviewers’ Comments on DFIN-D-21-00035 J. Christopher Westland 2022-07-30 Reviewer comments It was a pleasure reading your work from the point of view of the topic and the methodological development. But the paper is far from being publishable. It is written in a very unclear

	and negligent style, which does not make it suitable for publication. Please carefully address all the observations below in order to treat the problems in this manuscript. Read scientific articles in the field, see their structures, and apply this to your manuscript. Hereinafter are more precise observations. Additionally, when you submit a manuscript, you have the possibility to check and only afterwards approve the submission. Thank you for the kind words. I was very pleased with this reviewers suggestions, which I feel are very accu- rate. On rereading my paper after several months, I see these points to be valid and important suggestions to improving the paper and making it more accessible to readers. I have done my best on this revision of the paper, to create a revised manuscript that will rectify the weaknesses that this reviewer has identified. The abstract is clear regarding the aims, key methods and important findings but more attention to the ending phrase, it is ambiguous and doesn't have correct ending. This may imply that the abstract was too long and the submission platform has considered only the part satisfying the official limits. I agree with you on re-reading my own paper after a year. I have now completely rewritten this. Too many highlights - there are usually 3 to 5 catchy ideas, not a summary of the research. Additionally, highlights are usually short statements, of maximum 85 - 100 characters, including spaces. 1I concur with the reviewers observation and have reduced this list to four (4) short 'highlights' that more correctly meet the objectives of summarizing important aspects of the research. The author tries to summarize the current state of the topic and limitations of knowledge in the field but the ideas are spread and not very concise. I have made this section more concise. I've removed material that was informative but not directly related to the research, its motivation and its conclusions. It is not very clear what the author wants to communicate regarding the problem statement and research objectives. Yes, it does states that it intends to test several predictors for liquidity on cryptocurrency market, but the problem statement is ambiguous and unclear. I have taken efforts to synchronize all sections of the paper concerning assertions, hypotheses and motivation. I have also tried to remove material throughout the exposition that I had felt was informative but not directly related to the research, its motivation and its conclusions. Research question is too long and not clearly formulated. The reader cannot distinguish between what impacts what. This has been revised, and shortened, and focused on whether we should consider digital cash in the form of cryptocurrencies, to be true cash Additionally, the place of the working hypotheses is not in the Introduction. I like to present my research question, considerations of why it is important and the working hypotheses as close to the beginning of a paper as possible. I think the referee is correct that these probably should not be in the introduction. I've moved these to the prior literature section, as a part of my attempt to focus all of

	the content of this revision on the research directly. I've generally kept the prior literature section concise and germane to the research, and the working hypotheses fit here, because they help the reader (and myself) see what is the relevant prior literature. The author clearly defines the aim, and it is consistent with the rest of the manuscript. Thank you for the kind words. I will work to rectify other shortcomings of my paper. 2It is difficult to follow the phrases, they are too long and follow a complicated topic. Ideas are not grouped into topics. I apologize, as the reviewer was correct in criticizing the organization of the original submission. I have edited through a number of passes, to generate a comprehensive revision, shortening and clarifying many of the points made in the earlier paper, but remove material that was peripheral to the main theme and research. Where phrases are longer than necessary, I've tried to shorten these and convert to active voice where it made sense. Figures 1-5 have the same name but use a different perspective to present data - please respecify the titles in order for the reader to understand exactly what the figure is about. Which is the goal for the usage of these figures? I can not tell, as it is not properly explained. Which is the main idea that the reader should get from these figures? Once again: what is the goal of figures 6 - 10? They lack explanations. I have completely revised the figures and their accompanying text. I think the reviewer was spot on with this objection, as each figure should be included to make a point. I have revised the figures 1-10 with clarity and relevance to the research work in mind. I removed most of the purely descriptive tables and figures. Now all of the accompanying tables and graphs are directly related to arguments or conclusions drawn in the text. The design and methods are appropriate for the aim of the research. The samples are clearly described, and the validation tests included. But the presentation of the methodology is, once again, bad. Moreover, the methodological part and the results one are overlapping - there is not a clear distinction between them. Thank you again for the kind words. I have done my best on this revision of the paper to shorten and clarify the descriptions and arguments that this reviewer has identified as being poorly organized and overly wordy. Results could be described in greater detail and compared to current findings in the field. There is no idea related to the current literature in any of the Results parts. Isn't there anything similar in the literature? I have expanded the comparisons to other literature on cryptocurrencies. When I began this research project, there were very few studies that had been done on the cryptocurrency markets. The overall literature is still relatively small, despite the enormous amount of wealth invested in cryptocurrencies. 3The implications for future research are also discussed. Conclusions could explain more the impact of the study and results obtained, especially from the point of view of the policy implications. I have tried to stay conservative in this revision, in describing what I think is appropriate future research.

	I think whenever you have complex models like this one, that require the acquisition and parsing or large datasets, it is important to beware of overfitting a model – i.e., drawing conclusions that are not robust, and may be weakened or invalidated in a replication of the research. Most of the future research I suggest involves revising my implementation of Glosten's model to assure that conclusions from this research can be validated and are robust. I suggest that the combinations of predictors model would benefit from a proper theoretical model to underpin the results, and suggest that as potential future research. But I do not want to overstep; I also think that the work required to make these finding more robust and replicable are likely to require substantial additional work in future studies.
Response to Reviewers:	Response to Comments on Accepted Version of Determinants of Liquidity in Cryptocurrency Markets J. Christopher Westland University of Illinois at Chicago (westland@uic.edu) 2022-12-03 Comment: The abstract is clear regarding the aims, key methods and important findings but more attention to the ending phrase, it is ambiguous and doesn't have correct ending. Thank you for the kind words. I have edited to create a more definitive ending. Comment: Too many highlights – there are usually 3 to 5 catchy ideas, not a summary of the research. Additionally, highlights are usually short statements, of maximum 85 – 100 characters, including spaces. I have tried to be concise and focused on my accomplishments in the paper, in this revision. I hope the reviewer finds my revision satisfactory Comment: The author tries to summarize the current state of the topic and limitations of knowledge in the field but the ideas are spread and not very concise. To some extent, I have found that confusion over the topic is unavoidable, given that there are so many extremely contradictory claims made about cryptocurrency. Personally, I am skeptical of many of these claims, feeling that there may be "no there, there". But I have worked to be evenhanded in the current draft and present a comprehensive review of the topic and research on it so far. The actual quantity of reliable and high-quality research on the topic is, in my opinion, fairly small. There are many questions that remain unanswered, and that contributes to ambiguity. Comment: It is not very clear what the author wants to communicate regarding the problem statement and research objectives. Yes, it does states that it intends to test several predictors for liquidity on cryptocurrency market, but the problem statement is ambiguous and unclear. I have reread the entire paper for clarity and have expanded my articulation of the RQ's and where these appear in prior research and in actual markets. I have tried to reiterate these throughout the paper, where I think they will clarify particular methods I have used, or where they might clarify the interpretations of results. I hope the reviewer finds this an improvement over my prior draft. Comment: Research question is too long and not clearly formulated. The reader cannot distinguish between what impacts what. Additionally, the place of the working hypotheses is not in the Introduction. I have repeated these goals throughout the model development and empirical tests. I think that this allows the reader to see why these are important questions in understanding these markets. I have tried to clarify the need for these particular research questions and working hypotheses throughout the paper, emphasizing where a specific test is important for a specific hypothesis.

	Comment: The author clearly defines the aim, and it is consistent with the rest of the manuscript. Thank you for the kind words. I have taken pains in this version to make sure that my overall goals are articulated, and repeated throughout the manuscript. Comment: It is difficult to follow the phrases, they are too long and follow a complicated topic. Ideas are not grouped into topics. I have edited the entire document to try to break up long sentences, and simplify syntax. I hope the reviewer finds this to be satisfactory. Comment: Figures 1-5 have the same name but use a different perspective to present data – please respecify the titles in order for the reader to understand exactly what the figure is about. Which is the goal for the usage of these figures? I can not tell, as it is not properly explained. Which is the main idea that the reader should get from these figures? These provide graphic support for my assumption that the top 10 or so cryptocurrencies essentially define the total cryptocurrency market; this supports the generalizability of the results. I have articulated this in the text. Comment: Once again: what is the goal of figures 6 – 10? They lack explanations. These are intended to provide a better understanding of the monetary transfers between particular cryptocurrency monetary investments. If we assume that prices are driven by monetary investment in the cryptocurrency market overall (since the underlying cryptocurrencies don't have intrinsic values) then this is important. I have articulated this in the text. Comment: The design and methods are appropriate for the aim of the research. The samples are clearly described, and the validation tests included. But the presentation of the methodology is, once again, bad. Moreover, the methodological part and the results one are overlapping – there is not a clear distinction between them. I have reread this section to try to better categorize and articulate the particular metrics and methodologies to compute them that are needed in the analysis. Again, I hope this reviewer finds my revisions satisfactory. Comment: Results could be described in greater detail and compared to current findings in the field. There is no idea related to the current literature in any of the Results parts. Isn't there anything similar in the literature? The implications for future research are also discussed. There is nothing that I could find through Google Scholar or through conversations with my colleagues that indicate that anyone has done similar research. Interest in cryptocurrency is quite recent (in the past 4 years) so there has not been much time to build a repository of studies or literature. Firms that are trading are typically secretive about their research; much of the advisory literature is pure vendor hype. In addition, ELOB at the level of accessibility and detail that I have drawn on have only been available in cryptocurrency market platforms. Anyway, I have gone through my manuscript to see whether I could do a better job with articulation, and have made some modifications and expansions. Comment: Conclusions could explain more the impact of the study and results obtained, especially from the point of view of the policy implications. Again, I have tried to improve my articulation.

Determinants of Liquidity in Cryptocurrency Markets

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2021-10-08

Abstract

This research identified predictors of cryptocurrency liquidity and explored whether cryptocurrency is a true cash equivalent. Liquidity is important because cryptocurrencies aim to be cash substitutes, and thus totally liquid. Greater liquidity is correlated with more profitable trading, better price discovery; and more profitable market operation. The research tested five hypotheses concerning liquidity and its predictors, for a set of cryptocurrencies that represent ~90% of volume and market capitalization, thus are generalizable. Price was strongly supported as a predictor of liquidity, while volume was not. Fungibility, in the sense of 'mutual interchangeability of particular pairs of cryptocurrencies, was not found to be a good predictor of liquidity, leading us to question whether cryptocurrencies can truly be considered 'cash equivalents.' I also tested whether price and volume embedded in own-price elasticity was a predictor of liquidity, and rejected this hypotheses. Finally, an analysis involving step-wise regression unambiguously selected a combination (3) daily volume, and (4) own-price elasticity. Explanatory power was slightly better than other predictors, but lacking a structural model incorporating these predictors, the results here are suggestive of future research studies, and potential blockchain; electronic markets; liquidity_

Highlights

- This research identified predictors of cryptocurrency liquidity and explore whether cryptocurrency is a true cash equivalent.
- The research objective is to provide quantitative support for a definition of liquidity based on measurable quantities in cryptocurrencies markets, and to identify determinants of liquidity
- Greater liquidity is correlated with more profitable trading, better price discovery; and more profitable market operation.
- Liquidity is important because cryptocurrencies aim to be cash substitutes, and thus totally liquid.
- The research tested five hypotheses concerning liquidity and its predictors, for a set of cryptocurrencies that represent ~90% of volume and market capitalization, thus are generalizable.
- Price was strongly supported as a predictor of liquidity, while volume was not.
- Fungibility, in the sense of 'mutual interchangeability of particular pairs of cryptocurrencies, was not a good predictor of liquidity, leading us to question whether cryptocurrencies can truly be considered 'cash equivalents.'
- Own-price elasticity (embedding price and volume) as a predictor of liquidity was tested and rejected.
- Analysis through step-wise regression unambiguously selected a combination of four predictors for cryptocurrency liquidity: (1) implicit commission on trades, (2) market capitalization, (3) daily volume, and (4) own-price elasticity.

Liquidity in Cryptocurrency Markets

Liquidity is a measure of a market's ability to address the demands of impatient traders, and is an important feature of cryptocurrencies that aim to be cash substitutes, and thus totally liquid. This research attempts to identify quantitative predictors of liquidity, in order to objectify a term that has tended to be used mostly in a qualitative and descriptive manner. Such qualitative constructs are common in the social sciences, including economics, and are typically modeled as latent constructs which cannot be measured directly, but where predictors of indicators can be found that can individually or in combination provide measures of the latent construct.

Cryptocurrency markets trade in classes of partially fungible 'cryptocurrency' assets, similar to Forex and stock markets. These markets are valuable to traders because they can offer liquidity and best price discovery with anonymity. Market liquidity is a measure of how quickly one can buy or sell assets while assuring minimal movement in the asset's price. Order flow is attracted to more liquid markets, and so important is liquidity to the pricing, volume and profitability on a market platform that many markets innovate with unique 'market making' functions to improve liquidity, e.g., providing Specialist functions in the New York Stock Exchange, encouraging short selling and derivatives, and so forth. Since the proliferation of electronic limit order books (ELOB) and electronic 'trading floors' since the 1990s, the speed of order fulfillment has increased exponentially, with traders in most financial markets expecting millisecond completion today. Cryptocurrency markets have only developed over the past decade and because of that, have been able to incorporate the most advanced elements of other electronic markets, including public ELOBs, market and limit orders, short sales, derivatives and other innovations that bolster liquidity. Liquid markets offer traders five benefits (Lybek and Sarr 2002):

1. low transaction costs and best price discovery (tightness in bid-ask spreads),
2. rapid trade completion (speed);
3. large numbers of buy and sell orders (depth in the ELOB);
4. a wide selection of fungible or near fungible assets (breadth); and
5. price stability (resiliency).

Greater liquidity is correlated with more profitable trading due to among other things, better price discovery; and more profitable market operation, due to among other things, higher volume and higher per transaction revenue from trading. Information disseminated through a public electronic limit order book also contributes and complicates the assessment of liquidity.

Nonetheless, most definitions of liquidity tend toward the qualitative and descriptive, and are somewhat variable in different contexts. Liquidity is a latent construct that is observed in the measurements, but not directly measurable itself. The current research aims to provide quantitative support for a definition of liquidity based on measurable quantities in cryptocurrencies markets.

I address the following research question in this study:

> **Research Question:** Is market liquidity of a particular cryptocurrency on a particular electronic limit order book trading platform increased with an increase in price, volume, fungibility, own-price elasticity, and/or particular combinations of factors?

Following established norms, I restated the research question as a series of five hypotheses:

- H_1: Increasing *price* increases *liquidity*
- H_2: Increasing *market volume* increases *liquidity*
- H_3: Increasing *fungibility* increases *liquidity*
- H_4: Increasing *own-price elasticity* increases *liquidity*
- H_5: *Liquidity* can be increased with *combinations of factors*

This research study is structured as follows. Section 2 briefly reviews prior motivating literature on cryptocurrencies and liquidity in electronic markets. Section 3 explains the choice of data sources for this research, and their extraction, curation and analysis. Section 4 analyses the data to calculate liquidities for each of the cryptocurrencies in this study. Section 5 tests models with these predictors of liquidity. Section 6 summarizes conclusions and discusses their implication for trading and market structure.

Prior Literature

Liquidity is a measure of a market's ability to address the demands of impatient traders. Liquidity demanders are more likely to be privately informed, through research or inside knowledge of the market, than are passive liquidity suppliers, who may be more concerned with price stability and predictability (Biais, Glosten, and Spatt 2005). (Easley, Hvidkjaer, and O'hara 2002) show that where there is a higher chance of informed trading, we can expect higher returns in the form of a volatility risk premium. (Grossman and Stiglitz 1980) demonstrated why markets need uninformed and informed traders – the volatility in prices and volume brought by uninformed liquidity suppliers makes continuous profit possible for informed traders. (Silver 2012) uses the metaphor of "sharks" (informed players) and fishes" (uninformed players) in poker to illustrate how these information asymmetries drive financial markets. A liquid market requires an unending supply of "fish" if the "sharks" are to make a profit. Fish are willing to make price concessions to "sharks" as a way of lowering their risk. They tend to panic and fold too early, especially when they have money committed, leading to a steady flow of revenue into the sharks' pockets.

More than half of asset markets, including most cryptocurrency markets, now use an electronic limit order book. This was not the norm when (Glosten 1994) presented his seminal model of an electronic limit order book market, but since that time, the major asset markets around the world have implemented electronic limit order book systems. Cryptocurrency markets invariably use electronic limit order books with relatively low transaction costs and high volumes. Cryptocurrency traders have a rich collection of order choices including limit, stop limit, market, and various derivatives. Each of these supplies of demands liquidity in specific ways.

Many types of information fuel information asymmetries in Bitcoin markets: e.g., demand to convert other assets to Bitcoin; changes in the total supply of Bitcoins through mining and recirculation of 'dark pools'; uncertainties in reserve currencies such as the dollar, where, like gold, Bitcoins may be seen as a 'safe haven' from macroeconomic uncertainties, and so forth. Bitcoin's supply is algorithmically capped at 21 million, out of which around 19 million Bitcoin have already been mined of which Satoshi Nakamoto owns around 1.1 million (Phillips 2020) and another 3.7 million Bitcoins have not been used in the past 5 years (Insights 2020) all of which contribute to price volatility. In addition, around 2700 Bitcoin have been sent to 'burn addresses' – vanity addresses with no known private key – and are likely out of circulation, along with several thousand inaccessible Bitcoin belonging to deceased owners who left no records (Phillips 2020). There has been a rapid growth in derivatives, and now about one-third of the volume of cryptocurrency trading has moved into derivatives markets with their much greater volatility. Regulation of cryptocurrencies is rapidly evolving, and generally seeks market transparency and taxation, features that cryptocurrencies may systematically try to thwart (Congress 2020).

Limit order book econometric models may be either static or dynamic. Static models are supply-demand equilibrium models, where private information is injected into a liquidity-providing market only on the demand side. The limit order book determines the supply inventory, and demanders arrive randomly to appropriate a portion of the supply through aggressively priced market orders. (Glosten 1994) provided the seminal electronic order book static model where risk-neutral limit order posters compete for supply, and the market clears where there is no excess profit to be gained. A follow-up study by (Biais, Glosten, and Spatt 2005) limited the market participation of strategic suppliers, a model that converges to the (Glosten 1994) results asymptotically. Parallels appear in (Seppi 1997) and (Parlour and Seppi 2003) who consider NYSE-type markets with specialist functions whose role is price stabilization and injecting more liquidity. (Biais and Bossaerts 1998) found that compared with such specialist-enabled markets, pure electronic limit order book markets improve the competitive equilibrium obtained. (Bloomfield, Tayler, and Zhou 2009) concluded that in electronic limit order book markets, market orders are a primary point of injection of private information. (Harris and Hasbrouck 1996) found, in the hybrid NYSE market, that specialists and floor brokers do indeed trade on superior private information.

In contrast, dynamic models start with a queue of undifferentiated traders who want to use the market. Impatient traders are willing to submit market orders for immediate execution for a risk-premium equal to the bid-ask spread. Limit order traders may wait forever for a trade, while market order traders experience near-zero delay, while injecting new information into the market every time a market trade occurs. This injection of risk information into the market is called "picking-off risk" and causes limit orders to execute more often with higher price variance in the market.

(Sandås 2001) tested the (Glosten 1994) model for stocks traded on the Stockholm Stock Exchange (SSE). The SSE is a relatively simple and thinly traded market, thus the inherently asymptotic results of the Glosten model failed to obtain. The massively larger volumes in cryptocurrency markets should converge to Glosten's outcomes, a hypothesis that the current research tests. I believe that cryptocurrency data is likely to fit Glosten's models better, for two reasons:

1. both limit and market orders have the opportunity to make markets, injecting private information into their markets, because cryptocurrency fees and commissions are rapidly approaching zero, and are orders of magnitude smaller than fees charged in asset markets in the 1990s.

2. limit order activity is rapidly increasing because of radically lower fees and technological development. In earlier research by (Sandås 2001) the ratio of limit to market orders was 1.7; asset markets typically have ratios of 5 to 10; in the current research, the Kraken-Bitcoin ratio of limit to market orders is around 20

Prior research has identified the role of *market size* in liquidity. (Sensoy 2017) investigated institutional investment and ownership of assets in markets, finding that these lead to enhanced systematic liquidity risk by increasing the commonality in liquidity. (Chung and Chuwonganant 2018) found that not only market size, but that tick size influenced liquidity in NASDAQ and NYSE stocks. (Będowska-Sójka 2018) explored the assumption that bigger markets, measured by capitalization, offer more liquidity; they found mixed results across international asset markets. (Badarau and Sangaré 2019) investigated the role of market size in liquidity traps.

Prior research has identified the role of *own and cross-price elasticity* of demand in liquidity. (Nakata and Schmidt 2019a) and (Nakata and Schmidt 2019b) found that price elasticities of demand are strong influencers of liquidity and important predictors of liquidity traps in government bond markets and their consideration is essential in any prescription for optimal commitment policy.

A particularly interesting stream of research has recently emerged around *fungibility* and liquidity, partly driven by non-fungible tokens (NFT) that certify that a digital asset is unique, and thus nonfungible. This area is young, and there are still question surrounding whether NFTs are just a fad, or indeed can generate some sort of liquid market. (Raman and Raj 2021) define various features affecting fungibility and liquidity. (Gomez, Weiss, and Krishnamurthy 2019) present empirical research that computes "fungibility scores" for telecommunications bandwidth assets. (Arslanian and Fischer 2019) look at the role of tokenization of physical assets, especially unique assets such as art, in improving fungibility and enabling liquid markets. (Wachter, Jensen, and Ross 2021) investigated composability, transferability, and fungibility in creating 'liquidity pools.'

Within cryptocurrencies, there has been an emphasis on differentiating coins – either on 'proof of work' concepts or price stability – to make coins *less fungible* and, ceteris parabus, more liquid. Even though a differentiated cryptocurrency potentially has a smaller market, the concern is that limited sources of coins could potentially disappear, wrapped in other currencies that would then benefit from greater liquidity. The concern is not merely academic. (Copeland June 8, 2021) observes that, currently, a substantial proportion of Bitcoin's circulating supply is now locked into the Ethereum blockchain. The Block's Data Dashboard shows that 240,000 bitcoin has now been wrapped onto Ethereum, representing 1.3% of its circulating coins, and 1.1% of Bitcoin's ultimate total supply).

Data Acquisition and an Overview of the Cryptocurrency Market

Essential features of cryptocurrency markets are captured in figures 1 through 5.[1] Bitcoin (BTC) is by far the largest, accounting for just under half of total market capitalization.

In figure 2, circulating supply and daily volume are both dominated by Shiba Inu Token (SHIB) a joke cryptocurrency based on joke cryptocurrency Dogecoin, and branding itself "the Dogecoin killer." The SHIB token does not have any smart contract utility, is not backed by any asset or rights; it is simply a transferable token whose miners and traders have created more volume and supply than anything else in the market. Tether (USDT), the largest stablecoin 'tethered' to the US dollar, has an exceptionally high volume because many US dollar denominated cryptocurrency trades are actually made in USDT rather than fiat US dollars. Stablecoins, by design, are more fungible than other cryptocurrencies, but also vastly different in terms of price elasticity (ideally zero) and liquidity (ideally perfect).

In figure 3, BitTorrent Token (BTT) tokenizes BitTorrent decentralized file sharing protocol, and has the largest circulating supply of coins, after SHIB and followed by Dogecoin (DOGE).

Figure 4 shows four coins with significantly higher price than other cryptocurrencies. Yearn.finance Coin (YFI) offers an Ethereum token for their managed investment platform which makes strategic transfers of funds around the decentralized finance ("DeFi") ecosystem in an effort to generate a high return. They have been strikingly unsuccessful, and their Coin price has steadily declined. The other three have risen in tandem with Bitcoin (BTC), which is by far the most expensive cryptocurrency. Bitcoin BEP 2 (BTCB) is a Bitcoin-pegged token on the Binance chain, or what is known as a wrapped Bitcoin. Similarly, there is Wrapped Bitcoin (WBTC) is an ERC-20 token wrapped on the Ethereum blockchain, created to allow Bitcoin holders to participate in decentralized finance ("DeFi") apps that are popular on Ethereum.

Figure 5 shows that despite the vast price and volume disparities, trading volatility tends to be similar across the largest currencies. This might be expected, as wrapped coins such as WBTC and BTCB were created specifically to make the most widely used coins fungible.

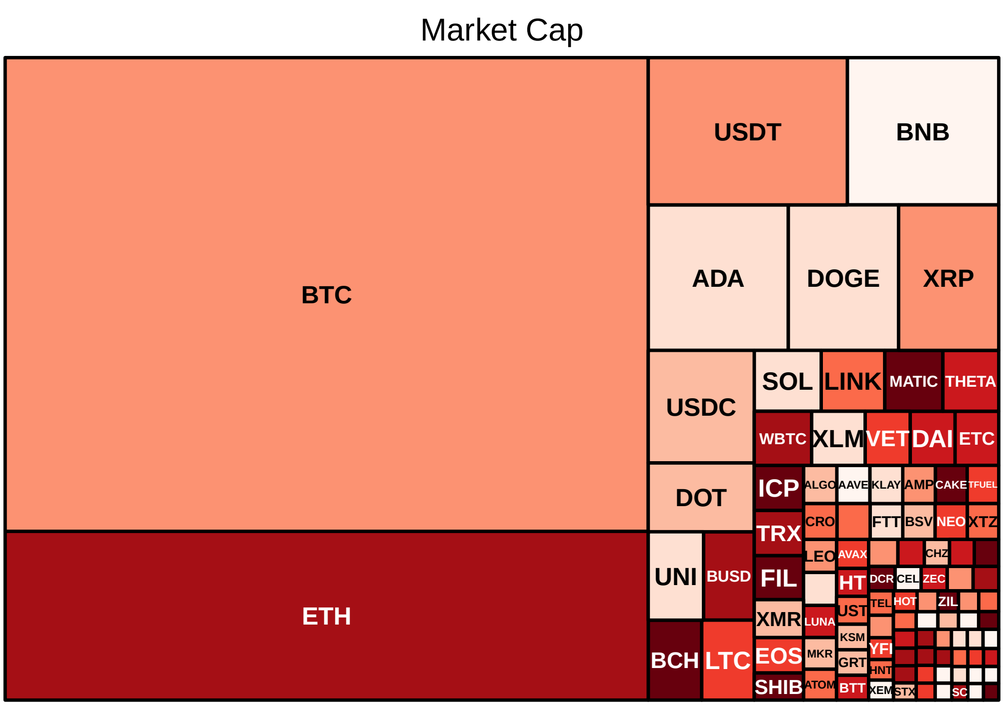

Figure 1: Comparative Metrics for the Cryptocurrency Markets

[1] Source: https://coinmarketcap.com/ downloaded June 21, 2021

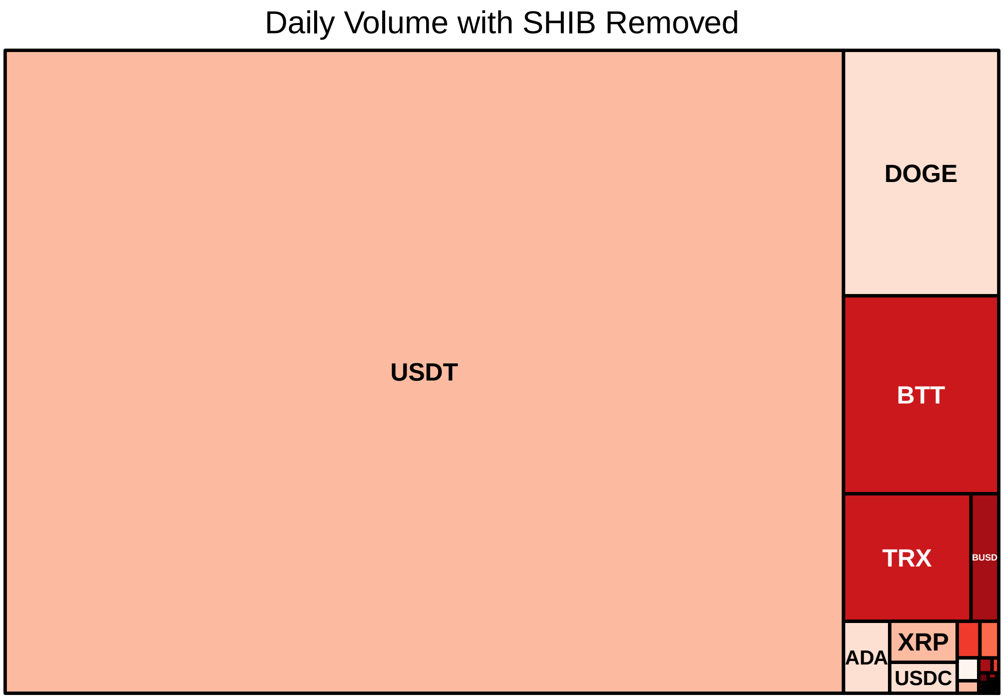

Figure 2: Comparative Metrics for the Cryptocurrency Markets

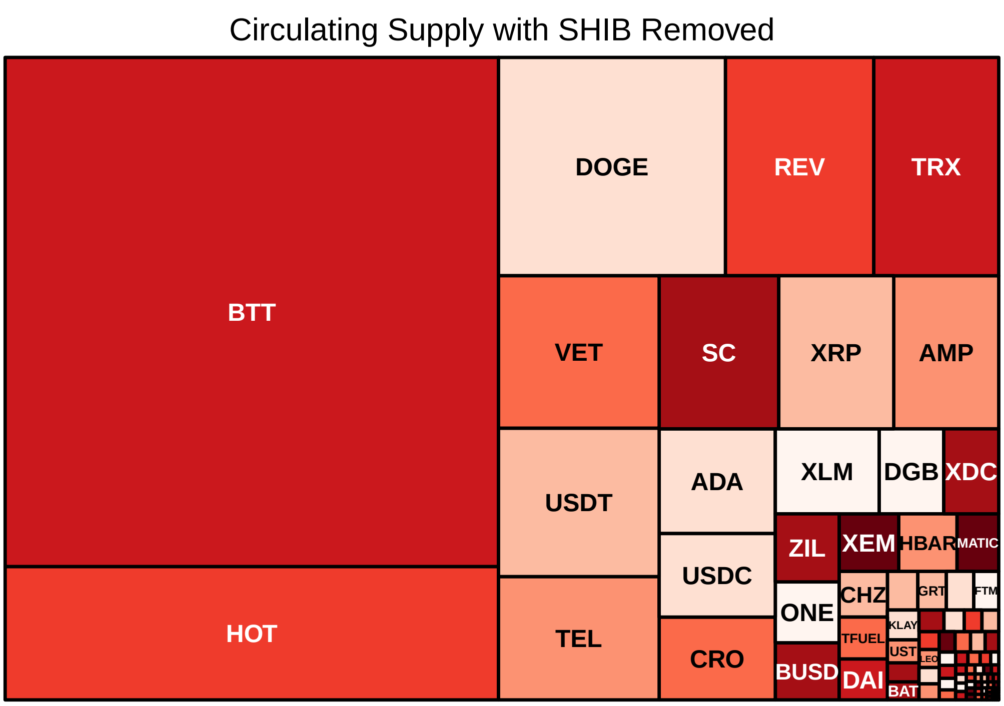

Figure 3: Comparative Metrics for the Cryptocurrency Markets

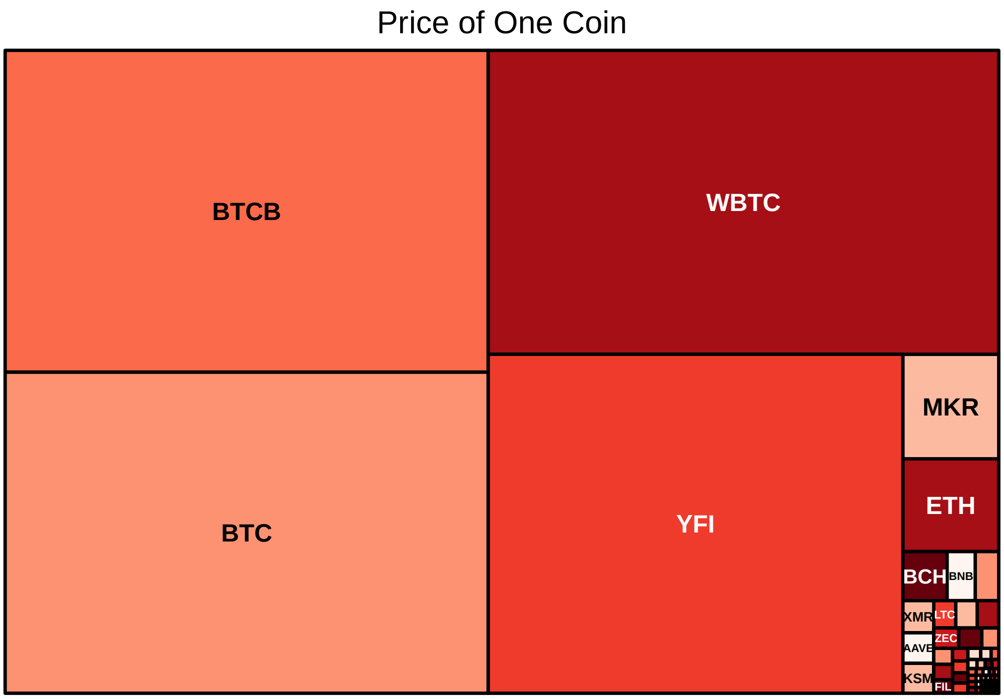

Figure 4: Comparative Metrics for the Cryptocurrency Markets

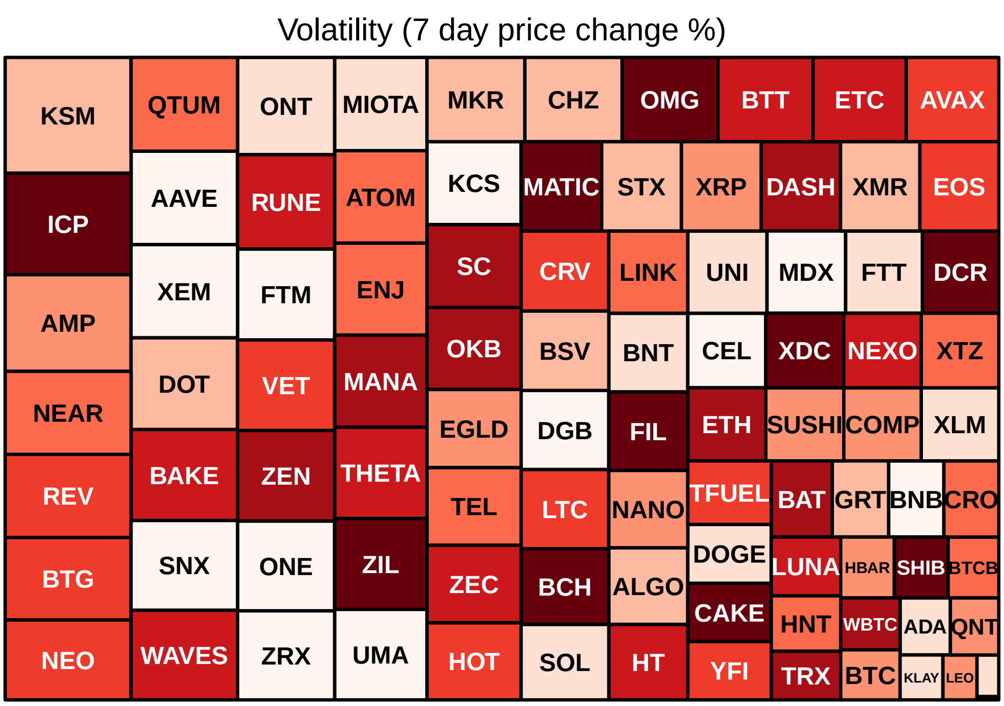

Figure 5: Comparative Metrics for the Cryptocurrency Markets

Table 1: Largest Crytocurrency Exchanges

Exchange	Daily Volume $B	Weekly Visits	Number of Markets	Number of Coins	Fiat Currencies
Binance	33.16	38475284	1290	370	AED, ARS, AUD +43 more
Coinbase	5.66	3891464	232	72	USD, EUR, GBP
Huobi	9.59	1470777	973	332	ALL, AUD, BRL +47 more
Kraken	2.27	3573941	312	69	USD, EUR, GBP +4 more

This research investigates liquidity in markets for the 12 largest cryptocurrencies, which comprise 90% of total cryptocurrency market capitalization. It considers specifically Forex-type cryptocurrency spot exchanges..[2] Table 1[3] lists the four largest cryptocurrency exchanges by daily dollar volume.

Data Acquisition

Data acquisition for this study required selection of: (1) a trading platform; and (2) a set of cryptocurrencies to study. In 2021 there are over 500 cryptocurrency exchanges, with 259 of these exchanges tracked on CoinMarketCap; others are in 'start up' phase or some, such as Venus, represent more involved lending and payment ecosystems.[4] In 2021 there are more than 4000 cryptocurrencies,[5] of which only 12 account for around 90% of market capitalization.

The Kraken exchange was chosen for this study because of its API allows real-time order book information extraction. Kraken is the second largest cryptocurrency exchange in the US by capitalization, and supports both limit and market orders for Bitcoin, as well as short sales and derivatives. Kraken is considered to be more technically sophisticated than market leader CoinBase, and attracts more informed traders. Globally the top 4 exchanges (based on daily volume) are Binance ($ 5.46B), Huobi ($ 3.40 B) Coinbase ($ 0.35B) and Kraken ($ 0.21) from CoinMarketCap. Coinbase is beginner-friendly, while Kraken has a wider selection of cryptocurrencies. Coinbase also hides their order book from the API, making calculations of liquidity impossible using the sophisticated models applied in this study. Huobi and Binance are either not available in full form for traders in the US, or only provide heavily restricted trading in the US, nor are APIs and order book information available.

I acquired data used in this study directly from Kraken's native RESTful APIs using custom code. Kraken is throttled to protect against DDOS attacks, and the code dealt with that, as well as the nanosecond resolution of trade times, which is too small a resolution for standard software arithmetic to handle.

Data collection scraped the Kraken API for these top 12 cryptocurrencies' activity on the Kraken trading platform in the period from 2017-03-29 19:45:00 to 2020-09-30 23:45:00 to investigate research questions on liquidity and cross-elasticities of cryptocurrency prices and volumes. Table 3[6] lists the 12 largest cryptocurrencies by market capitalization, which account for about 90% of total market capitalization for cryptocurrencies. Figures 6 through 10 map the price architecture of the data acquired through the Kraken API.

Two cryptocurrencies show a stripe of unusually low correlations, suggesting a lack of fungibility.

[2] Technically, Venus (https://venus.io/) could be considered the largest processor of cryptocurrency transactions by volume as it is a decentralized finance-based lending and credit system that feeds into the Binance Smart Chain using a synthetic stablecoin. This is a credit system rather than an exchange

[3] as of June 21, 2021. Source: https://coinmarketcap.com/rankings/exchanges/

[4] Source: https://www.cryptimi.com/guides/how-many-cryptocurrency-exchanges-are-there

[5] Source: https://www.investopedia.com/tech/most-important-cryptocurrencies-other-than-bitcoin/

[6] as of 2020-09-30 Source: https://coinmarketcap.com/rankings/exchanges/

Table 2: Largest Crytocurrency Markets

Coin	Average Price (USD)	Volume	Circulating	Market Cap (USD)	Minimum Order
BTC	12990.94	2.42e+17	1.85e+07	2.41e+11	0.001
ETH	407.44	1.02e+18	1.13e+08	4.61e+10	0.020
USDT	1.00	3.72e+21	1.63e+10	1.63e+10	5.000
XRP	0.25	1.48e+19	4.52e+10	1.14e+10	30.000
BCH	271.40	2.15e+16	1.86e+07	5.04e+09	0.025
LINK	12.28	1.29e+18	3.89e+08	4.77e+09	2.000
BNB	30.19	4.16e+16	1.44e+08	4.36e+09	NA
LTC	58.94	3.74e+17	6.57e+07	3.88e+09	0.100
DOT	4.31	3.30e+16	8.53e+08	3.68e+09	1.000
BSV	182.98	1.31e+16	1.86e+07	3.39e+09	NA
ADA	0.11	7.12e+18	3.11e+10	3.33e+09	50.000

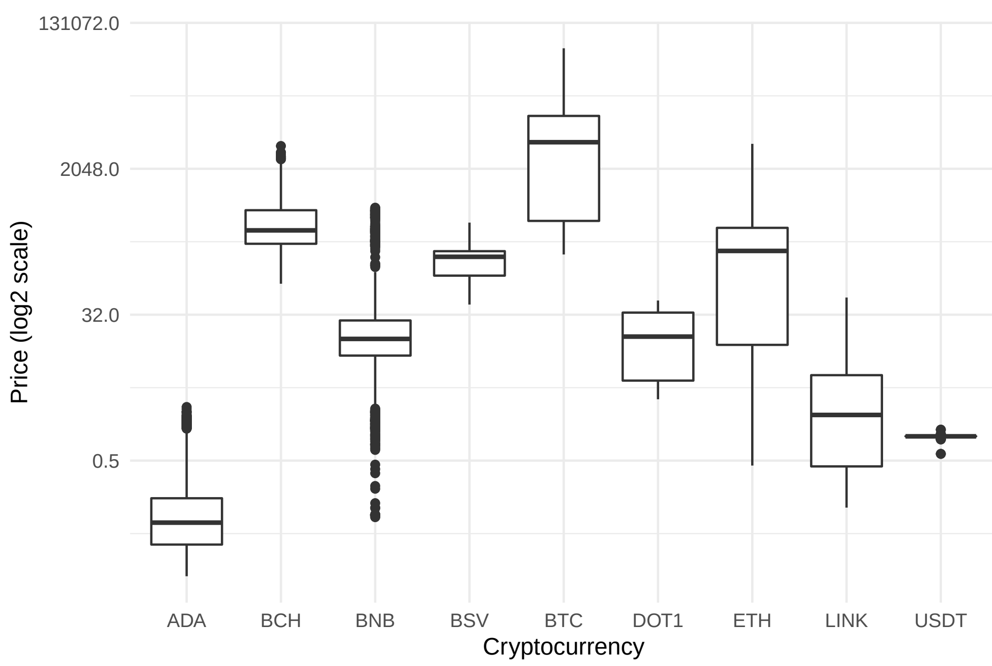

Figure 6: Price Architecture of Largest Cryptocurrencies

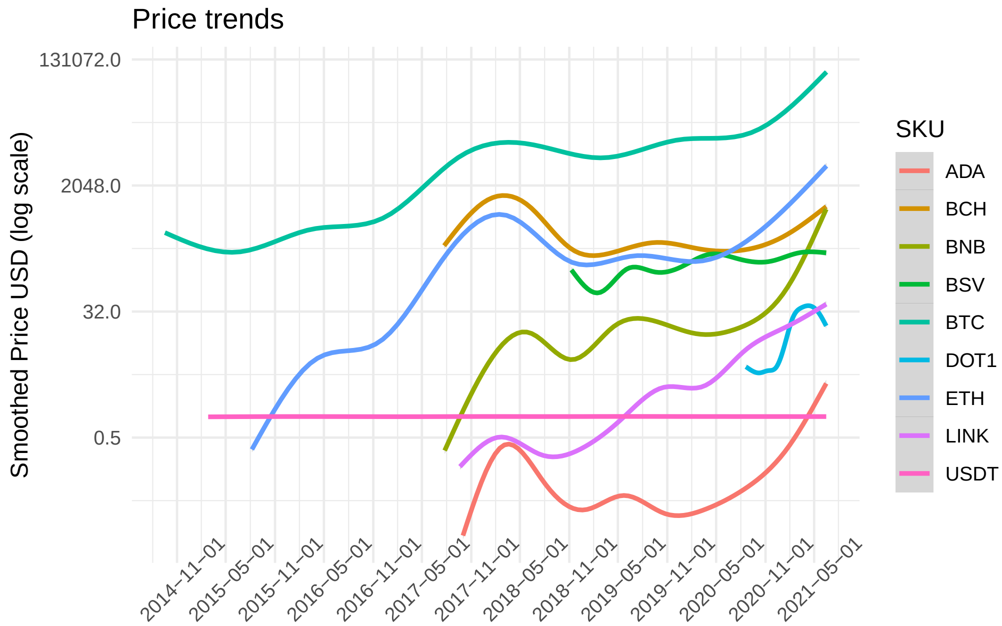

Figure 7: Price Architecture of Largest Cryptocurrencies

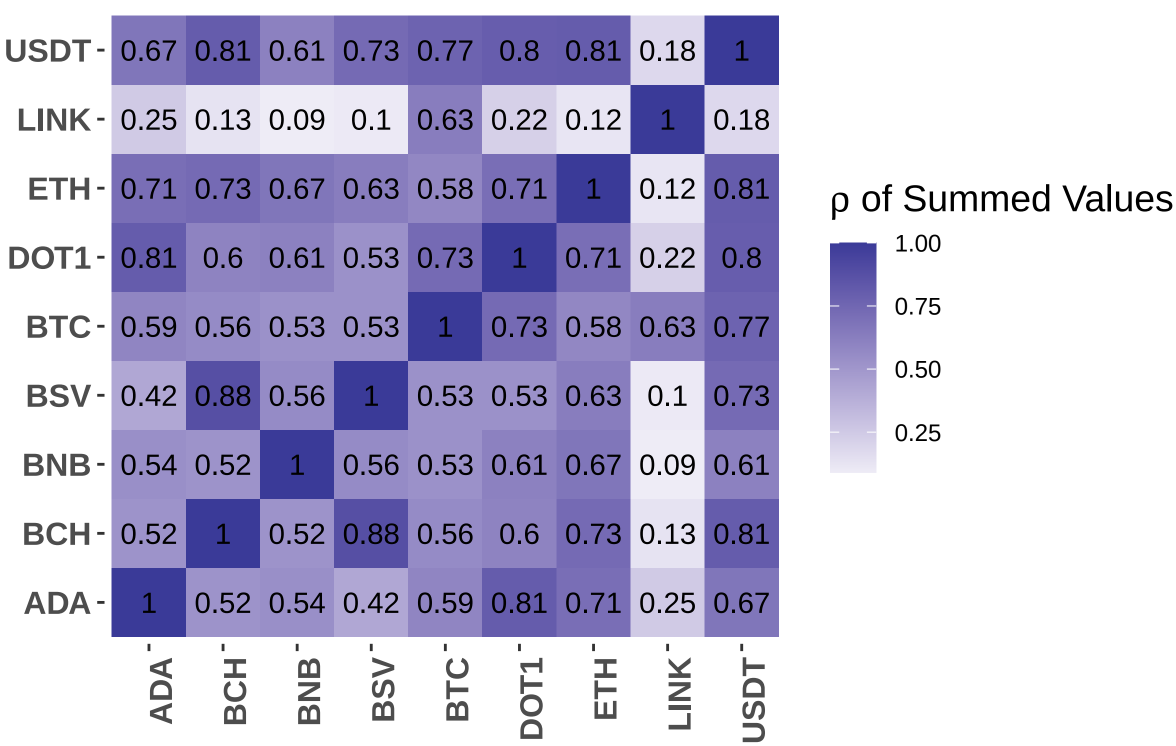

Figure 8: Correlations of Cryptocurrency Metrics

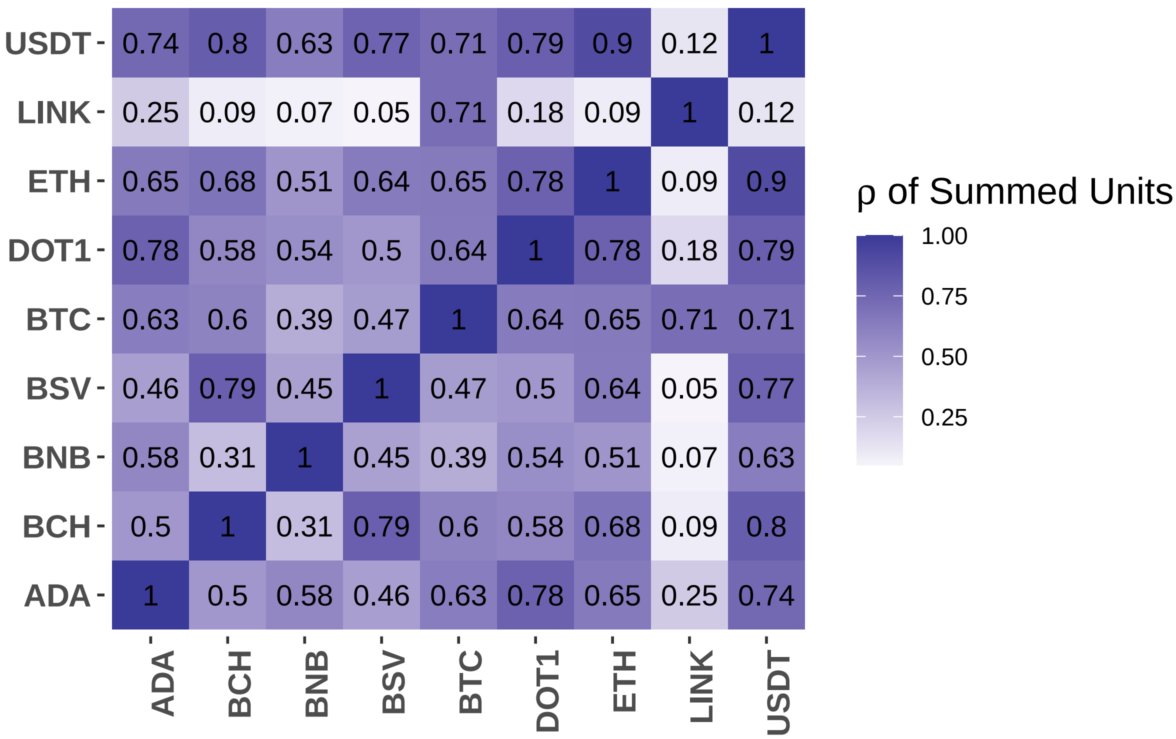

Figure 9: Correlations of Cryptocurrency Metrics

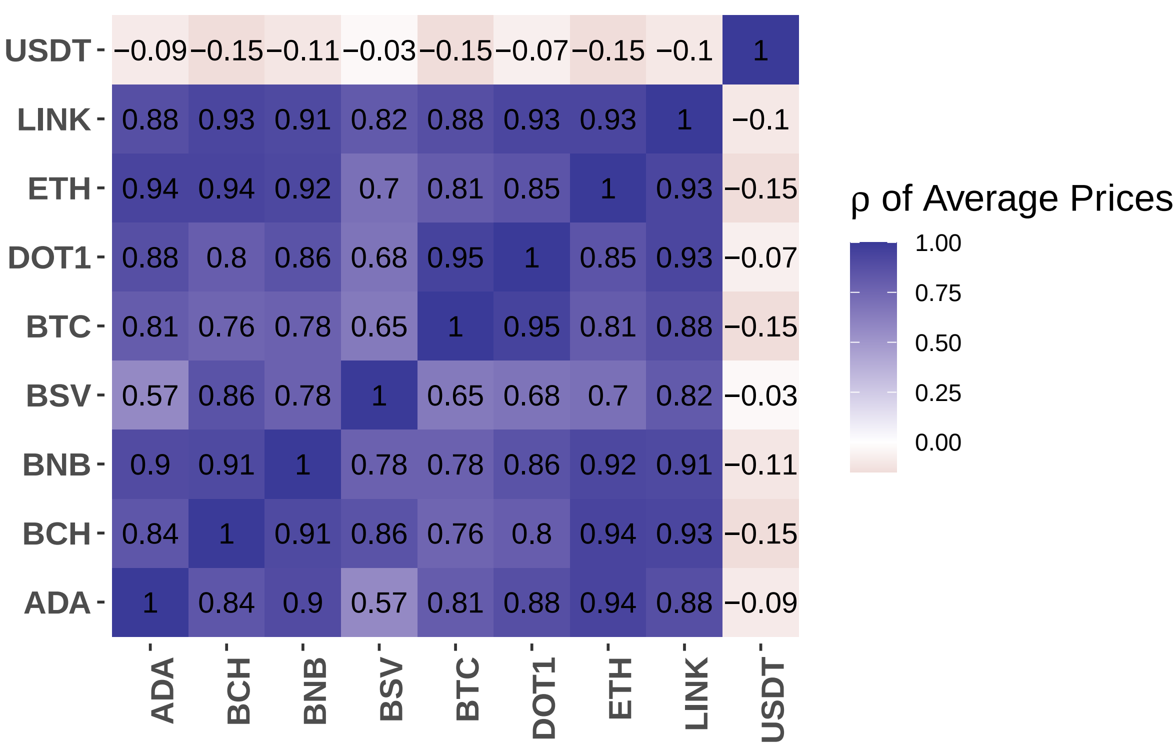

Figure 10: Correlations of Cryptocurrency Metrics

Chainlink (LINK) offers a service providing smart contracts with information from the outside world. It is the layer that queries, verifies, and authenticates external data sources and then forwards that information through their "oracle network" network that provides data to smart contracts on the blockchain. Many Ethereum applications use "oracles" nd indeed Chainlink's token is Ethereum based. The objective of Chainlink's network structure is to control dishonest centralized data-feed providers by using a distributed network of nodes to verify data. The low correlations on summed values and units suggest that dishonest behavior is widespread, and Chainlink's structure is effectively controlling this behavior within its network.

Tether (USTD) is the largest stablecoin 'tethered' to the US dollar. Many US dollar denominated cryptocurrency trades are actually made in USDT rather than fiat US dollars. Stablecoins, by design, are more fungible than other cryptocurrencies, but also vastly different in terms of price elasticity (ideally zero) and liquidity (ideally perfect). Since Tether's price is pegged at $1 and diverges only in periods of extreme volatility in the cryptocurrency markets, USTD's correlation with other currencies is near zero.

Liquidity, Trade Volume, Implicit Commissions and Elasticities

Statistics Computed from Glosten's Model

Access of information from Kraken's electronic limit order book (ELOB) was important in eliciting the information injected into a specific cryptocurrencies market by the market orders. The large number of limit orders enables the assessment of information content of market orders. On average, the order book accumulated around 20 limit orders between each market order, which is substantially in excess of similar figures in traditional asset markets, which typically accumulate 5 to 10 limit orders per market order, reflecting lower charges in general for limit orders in cryptocurrency markets. Figure 11 shows that market orders have more aggressive price moves than limit orders, supporting the idea that these trades are confidently made on new information available to the trader.

Interestingly, limit orders seem to show more volume swings than market orders (figure 12), suggesting two things: (1) market orders are concerned that they will move the price (unfavorably) too much, and thus tend to trade in small blocks, and (2) limit orders represent a portfolio optimizer's "wish list," and where the "wish" is executed, they want to buy or sell as much at that price as they can or have in inventory.

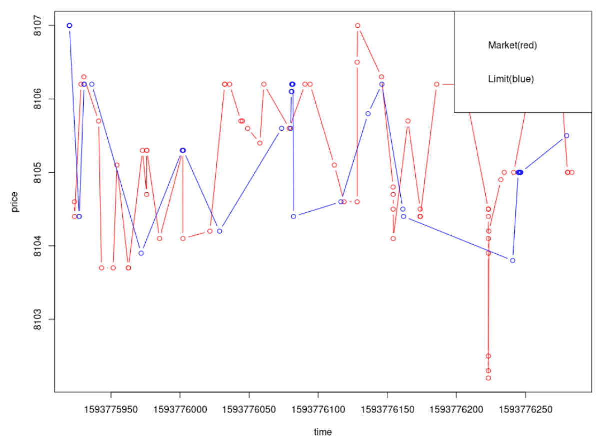

Figure 11: Market orders display significantly more aggressive price moves than limit orders

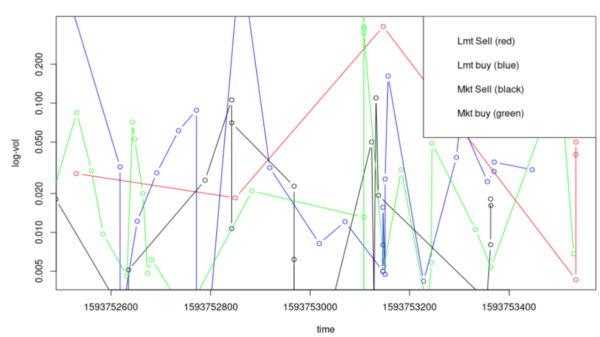

Figure 12: Bitcoin trade dynamics (volumes of 200 trades)

This research followed (Sandås 2001) of the (Glosten 1994) structural model. The Glosten model interestingly implies both forward and reverse Granger causality. For example in the case of an upcoming press release, press-release induced order flow may cause an immediate quote update and portfolio rebalancing (Vayanos 2001).

Table 3: Modeling Parameters

Parameter	Description
p(i,t)	price of the i^th best order (asks i>0 bids i<0) at time t
q(i,t)	quantity of the i^th best order (asks i>0 bids i<0) at time t
X(t)	the market order size (positive or negative)
Z(t)	the state of the order book
v(t)	the true value of the asset (Bitcoin) after a market order X(t arrives, and
v(t)= c + v(t-1) + alpha X(t)+ eta(t)	asset value update formula
alpha	key modeling parameter which measures the average information content of arriving market orders
c	a consumption parameter that is set by the underlying market
eta(t)	effect of information that arrives between trade times t-1 and t
lambda	expected absolute value of the limit order volume
gamma	the fixed order-processing cost of incoming market orders

(Hansen 1982) introduced the two-step generalized method of moments (GMM) to applied economics and finance, where it provides a generic method for estimating finite-dimensional parameters in semi-parametric models. GMM starts by positing a centralized moment condition, a system of $q \times 1$ potentially nonlinear equations $E[g(\theta_0, x_i)] = 0$ used to estimate parameters $\theta_0 \in \Re^p$. Boundary conditions may additionally be specified to insure a unique solution.

Figure 13 schematically describes the operation of market orders in a Glosten market. Trading events are assumed to arrive randomly, and in the period between market orders, limit order traders post to the ELOB attempting to adjust their portfolios; illustrated in the following timeline:

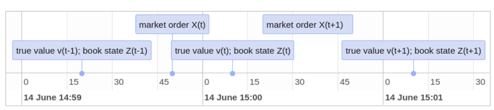

Figure 13: Trading event random arrival

where:

- X_t is the market order size,
- v_t is the true value of the cryptocurrency after a market order arrives, and
- Z_t represents the current state of the ELOB.

Market orders of size X_t arrive at t, buys (positive) and sells (negative) have the same probability of occurring, and $X_t \perp\!\!\!\perp X_s$ for $s \neq t$. Order size is monotonic increasing on waiting time, since traders have the option of splitting or consolidating orders as their private values change, thus a two-sided exponential distribution for waiting times is the most appropriate assumption:

$$f(X_t) = \frac{1}{2\lambda} e^{\frac{|X_t|}{\lambda}}$$

where $\lambda > 0$ is mean order size. The central parameter of the research is α which captures information about the underlying 'true' asset value from an arriving market order, i.e., how much of that information is impacted into the trading mechanism with the arriving market order. Thus, true value v_t after the market order arrives at t is:

$$v_t = E[v_t|v_{t-1}, X_t] + \eta_t = c + v_{t-1} + \alpha X_t + \eta_t \tag{1}$$

where:

- η_t reflects information that arrives between trade times $t-1$ and t.

The model assumes fixed limit order processing cost γ and the various prices of a market order of volume X_t elicits a response of limit order postings to the ELOB until breakeven. For example, let $p_{1,t} \geq v_t$ be the lowest price at which it is advantageous to supply a limit sell order. Limit orders will be posted to the ELOB up to and at this price. The expected profit on the $q_{1,t}-$th share at price level $p_{1,t}$ is given by:

$$E[(p_{1,t} - E[v_{t+1}|X_{t+1}] - \gamma) \times I_{[X_{t+1} > q_{1,t}]}] \tag{2}$$

where $E[(p_{1,t} - E[v_{t+1}|X_{t+1}] - \gamma)$ expected markup from true value, and conditional on the next market order X_{t+1}

- ($I_{[X_{t+1} > q_{1,t}]}$ is *1* if $X_{t+1} > q_{1,t}$ in which case the limit order executes)

Orders arrive at the market up to the point at which the 'true' value is reflected in the last limit order, or a trade clears:

- this process generates an equilibrium depth of $q_{1,t}$ at the best ask price $p_{1,t}$
- the next order arrives at one tick above $p_{1,t}$ generating potential revenue on execution is one tick higher than on $p_{1,t}$.

Figure 14 provides a plot of how these decisions happen in ~100 trades in my dataset from Kraken's July 6th 2020 Bitcoin trading. Notice the behavior of limit buy or sell trades (blue and red lines) after the price point set by a market buy or sell trade (green and black lines). Figure 15 provides a broader snapshot of the limit order book (top) and the actual execution of market and limit orders in the same period. Figure 16 zooms in on the order book's best four orders on either side of the market price. Taken together these provide a detailed snapshot using empirical data, of the trading processes in Glosten's model.

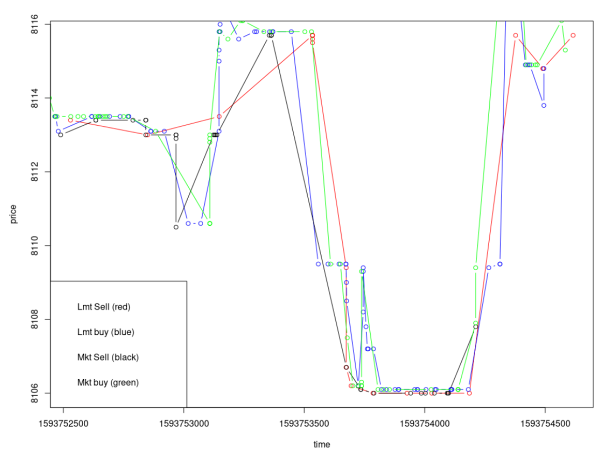

Figure 14: Trading behavior of limit orders placed following a market order execution

Thus the ELOB state at any point in time t is:

- bid $p_{-k,t}$ and ask $p_{+k,t}$ prices for $k = 1, 2, 3, \dots$ and
- depths ($q_{-k,t}$ and $q_{+k,t}$) for $k = 1, 2, 3, \dots$

The equilibrium equations show that the information injected into the market during trades is measured by α which is a key determinant of liquidity. The following recursions define the depths (and thus state of the ELOB) on both sides of the ELOB, with α as a key determinant of book liquidity:

$$q_{-k,t} = \frac{v_t - p_{-k,t} - \gamma}{\alpha} - \sum_{i=-1}^{-k-1} q_{i,t} - \lambda \qquad k = 1, 2, \dots \quad (bid \quad side) \tag{3}$$

$$q_{+k,t} = \frac{p_{+k,t} - v_t - \gamma}{\alpha} - \sum_{i=+1}^{+k-1} q_{i,t} - \lambda \qquad k = 1, 2, \dots \quad (ask \quad side) \tag{4}$$

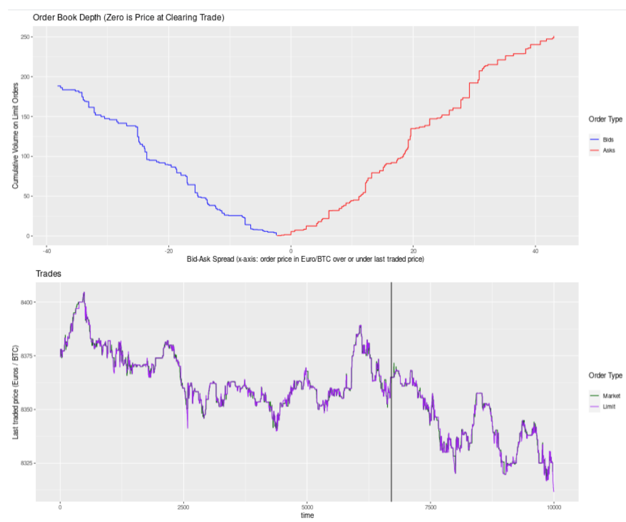

Figure 15: Depth of Full Order Book and Market Price

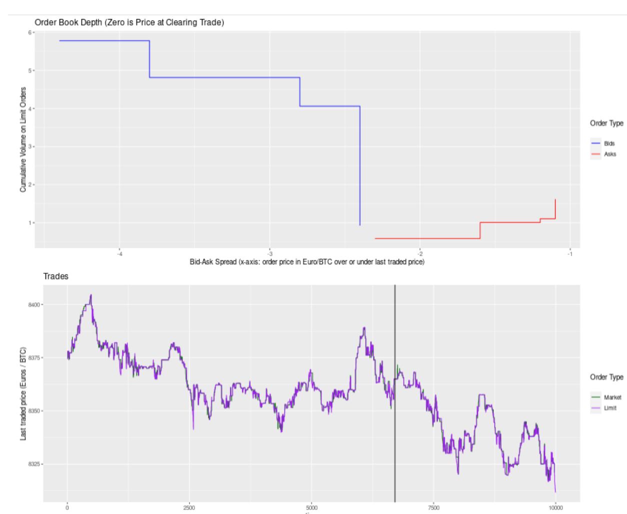

Figure 16: Best Four Orders on Either Side and Market Price

I followed Sandås (2001) model using three sets of moment conditions: two of these are based on equation (4) where limit orders are posted to the ELOB until equilibrium price, and then we take a snapshot at time t just before the arrival of the next market order X_{t+1}. The third condition sets expected market order size equal to some fixed λ.

The ***break-even moment conditions*** pulls information from the ELOB and removes the fundamental true value by adding the equilibrium depth associated with the k^{th} price at the bid side of the book to the same equilibrium equation at the ask side of the book. We assume that these equations hold up to an error term:

$$E\left(p_{+k,t} - p_{-k,t} - 2\gamma - \alpha\left(\sum_{i=+1}^{+k} q_{i,t} + \sum_{i=-1}^{-k} q_{i,t} + 2\lambda\right)\right) = 0 \qquad k = 1, 2, ... \tag{5}$$

The ***updating restriction moment conditions*** subtracts $p_{\pm k,t+1}$ from $p_{\pm k,t}$ removing the 'true' asset value v_t giving:

$$E\left(\Delta p_{+k,t} - \alpha\left(\sum_{i=+1}^{+k} q_{i,t+1} - \sum_{i=+1}^{+k} q_{i,t} - c - \alpha X_t\right)\right) = 0 \qquad k = 1, 2, ... \quad (ask \;\; side) \tag{6}$$

$$E\left(\Delta p_{-k,t} - \alpha\left(\sum_{i=-1}^{-k} q_{i,t+1} - \sum_{i=-1}^{-k} q_{i,t} - c - \alpha X_t\right)\right) = 0 \qquad k = 1, 2, ... \quad (bid \;\; side) \tag{7}$$

where $\Delta p_{k,t} = p_{k,t} - p_{k,t-1}$

Market order size conditions set λ equal to the expected size of market orders:

$$E\left(|X_t| - \lambda\right) = 0 \tag{8}$$

Generalized method of moments (Hansen 1982) estimation was applied to an ELOB model restricted to the four best quotes on both sides yielding 13 moment conditions: 4 break-even (5), 8 updating (6), and 1 market order size (7). Time ticks represent the arrival of a market order, and the ELOB state is shown just ahead of the next market order arrival. The time between market orders is assumed to be sufficient for limit order posters to adjust their positions. This makes sense in, for example, the Kraken Bitcoin market where ~20 limit orders are submitted for every market order.

The computed statistics from the Glosten model for the cryptocurrencies in this study are summarized in table 4.

All estimates t-statistics and J-statistics (J is distributed χ^2_9) were significant at $< .001$ level.

We can also compare the fit of the (Glosten 1994) model statistics to corresponding estimators from the two prior studies that attempted empirical fit: (Sandås 2001) and (Beltran-Lopez, Grammig, and Menkveld 2012). In this table, just the Bitcoin calculations are shown, but others can be compared using table 4's statistics.

To some extent, the three rows compare 'apples to oranges' as transaction sizes and prices are substantially different between a share of stock which is likely to have prices under \$100 and volumes in the 10s and 100s; to Bitcoin, which has prices over \$10,000 and volumes in fractions of one Bitcoin. The scale (price and transaction volume) is substantially different in the three different datasets, causing the large differences in the λ and c estimates. The α estimates should be consistent. The small γ in the current research reflects the cost of trading Bitcoin.

Table 4: Liquidity, Transaction Cost and Order Size of Crytocurrencies by Market Cap (Glosten Model)

Coin	Liquidity (alpha)	Implicit transaction cost (gamma)	Normalizing coefficient (c)	Average Order Size (lambda)	J-test fit	Sample Size
BTC	0.639000	26.193000	-27.803000	43.480	1.3530e+03	9766000
ETH	0.000718	0.064887	-0.004773	6.647	6.4770e+03	64656
USDT	0.000000	0.000113	0.000013	338.130	1.7400e+02	39200
XRP	0.000000	0.000055	-0.000002	2198.300	3.2180e+03	386496
BCH	0.002967	0.123584	-0.006780	2.291	1.1810e+03	10176
LINK	0.000002	0.010185	-0.000322	183.240	1.1486e+04	8350
BNB	NA	NA	NA	NA	NA	NA
LTC	0.000113	0.050598	-0.000430	3.796	2.6409e+04	222336
DOT	0.000001	0.003762	-0.000136	219.410	1.4372e+04	680000
BSV	NA	NA	NA	NA	NA	NA
ADA	0.000000	0.000036	0.000000	4013.400	1.9943e+19	27600

Table 5: Comparison of Research Results

Study	alpha	gamma	c	lambda
Current Research averages	0.53683	23.07667	-25.14	47.80217
Beltran, 2012	0.01000	-0.01000	1.38	0.03000
Sandaas, 2001	2.60000	-0.99000	11.17	11.45000

Price Elasticities and Cross-Elasticities

Price elasticity of demand is defined as $\eta = \frac{\Delta D/D}{\Delta P/P}$ where D is demand volume, and P is price of the asset in demand. Elasticity can be conceived in terms of an asset's 'own-price' elasticity η_{d_p} or that asset's demand elasticity with respect to the price q of another asset η_{d_q} - i.e. the 'cross-elasticity.'

In figure 17 which overlays a heatmap onto the cross-elasticities to highlight specific relationships, specific cryptocurrency pairs do not necessarily exhibit symmetric cross-elasticities. For example the cross-elasticity of $BCH \rightarrow ETH = 0$ while cross-elasticity of $ETH \rightarrow BCH = 10.05$. This is due to the Income Effect - the amount of money in the total cryptocurrency market is nearly constant over short time periods. Marshallian and Hicksian demand maximize investor utility from owning cryptocurrencies. Keeping total budget fixed and maximizing utility obtains Marshallian demand; setting a target utility and minimizing the cost obtains Hicksian demand. The cross price elasticities of a Hicksian demand function, where utilities are held constant, are symmetric because of Slutsky symmetry conditions. Assuming there is no Income effect of a price change, the cross-substitution effects in two asset markets are symmetric. For Marshallian demand, where income is held constant, cross price elasticities are asymmetric and even the signs can differ. Empirical studies often display asymmetric price elasticities, as is the case in this study. (Bonfrer, Berndt, and Silk 2006)

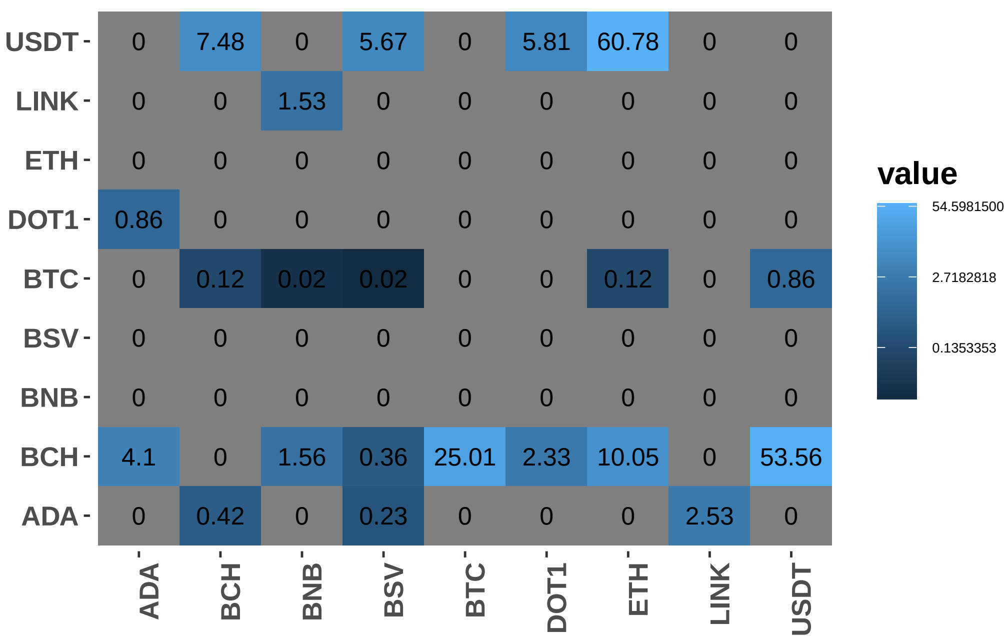

Figure 17: Cross Price Elasticities of Demand for Top Cryptocurrencies

Figure 18 incorporates dendrograms into the heatmap superimposed on cross-elasticity values in figure 17 which highlights differences in cryptocurrency fungibility. These dendrograms highlight the significant cross-price elasticities of Tether (USTD) and Bitcoin Cash (BCH). USTD is used in place of US dollars in many Ethereum (ETH), Bitcoin (BTC), Bitcoin Cash (BCH) and Bitcoin Satoshi Vision (BSV) and these peaks in elasticity represent periods of extreme price volatility in those coins. Bitcoin Cash (BCH) on the other hand tends to track Bitcoin (BTC) which being around 50% of total cryptocurrency market capitalization, exhibits strong cross-elasticities with other cryptocurrencies.

Note that Ethereum (ETH) has the most diverse and dynamic ecosystem, and has actively promoted its inclusion in decentralized finance (DeFi) ecosystems. Decentralized finance networks are designed to allow financial transactions in trustless and transparent protocols that run without intermediaries. Ethereum has over two hundred products designed for DeFi (see https://defiprime.com/ethereum). The growth of decentralized finance has increased its own price elasticity, as well as its cross-elasticity with Tether (USTD) because many DeFi transactions are completed on the Ethereum-Tether asset pair, rather than being completed into fiat currencies.

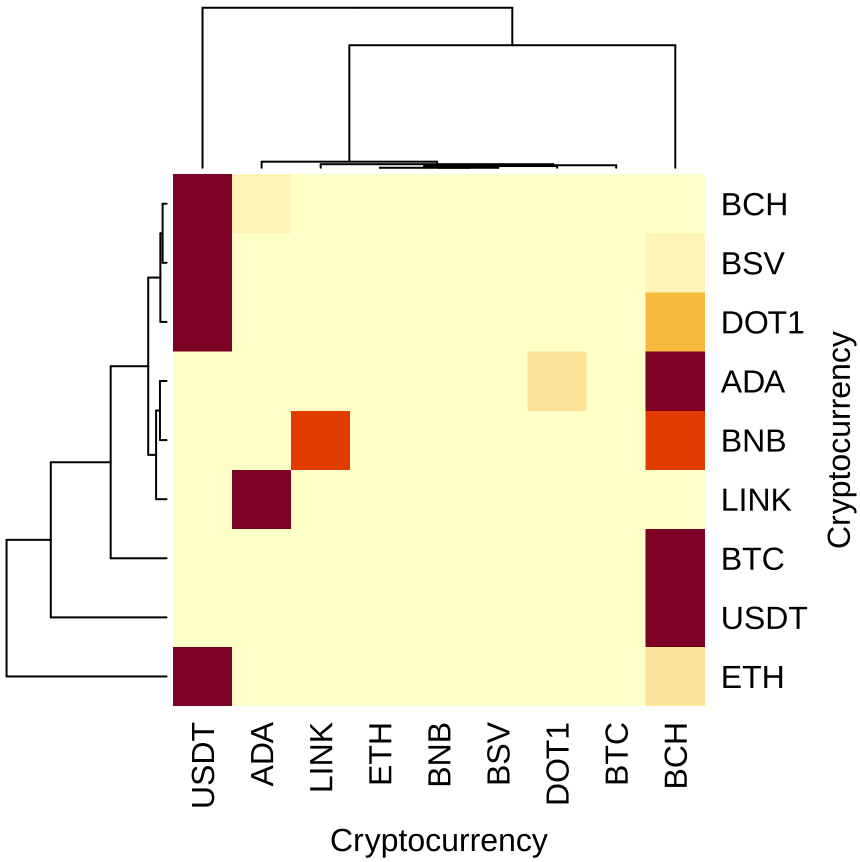

Figure 18: Cryptocurrency Cross Price Elasticities with Dendrograms

Table 6: Own Price Elasticity of Crytpocurrencies in this Study

Name	elasticity
ETH	1.737
BSV	1.468
BCH	1.464
BTC	1.367
ADA	1.341
BNB	1.240
LINK	1.019
USDT	1.000

Table 7: Regression of Liquidity on Price

term	estimate	std.error	statistic	p.value
(Intercept)	-0.006	0.003	-1.931	0.102
Price	0.000	0.000	79.732	0.000

Table 8: Regression of Liquidity on Box-Cox Transformed Price (B-C parameter = 3.245124)

term	estimate	std.error	statistic	p.value
(Intercept)	0.001	0	2.032	0.088
tp	0.000	0	565.369	0.000

Results of Hypothesis Testing

To test the research hypotheses, I ran OLS regressions on the statistics computed in the last section. The results are somewhat limited by the small number of cryptocurrencies that dominate almost all of the pricing and trading of cryptocurrencies. But results were significant, and in fact, represent ~90% of volume and market capitalization, thus are generalizable. Research conclusions are based on analysis of a small but compelling set of coins, backed by computed statistics, e.g., liquidity and imputed commission, that were estimated from very large datasets.

The research tests, in sequence, our five hypotheses:

- H_1: Increasing *price* increases *liquidity*
- H_2: Increasing *market volume* increases *liquidity*
- H_3: Increasing *fungibility* increases *liquidity*
- H_4: Increasing *own-price elasticity* increases *liquidity*
- H_5: *Liquidity* can be increased with *combinations of factors*

H_1: Increasing ***liquidity*** increases ***price***

H_1 is strongly supported by the research. To test H_1 I regressed computed Glosten-liquidity against an average price in the data acquisition period for the cryptocurrency. Table 5 summarizes the regression results.

I also tested whether a transformation of price might provide a better fit, using a Box-Cox model (Box and Cox 1964) with parameter ϱ choice optimized on the Shapiro–Wilk test (Shapiro and Wilk 1965). Box-Cox transformations stabilize variance, bringing the data more in line with a Gaussian distribution, which in turn improves the validity of correlations between variables.

The one-parameter Box–Cox transformations are defined as $y_i^\lambda = \frac{y_i^\varrho - 1}{\varrho}$ if $\varrho \neq 0$ and $y_i^\varrho = ln(y_i)$ if $\varrho = 0$. The Box-Cox model provides a smooth continuously varying of the transformation from concave to convex. With the current data, the regression of cryptocurrency price against volume ($\varrho = -0.33; R^2 = 0.28$) and price against the total count of coins circulating ($\varrho = -0.261; R^2 = 0.62$) suggest both have some predictive power in computing price. But the correlations are insufficient to be of any use as a trading strategy.

The regression was slightly improved (AIC moved from -52 to -83) by using $price^{3.25}$ over price, though this is not sufficient to abandon untransformed *price* as a predictor of liquidity

H_2: Increasing ***market volume*** increases ***liquidity***

In the testing of H_2 volume may be interpreted several ways. The Glosten model, which considers trading, as well as supply and demand reflected in the ELOB, computes an *implicit volume* λ that was tested as a predictor of liquidity. Table 7 summarizes the regression, and rejects λ as a predictor of liquidity.

Table 9: Regression of Liquidity on Glosten Computed Equilibrium Volume

term	estimate	std.error	statistic	p.value
(Intercept)	0.135	0.131	1.030	0.361
lambda	0.000	0.000	-0.457	0.671

Table 10: Regression of Liquidity on Actual Volume

term	estimate	std.error	statistic	p.value
(Intercept)	0.129	0.128	1.008	0.371
Volume	0.000	0.000	-0.412	0.701

Two other possible measures of volume could be *daily volume* and *circulating supply* for each cryptocurrency, extracted directly from market data. Tables 8 and 9 summarize the results of these regressions, which perform similarly to the regression of λ as a predictor of liquidity.

I also experimented with Box-Cox transformations to improve fit (tables 10 and 11) with mixed results.

The general conclusion from tests of H_2 is that volume is not a viable predictor of liquidity, and that though liquidity depends on price, it does not depend on volume.

H_3: Increasing ***fungibility*** increases ***liquidity***

Fungibility between a pair of cryptocurrencies is the ability to substitute one coin for the other. H_3 used functions of cross-price elasticities to provide a measure of the fungibility - in the sense of ‘mutual interchangeability - of particular pairs of cryptocurrencies. Since cryptocurrencies are basically currencies, they might be considered 'numéraire commodities,' potentially exchangeable for any other asset. But disparities in availability, price stability, and other factors may make one currency preferable for particular types of transactions over another.

Table 12 summarizes the cross-elasticities of the studied currencies, and is a tabular rendition of the information in figures 17 and 18.

I tried a number of different ways to map the distribution of cross elasticities of the major cryptocurrencies into a single number that could be used with regression on a small dataset. These covered the range of dispersion measures typically encountered in statistical analysis. InterQuartile Range (IRQ) provided the best fit. This seems reasonable given that many of the cross-elasticities are zero, while non-zero cross-elasticities were highly variable. In such circumstances, IRQ tends to filter the most important information in the variability into a form that works well with linear regressions. It tends to work well with skewed distributions or data sets with outliers. Table 13 provides regression results for liquidity vs. IRQ of cross-elasticities.

Though the IRQ provided the best fit out of all of the measures of cross-elasticity dispersion, that fit was still quite poor, with $R^2 \approx 8\%$. Tables 14 through 17 provide the regression results for liquidity on the other dispersion predictors.

H_4: Increasing ***own-price elasticity*** increases ***liquidity***

The hypothesis H_4 that increasing *own-price elasticity* increases *liquidity* provides a corollary to H_1 and H_2 that price and volume are predictors of liquidity. Own-price elasticity is a function of price and volume (and their rates of change). Given the qualitative definitions of liquidity, both price and volume are potential

Table 11: Regression of Liquidity on Circulating Supply of Cryptocurrency

term	estimate	std.error	statistic	p.value
(Intercept)	0.155	0.137	1.137	0.319
Circulating	0.000	0.000	-0.632	0.562

Table 12: Regression of Price on Box-Cox Transformed Volume (B-C parameter = -0.3355507)

term	estimate	std.error	statistic	p.value
(Intercept)	2421.658	1430.162	1.693	0.099
tvolume	21590947.483	5642227.554	3.827	0.000

Table 13: Regression of Price on Box-Cox Transformed Circulating Supply (B-C parameter = -0.2607883)

term	estimate	std.error	statistic	p.value
(Intercept)	-5264.368	1502.762	-3.503	0.001
tcirc	647288.804	81539.391	7.938	0.000

Table 14: Cross Price Elasticities of Studied Cryptocurrencies

model	ADA	BCH	BNB	BSV	BTC	DOT1	ETH	LINK	USDT
ADA	0.00	4.10	0	0	0.00	0.86	0	0.00	0.00
BCH	0.42	0.00	0	0	0.12	0.00	0	0.00	7.48
BNB	0.00	1.56	0	0	0.02	0.00	0	1.53	0.00
BSV	0.23	0.36	0	0	0.02	0.00	0	0.00	5.67
BTC	0.00	25.01	0	0	0.00	0.00	0	0.00	0.00
DOT1	0.00	2.33	0	0	0.00	0.00	0	0.00	5.81
ETH	0.00	10.05	0	0	0.12	0.00	0	0.00	60.78
LINK	2.53	0.00	0	0	0.00	0.00	0	0.00	0.00
USDT	0.00	53.56	0	0	0.86	0.00	0	0.00	0.00

Table 15: Regression of Liquidity on IRQ('Cross Elasticities')

term	estimate	std.error	statistic	p.value
(Intercept)	0.152	0.137	1.108	0.330
IRQ_of_x_elasticities	-0.013	0.023	-0.589	0.588

Table 16: Regression of Liquidity on Mean('Cross Elasticities')

term	estimate	std.error	statistic	p.value
(Intercept)	0.163	0.140	1.159	0.311
mean_of_x_elasticities	-0.015	0.022	-0.666	0.542

Table 17: Regression of Liquidity on median('Cross Elasticities')

term	estimate	std.error	statistic	p.value
(Intercept)	0.157	0.138	1.136	0.319
median_of_x_elasticities	-0.062	0.098	-0.632	0.562

Table 18: Regression of Liquidity on Std.Dev('Cross Elasticities')

term	estimate	std.error	statistic	p.value
(Intercept)	0.164	0.141	1.166	0.308
SD_of_x_elasticities	-0.008	0.012	-0.676	0.536

Table 19: Regression of Liquidity on MAD('Cross Elasticities')

term	estimate	std.error	statistic	p.value
(Intercept)	0.157	0.138	1.136	0.319
MAD_of_x_elasticities	-0.042	0.066	-0.632	0.562

Table 20: Regression of Own-price Elasticities against Liquidity

term	estimate	std.error	statistic	p.value
(Intercept)	0.005	0.625	0.009	0.993
elasticity	0.077	0.465	0.166	0.877

Table 21: Forward step-wise ANOVA

Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
	NA	NA	5	0.339	-15.232
+ gamma	-1	0.339	4	0.000	-93.332
+ mkt_cap	-1	0.000	3	0.000	-100.811
+ Volume	-1	0.000	2	0.000	-107.109
+ own_elasticity	-1	0.000	1	0.000	-116.358
+ c	-1	0.000	0	0.000	-Inf

predictors, and similarly, we might expect own-price elasticity to be a predictor of liquidity. The regression analysis, though strongly rejects this hypothesis, with an $adjusted - R^2$ of -0.24 and an AIC that is slightly positive.

H_5: Other *combinations of factors* can be identified that increase *liquidity*

H_5 can be restated as "Given all of the measured values that can be extracted from cryptocurrency trading platforms, what combination of these predictors offers the most information about liquidity?" I am also interested in testing whether other combinations of predictors that were obtained in this research could improve on the explanatory models investigated in the prior four hypotheses.

I use Akaike Information Criterion (AIC) and $adjusted - R^2$ to measures of whether one model better fits the data than another. Through the use of step-wise regression with an AIC objective function, I am able to improve slightly on fit statistics over the prior four hypotheses. The results of the step-wise regression are suggestive, and will be valuable in crafting future hypotheses for study.

Tables 21 and 22 show the step-wise regression results for a forward search, and tables 23 and 24 show these for a forward / backward search. Both directions unambiguously select the same combination of four predictors: (1) γ, (2) market capitalization, (3) daily volume, and (4) own-price elasticity. Table 25 shows the same four predictors in an OLS regression against liquidity, with $adjusted - R^2$ of 1.0 and AIC of -97. This is better than our individual tests of H_1 to H_4, but is only suggestive, because it lacks a prior model or mechanism explaining why these predictors would be selected.

step-wise regression results, in general, need to be interpreted with some skepticism. But they can be counted on to highlight the most probable relationships, and provide a fertile basis for building models for further research.

My findings from a step-wise regression on all of the measurements in this study show that:

1. an increasing implicit commission γ on trades is associated with increased liquidity, with a $p - value = 0.0006$. This suggests that trading platforms could or will charge more to trade in highly liquid cryptocurrencies. The actual commission structure in Kraken and other platforms is complex, with

Table 22: Forward step-wise Coefficients

	Estimate
(Intercept)	-0.0007605
gamma	0.0236907
mkt_cap	0.0000000
Volume	0.0000000
own_elasticity	0.0006281
c	-0.0008774

Table 23: 'Forward / Backward' step-wise ANOVA

Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
	NA	NA	5	0.3394893	-15.23243
+ gamma	-1	0.3394888	4	0.0000005	-93.33193
+ mkt_cap	-1	0.0000004	3	0.0000001	-100.81092
+ Volume	-1	0.0000001	2	0.0000000	-107.10871
+ own_elasticity	-1	0.0000000	1	0.0000000	-116.35802
+ c	-1	0.0000000	0	0.0000000	-Inf

Table 24: 'Forward / Backward' step-wise Coefficients

	Estimate
(Intercept)	-0.0007605
gamma	0.0236907
mkt_cap	0.0000000
Volume	0.0000000
own_elasticity	0.0006281
c	-0.0008774

a regressive commission system that could very likely penalize more liquid cryptocurrencies. Further research would reward the investigation of this hypothesis.

2. larger market capitalization is associated with decreased liquidity, with a $p - value = 0.076$. This may reflect the fact that large market cap coins have large individual values, which may dampen trading. Again, further research would reward the investigation of this hypothesis.

3. larger volume of trading is associated with increased liquidity. This result is somewhat tautological, since volume of trading is one indicator of liquidity. Nor is the $p - value = 0.133$ particularly reassuring. In my opinion, this is a result that adds little useful new knowledge.

4. the impact of own price elasticity on liquidity was explored previously, and here has a $p - value = 0.256$ that is equivocal. The step-wise regression suggests that there may be weak explanatory power in own price elasticity.

Conclusions and Discussion

In this research, I provided objective predictors of cryptocurrency liquidity which should provide useful in objectifying the concept of cryptocurrency as being a true cash-like asset. Liquidity is a measure of a market's ability to address the demands of impatient traders, and is an exceptionally important aspect of cryptocurrencies, which aim to be cash substitutes, and thus totally liquid. Greater liquidity is correlated with more profitable trading due to among other things, better price discovery; and more profitable market operation, due to among other things, higher volume and higher per transaction revenue from trading. Information disseminated through a public electronic limit order book also contributes to and complicates the assessment of liquidity (Lybek and Sarr 2002).

This research aimed to identify quantitative predictors of liquidity, in order to objectify a term that has tended to be used mostly in a qualitative and descriptive manner. Such qualitative constructs are common in the social sciences, including economics, and are typically modeled as latent constructs which cannot be

Table 25: Regression with Best Predictors of Liquidity (Mkt Cap $\times 10^{-12}$ and Volume$\times 10^{-21}$)

term	estimate	std.error	statistic	p.value
(Intercept)	-0.0005936	0.0002460	-2.412831	0.2501289
gamma	0.0246114	0.0000246	999.036790	0.0006372
mkt_cap	-0.0236182	0.0028180	-8.381178	0.0756009
Volume	0.0001381	0.0000293	4.705512	0.1333091
own_elasticity	0.0004620	0.0001966	2.349482	0.2561761

measured directly, but where predictors of indicators can be found that can individually or in combination provide measures of the latent construct. The current research aims to provide quantitative support for a definition of liquidity based on measurable quantities in cryptocurrencies markets.

The research tested five hypotheses concerning liquidity and its predictors, for a set of cryptocurrencies that represent ~90% of volume and market capitalization, thus are generalizable. Research conclusions are based on analysis of a small but compelling set of coins, backed by computed statistics, e.g., liquidity and imputed commission, that were estimated from very large datasets.

Price was found to be a good predictor of liquidity, with hypothesis H_1 is strongly supported by the research. I also tested whether this relationship might be non-linear, using a Box-Cox model (Box and Cox 1964) with parameter ϱ choice optimized on the Shapiro–Wilk test (Shapiro and Wilk 1965). Transformation slightly improved the model (AIC moved from -52 to -83) by using $price^{3.25}$ over price, though this was not sufficient to abandon untransformed *price* as a predictor of liquidity

Volume has also been suggested as a surrogate for liquidity, but multiple tests did not support this assumption. In the testing of H_2 I interpreted volume in three ways: (1) Glosten model *implicit volume* λ, (2) *daily volume*, and (3) *circulating supply.* I also experimented with Box-Cox transformations to improve fit with mixed results. My general conclusion from tests of H_2 is that volume is not a viable predictor of liquidity, and that though liquidity depends on price, it does not depend on volume.

Fungibility between a pair of cryptocurrencies is the ability to substitute one coin for the other. H_3 used functions of cross-price elasticities to provide a measure of the fungibility - in the sense of 'mutual interchangeability - of particular pairs of cryptocurrencies. Since cryptocurrencies are basically currencies, they might be considered 'numéraire commodities,' potentially exchangeable for any other asset. But disparities in availability, price stability, and other factors may make one currency preferable for particular types of transactions over another. The research did not support the assertion that inter-cryptocurrency fungibility is a predictor of liquidity. It did leave out a test of each of these cryptocurrencies against cash. Such data would have been impossible to obtain, given that most cash transactions are not centrally recorded on any exchange. But it does raise questions about whether cryptocurrencies truly are "cash equivalents."

I also looked at a corollary to H_1 and H_2 $-$ that price and volume are predictors of liquidity $-$ in hypothesis H_4 that increasing *own-price elasticity* increases *liquidity.* The regression analysis strongly rejected this hypothesis, with an $adjusted - R^2$ of -0.24 and an AIC that is slightly positive.

The final test involved a generalized analysis of variance through step-wise regression. H_5 could be restated as "Given all of the measured values that can be extracted from cryptocurrency trading platforms, what combination of these predictors offers the most information about liquidity?" This test unambiguously selected a combination of four predictors: (1) γ, (2) market capitalization, (3) daily volume, and (4) own-price elasticity. Explanatory power was slightly better than other predictors, but lacking a structural model incorporating these predictors, the results here are suggestive of future research studies.

In particular, these findings suggest the following future researchable hypotheses:

- $future - H_1$: an increasing implicit commission γ on trades is associated with increased liquidity.

  This suggests that trading platforms could or will charge more to trade in highly liquid cryptocurrencies. The actual commission structure in Kraken and other platforms is complex, with a regressive commission system that could very likely penalize more liquid cryptocurrencies. Further research would reward the investigation of this hypothesis.

- $future - H_2$: larger market capitalization is associated with decreased liquidity.

  This may reflect the fact that large market cap coins have large individual values, which may dampen trading. Further research would reward the investigation of this hypothesis.

- $future{-}H_3$: there is a more complex model involving own price elasticity, volume, price and commissions and that combination is associated with increased liquidity.

  A final comment on the analyses in this research involves the Glosten model of liquidity in an ELOB market. The Glosten model has in the past been difficult to apply empirically because the GMM methods required to calculate the statistics require massive amounts of data, and traditional securities markets simply have not had transparency, electronic platforms and trading volume to allow access to and analysis of a high enough volume of data. Fortunately, the Kraken platform APIs and the volume of trading on Kraken have allowed me to collect volumes of data several orders of magnitude larger than prior studies, which have facilitated the calculation of the implicit transaction cost parameter γ, the liquidity parameter α and the implicit volume parameter λ for the most widely traded cryptocurrencies.

The implicit γ and λ parameters provide interesting benchmarks. Stated commissions are comparable across platforms and cryptocurrencies, but these commissions can become complex because they are sensitive to volumes in a particular contract. They are also typically different than the computed values of γ. The computed λ seems approximately two magnitudes larger than the directly computed $E(|X_t|) \approx 0.20$ leading us to question what is happening. In the final moment condition, $\lambda = E(|X_t|)$, but GMM only approximately needs to enforce that condition. It is important to remember that trade volumes are indigenous to the trading platform, but prices are set across all platforms in the market, and any differences would quickly be arbitraged away. It is also likely that very large trades may be facilitated outside of any platform by a direct wallet-to-wallet transfer. The empirical value of $\lambda \approx 55$ might indeed reflect an empirical value commensurate with the price – i.e., off platform, wallet-to-wallet trades may be driving the prices in the market. Perhaps more conspiratorially, large traders ("whales") may actually be manipulating price changes in direct wallet-to-wallet transfer, and these later trickle-down to on-platform trading through a large number of profit-taking small market orders.

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