Competition and Product Quality: Fake Trading on Crypto Exchanges

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Abstract

How competition affects product quality and how product quality choices impact firms' operating performance are open empirical questions. We use a setting that is especially suitable to answering these questions: crypto exchanges, on which product quality is inversely related to fake (inflated) trading volume. We find that both static and dynamic competition measures are positively associated with fake trading, indicating that competition may lead to reduced product quality. Exchanges that inflate trading volume succeed in misleading investors in the short run but are punished in the long run, consistent with the tradeoff between short-lived increases in rents and future losses due to damaged reputation.

Keywords: Crypto exchanges, fake trading, competition, product quality, reputation.

JEL classification: G18, G23, L10, L13, L15.

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1 Introduction

The choice of product quality has long been recognized in the industrial organization literature as an important facet of the operating strategy of firms producing "experience goods", i.e., products whose quality is not observed until after the purchase decision (e.g., Klein and Leffler (1981), Shapiro (1983), Allen (1984), and Cooper and Ross (1984)).[1] A firm's decision whether to attempt to mislead its customers about the quality of its products involves a tradeoff between higher short-term gains and lower future profits due to damaged reputation. Product market competition can be important in shaping this tradeoff. On one hand, building and maintaining reputation is more valuable the larger the expected future rents relative to current rents. The larger the (expected) competition, which reduces future rents, the lower the incentive to maintain reputation (e.g., Dana and Fong (2011)). On the other hand, the strength of the reputation effect may increase in competition, as more intense competition expands consumers' outside options (e.g., Horner (2002)).

This paper empirically examines the relation between competition and firms' choices of their product quality, as well as implications of these choices for firms' future performance. We focus on an industry that is very well suited for an examination of this relation – crypto exchanges, whose role is to facilitate trades in pairs of assets at least one of which is a crypto currency. Crypto exchange industry is especially suitable for examining determinants and consequences of product quality choices in a competitive setting for several reasons.

First, trading volume on exchanges is positively related to anticipated product quality, as trading volume is generally perceived to be associated with market liquidity. Exchanges have access to an easily implementable technology for misleading consumers regarding the quality of their product: artificial inflation of trading volume through fake (wash) trading that outsiders do not immediately

[1]See also models of product quality choice in particular industries, such as Chemmanur and Fulghieri (1994) in the context of investment banks, and Bolton, Freixas, and Shapiro (2012) and Bar-Isaac and Shapiro (2013) in the context of credit rating agencies.

observe (e.g., Cumming, Johan, and Li (2011)).[2] Our examination of fake trading on crypto exchanges builds on the pioneering work of Cong, Li, Tang, and Yang (2021), who develop several measures of fake trading on crypto exchanges, some of which we adopt and expand in our study.

The reason trading volume is an important signal to market participants of an exchange's quality is that most aggregators of data on cryptocurrencies and crypto exchanges, such as www.CoinMarketCap.com, explicitly rank exchanges based on trading volume. In the absence of credible signals of exchanges' quality, many investors rely on these rankings in their choice of a trading venue.[3] Consistent with this conjecture, Gervais, Kaniel, and Mingelgrin (2001) find that in the context of traditional exchanges and equities, unusually high trading volume is followed by abnormally positive returns, suggesting that investors value increased liquidity. Importantly, while wash trading is forbidden in most asset markets,[4] the legality of wash trading on crypto exchanges is a grey area, due to insufficient regulation of crypto markets in most jurisdictions and to the cross-border nature of most crypto exchanges. Importantly, in our setting, it is the crypto exchanges themselves that may have the incentives to inflate volume. In contrast, in traditional markets it is usually investors who wash trades, e.g., for tax purposes (e.g., Grinblatt and Keloharju (2004)).[5]

The second reason for the suitability of crypto exchange industry for studying firms' product quality choices is that there are two crucial elements underlying the relation between product quality choice and reputation: the quality of a firm's product has to be unobservable ex-ante (as in the case of "experience goods"), and it has to be decipherable ex-post, at least partially. Both these elements are

[2] A crypto exchange can create fake volume in two main ways. First, it can execute back-and-forth transactions among its own wallets. Second, it can crease perverse incentives for investors to trade with themselves, e.g., by eliminating trading commissions for "top-tier" traders.

[3] Recently, in response to widespread concerns of trading volume inflation, www.CoinMarketCap.com and other aggregators began to rank exchanges based on additional criteria that are harder if not impossible to manipulate, such as web traffic to an exchange's website, the number of currencies listed, the number of currency pairs traded on the exchange, and the exchange's age. Some aggregators use a "holistic" approach for ranking exchanges, incorporating both hard and soft information.

[4] For example, in the United States, wash trading was made illegal after the passage of U.S. Securities and Exchange Act in 1934 and the Commodity Exchange Act in 1936.

[5] The most recent large-scale case of trading volume inflation occurred on the Canadian exchange CoinSquare, which inflated volume on its platform by 5.5 billion $U.S.

present in the crypto exchange setting: the quality of the product (i.e. the real depth of order books and realized slippage) can only be estimated gradually over time.

Third, the crypto exchange industry enables a more nuanced analysis of the relation between competition and product quality than most other settings. Although young, the industry is very dynamic, with numerous entries and several exits since the establishment of the first crypto exchanges in 2010.[6] Competition among crypto exchanges has many layers. On one hand, exchanges are heterogeneous both operationally – in terms of the set of currency pairs listed on them, and geographically – catering to partially overlapping sets of clients. On the other hand, competition among multiple trading platforms within a given currency pair is competition in largely homogeneous goods.

The development of the crypto market over the last decade saw a large increase in the competitiveness of the crypto exchange industry: During our 6.5-year-long sample period, the number of exchanges in our data set – `www.Kaiko.com`, which contains transaction-level data on dozens largest crypto exchanges – increased from one to 37, and the Herfindahl indices of concentration of the crypto exchange market, measured using the number of traded currency pairs, reported volume of trading, and reported number of trades, decreased from one to roughly 0.1.

We begin by developing measures of fake trading. As fake trading is unobservable and not directly detectable without information on addresses of accounts (crypto wallets) that performed the trade, we develop statistical fake trading measures at the most granular level possible. i.e., at the exchange-currency pair-month level. We estimate all the measures discussed below using both the trading volume and the number of trades series.

Our first measure, also used in Amiram, Bozanic, and Rouen (2015) in the context of detection of errors in financial statements, in Michalski and Stoltz (2013) in the context of detection of errors in macroeconomic data, and, most relevant for our study, in Cong et al. (2021) for detection of wash

[6]Bitcoinmarket.com went live in March, 2010, followed in July 2010 by Mt. Gox. Both exchanges are now defunct. According to `www.CoinMarketCap.com`, there are over 300 crypto exchanges specializing in spot markets.

trading on crypto exchanges, is deviations of the frequencies of first digits of either the trading volume or the number of trades within short time intervals from Benford's Law (Benford (1938)).

Our second measure of fake trading, which is novel to the literature, is based on the deviation of the distribution of trading volume/number of trades within short intervals from log-normal distribution. Typical trading volume series tend to be distributed log-normally (e.g., Richardson, Sefcik, and Thompson (1986) and Ajinkya and Jain (1989)). Deviations from log-normality can be a sign of data manipulation.

Our third measure, which is also novel to the literature, is based on a machine-learning non-parametric algorithm called EDM (E-Divisive with medians), which identifies structural breaks in data series. The larger the number of identified structural breaks in the trading volume or number of trades series, the higher the chance of data manipulation. While well known in the computer science literature, this measure is new not only to the crypto exchanges literature but to finance literature in general to the best of our knowledge.

Since the measures discussed above aim to identify particular deviations from normal trading patterns and none of them is likely to be capable of identifying the majority of such deviations, we aggregate these measures by computing their principal components. While we focus on principal-component-based measures in the analysis, the inferences are largely unchanged when using individual fake trading measures.

We validate our fake trading measures in several ways. First, we show that our estimates of fake trading tend to be the lowest for exchanges with the highest web popularity, for the oldest exchanges, and for the minority of exchanges that are regulated to some degree. On the contrary, exchanges with reported cases of manipulation tend to have some of the highest fake trading measures. Second, we find that fake trading measures are higher for exchanges with relatively low levels of self-imposed regulation and compliance, and relatively low transparency levels. Third, we estimate other, more intuitive fake trading measures, which are based on contemporaneous correlations between either the number of trades or trading volume in a given currency pair on a given exchange with the same variable aggregated for that currency pair on all exchanges. The idea is that fake trading, which is unlikely correlated across exchanges, depresses these correlations. We find that our statistical fake trading measures are significantly associated with alternative, correlation-based, measures. Fourth, we use a pseudo-natural experiment – the ban on operation of crypto exchanges in China in 2017, which led to their exodus to other locations, mostly to Hong Kong and the rest of Pacific Asia. We perform a difference-in-differences analysis of changes in fake trading measures on exchanges subject to the ban and find that exchanges that moved out of China following the ban into jurisdictions with higher regulation/compliance standards reduced the extent of their fake trading substantially.

Having validated our measures of fake trading volume, we use them to examine the relation between static and dynamic aspects of exchanges' competitive environment on one hand and the extent of fake trading on their platforms on the other hand. Our most important finding with respect to static competition is that exchanges do not fake trading equally in all currency pairs. Pairs especially prone to volume manipulation are those that are being traded on many exchanges and those in which the concentration of trading across exchanges is low, i.e. in cases in which competition among exchanges is strong. For example, a one-standard-deviation increase in the trading-volume-based Herfindahl index of a currency pair across exchanges is associated with a 0.1-0.2 standard-deviation reduction in fake trading measures in that currency pair. In addition, older and larger exchanges tend to exhibit lower fake trading measures, consistent with these exchanges having larger incentives to maintain reputation. At the same time, exchanges that are more diversified across currency pairs tend to have higher estimated fake trading measures, consistent with the result in Dana and Fong (2011) that multimarket competition mitigates reputational damages of opportunistic strategies.

We then examine how dynamic competition environment, i.e., changes in exchanges' competitive landscape, influences their strategies. In particular, we analyze how entry and exit of an exchange's competitors in a given currency pair impact the extent of fake trading on the focal exchange. In doing so, we define three types of competitors: general – any exchange that commences/ends trading in the relevant currency pair; geographical – a subset of competitors operating in the focal exchange's geographical area; and operational – an exchange that has the largest overlap with the focal exchange in the set of currency pairs traded on both. We find that entry (exit) by competitors tends to increase (decrease) fake trading estimates at the exchange-currency pair level, especially when the initial extent of competition that the focal exchange is subject to in a given currency pair is large. Consistent with our findings regarding the effects of static competition on fake trading, this result demonstrates that reputational concerns are decreasing in the extent of competition, in line with Dana and Fong (2011).

The last part of our analysis concerns short-run and longer-run effects of fake trading. We examine the effectiveness of trading volume inflation in light of the conjectured tradeoff between short-term gains versus long-term losses due to harmed reputation. We obtain two interesting results. First, inflating trading volume by an exchange in a given currency pair in a given month increases estimated real trading volume (i.e. trading volume controlling for fake trading estimate) in that pair over the course of next month – a one-standard-deviation increase in fake trading measures in a given month raises next month's real trading volume by 0.11-0.16 standard deviations. This suggests that trading volume inflation is beneficial to exchanges in the short run. Second, by augmenting the regressions of trading volume on lagged fake trading by instrumented lagged trading volume, we find that investors tend not to distinguish between fake and real trading volume in the short run. This result is consistent with inability of market participants to decipher the quality of an experience good immediately upon purchasing it.

We then analyze longer-run effects of fake trading. In doing so, we recognize the possibility that the insignificant relation between past fake trading measures and current trading volume may be due to the inability of our fake trading estimates to measure current fake trading adequately. Thus, we focus on non-volume-based outcomes, i.e., alternative measures of exchanges' operating success. The first such outcome variable is exchange's web popularity, as measured by its Alexa rank. We find that the effect of fake trading on the web popularity of an exchange is positive and economically large at the short-term horizon of three months: a one-standard-deviation increase in fake trading measures leads to a 1.5-1.9 standard-deviation increase in an exchange's web popularity. These effects become weaker at progressively longer horizons and are eventually reversed at the twelve-month horizon: a one-standard-deviation increase in fake trading measures over the past twelve months is associated with a 2.7-3.4 standard-deviation reduction in exchange's web popularity.

Our second measure of operating success is an estimate of exchange's revenues from commissions on the legitimate part of trading on its platform. The results obtained using estimated-commission-revenue-based measure of operating success are largely consistent with the results for the web-popularity-based measure. The effect of fake trading on short-term (three-months) estimated trading commission revenue is positive: a one-standard-deviation increase in fake trading measures is associated with a 0.4-0.5 standard deviation increase in estimated commission revenue. This effect becomes smaller at the six-month and none-month horizons. Longer-term (twelve-months) results indicate reversal: a one-standard-deviation increase in fake trading measures leads to a 0.2-0.3 standard deviation decrease in trading commission revenues. Overall, these results indicate that exchanges that fake trading volume tend to succeed initially in misleading traders but are usually punished eventually, consistent with the tradeoff involved in choosing an opportunistic strategy of volume inflation – between short-term gains and long-term losses.

Our paper makes three main sets of contributions. Although we use a unique setting, our first set of contributions is quite general. We contribute to the literature on investment in reputational capital through product quality in the face of competition (e.g., Chamberlin (1933), Abbott (1955), Klein and Leffler (1981), Shapiro (1983), Horner (2002), and Dana and Fong (2011)). Although there exists empirical literature that examines the relation between competition and product quality, which generally finds that this relation is positive (e.g., Matsa (2011), Domberger and Sherr (1989), and Mazzeo (2003)), there is little empirical work that examines this relation in the context of "experience goods," for which long-term reputation is key. One exception is Becker and Milbourn (2011), who focus on the credit rating industry and examine the effects of entry by Fitch on the quality of ratings produced by two incumbent rating agencies – Moody's and S&P. Becker and Milbourn (2011) find that an increase in competition has an adverse effect on product quality, as proxied by the reliability of credit ratings.[7]

In addition to providing an out-of-sample corroboration of the result in Becker and Milbourn (2011) that increased competition leads to lower product quality, we contribute to the literature on product quality and reputation along the following dimensions. First, we examine the effects on product quality of both the existing competitive landscape (static competition) and changes in it (dynamic competition). Second, the competitive landscape itself is more diverse in our setting, with multiple layers of competition – both in terms of currency-pair-level markets and in terms of geographical and operational aspects of competition at the exchange-level. Third, we examine the effectiveness of an opportunistic strategy of attempting to inflate the perception of product quality, i.e. we analyze whether fake trading has short-term benefits. Fourth, we analyze whether there is a tradeoff between short-term benefits and long-term reputational costs. Our findings that exchanges that inflate trading volume succeed in misleading investors in the short run but are punished in the long run are consistent with the model of Mailath and Samuelson (2001), in which reputation is built gradually and dissipates gradually.

Our second contribution is to the literature on competition and unethical behavior. Shleifer (2004) shows that unethical conduct is sometimes a consequence of product market competition. Consistent with Shleifer (2004), Luca and Zervas (2016) show that increased competition leads to more fake reviews of restaurants on Yelp platform. Bennett, Pierce, Snyder, and Toffel (2013) demonstrate that competition reduces the quality of tests ("testing leniency") in the vehicle emissions testing market. Karpoff, Lee, and Martin (2008) examine implications of announcements by regulators of discovery of financial misrepresentation ("cooking the books") and find that indirect penalties imposed by the market in the form of negative announcement returns dwarf the direct penalties imposed by the authorities. In our setting, characterized by generally lax regulation and enforcement, the extent of

[7]See also Mathis, McAndrews, and Rochet (2009) for evidence of a negative relation between rating quality and expected costs of lost reputation.

"cooking the order books" is rarely determined precisely and is gradually discovered by the market. Nevertheless, market participants can eventually see through much of the fake trading on exchanges and penalize them in the long run.

Our third contribution is to the nascent literature examining the behavior of crypto exchanges, which are one of the more important players in the crypto market (e.g., Amiram, Jørgensen, and Rabetti (2022), Cong et al. (2021), Cong, Landsman, Maydew, and Rabetti (2022), and Griffin and Shams (2020)). We complement Cong et al. (2021), who perform the first large-scale analysis of fake trading on crypto exchanges, along the following dimensions. First, we corroborate their findings that a significant proportion of trading in four major cryptocurrencies against $U.S. is likely fake. We show that these results continue to hold in a sample that includes almost the entire population of most important crypto currencies. Second, we analyze market-level, exchange-level, and currency pair-level characteristics that are associated with the extent of fake trading, focusing on competition-related determinants of fake trading. Third, we examine implications of fake trading on future short-term and longer-term measures of exchanges' performance. Finally, we introduce novel statistical fake trading measures.

The remainder of the paper is organized as follows. The next section describes our data sources. In Section 3, we characterize the main empirical regularities of the crypto exchange industry. In Section 4, we describe our measures of fake trading and perform several validation analyses. In Section 5, we examine the relation between static and dynamic competition among exchanges and fake trading on them. Section 6 examines short-term and longer-term effects of fake trading on an exchange on its future legitimate trading volume and on its future operating performance. Section 7 concludes. Appendix A describes the evolution of the crypto market. Appendix B provides examples of methods for fake trading detection. Appendix C contains robustness results. Appendix D provides definitions of all variables used in the analysis.

2 Data

2.1 Main data source

Our main data source is Kaiko database (www.Kaiko.com), which provides details of every executed transaction on over 100 crypto exchanges, including currency pair, price, volume, and timestamp.[8] We currently focus on major exchanges, which we define as those that feature at least one currency pair in which the base currency is Bitcoin (BTC), Ether (ETH) or Tether (USDT). There are 41 of these, and they are responsible for 91% of the overall reported trading volume during our sample period. The base currencies of these pairs have important functions in the cryptocurrency markets. Bitcoin (BTC) is the oldest cryptocurrency. Ether (ETH) is the base currency for most tokens created in initial coin offerings (ICOs). Tether (USDT) is the main currency pegged to a fiat currency ($U.S.) and does not suffer from the high volatility of Bitcoin and most other cryptocurrencies.[9] We validate our data by comparing it to data on www.CoinMarketCap.com, which is the leading source of price and trading volume data on over 300 crypto exchanges, but unfortunately reports data at a low (daily) frequency. In contrast, Kaiko data is provided at a frequency of one second.

Our sample period begins in June 2013 and ends in September 2019. We are currently in the process of expanding our dataset along the following dimensions. First, we have obtained data up to July, 2021, i.e. we now have almost two additional years of data, which is crucial in this new and rapidly developing market. Second, we now have trading data on close to 60 crypto exchanges. Third, are extending our fake trading estimation to all crypto pairs, not just those involving BTC, ETH, and USDT as base currencies. All in all, the next version of the paper will cover almost the entire

[8]Kaiko collects, normalizes, and stores terabytes of historical cryptocurrency data from dozens of spot and derivatives exchanges. The procedure consists of retrieving the data either by using an exchange's API or by taking frequent snapshots of its web-based platform.

[9]To ensure that all relevant currency pairs are included in the analysis, we filter for inconsistencies in pair names. One type of inconsistency is pair ordering. For instance, in some exchanges the pair USDT-BTC is named as BTC-USDT. Another type of inconsistency is variations in the cryptocurrency ticker symbol. For example, Bitcoin Cash appears as BCH, BTCH or BTCASH on various exchanges.

population of trades on crypto exchanges.[10]

2.2 Other data

We use numerous additional data sources that supplement Kaiko data. We obtain exchange characteristics, such as adoption of anti-money-laundering measures (AML), the existence of know-your-customer requirement (KYC), and exchange location from www.CoinGecko.com and www.Cointelligence.com. The time series of web traffic data are obtained from www.Alexa.com. We collect time series data on the technological development of exchanges, proxied by their code revisions on the most popular open-source platform, Github, from www.Github.com, and time-series evolution of exchanges' social media activity on two of the most popular social media platforms, Reddit and Twitter, from www.Reddit.com and www.Twitter.com, respectively. In separating crypto coins and tokens, we employ data from Lyandres, Palazzo, and Rabetti (2021), who collect token issuance data from 11 leading ICO aggregators and construct the most comprehensive data set of token issuance.

3 The crypto exchange industry

Panel A of Table 1 presents summary statistics of the cryptocurrency market over the duration of our sample (currently 76 months; to be expanded to 98 months in the next version).

[Insert Table 1 here]

The first row in Panel A of Table 1 presents aggregate crypto market capitalization, obtained from www.CoinMarketCap.com, which likely covers the whole population of crypto exchanges and currencies. The second row presents crypto market capitalization statistics aggregated within our Kaiko-based dataset. Our data covers a large fraction of the whole crypto market: In a median month, 82% of the crypto market capitalization is included in our data, and this proportion is higher during the

[10] The size of the dataset is several terabytes, and estimating fake trading measures at the exchange-currency pair-month level takes significant time.

latter part of the sample, characterized by larger market size, as evident from the higher ratio of mean market capitalizations of currencies covered by the two data sets (87%).

The mean number of distinct cryptocurrencies traded on exchanges in a given month, covered in our data, is 262, whereas at the end of our sample period, 967 currencies were traded on crypto exchanges. Over half of these are crypto tokens, which were issued via an ICO, whereas the rest are coins.[11] The mean number of new cryptocurrencies appearing on exchanges on a monthly basis is 33 and the mean number of currencies that exit the market in a given month is 8; the medians are much lower, 2.5 and 0 respectively. The mean number of distinct cryptocurrency pairs traded on exchanges in a given month is 428, and at the end of our sample period, over 1,700 distinct pairs were trading on various exchanges; two thirds of these pairs involve crypto tokens. On average, 54 (10) currency pairs appear (disappear) in a given month.

The mean reported aggregate monthly trading volume is $U.S. 38 billion or 6 million BTC. There are close to 100 million reported trades on average per month. The distributions of trading and of the number of trades are very skewed – the medians are one-to-two orders of magnitude lower than the means. Importantly, reported values of trading volume and the number of trades may be highly inflated due to abundance of fake (wash) trades on crypto exchanges, documented in Cong et al. (2021) – a finding that we corroborate and extend in this paper.

Cryptocurrencies are traded on multiple exchanges. The crypto exchange market (covered by Kaiko data and satisfying our selection criteria) grew from a single exchange – Bitfinex – in 2013 to 37 exchanges at the end of our sample period. The market is quite dynamic: on average, a new exchange is established every two months; exchanges do not seem to exit the market often – only four exchanges

[11] While both tokens and coins are used to define a unit of value, there are important differences between them. First, tokens are built on top of existing blockchains, such as Ethereum, while coins, such as Bitcoin, Ether, or Litecoin, are unique digital currencies, which are based on their own, standalone blockchains. Second, and perhaps more importantly, coins are used mostly as a method of payment or a store of value, whereas tokens are also used to activate features on decentralized applications (DApps) they were designed for.

disappeared during our sample period, three of them in 2019.[12] The last three rows in Panel A of Table 1 describe the competitive landscape of the crypto exchange market, in particular the summary statistics of the market's Herfindahl indices, computed using three metrics: the number of currency pairs trading on an exchange in a given month, the reported volume of trades on an exchange during a month, and the reported number of trades on an exchange during a month. Figure 1 presents the evolution of the three HHI-based measures of crypto market concentration.

[Insert Figure 1 here]

The market concentration has clearly declined over time – from close to one throughout 2016 to 0.07–0.14 in late 2019, a decrease that coincides with the increase in the number of unique currency pairs.

Panel B of Table 1 presents statistics at the level of a cryptocurrency pair. Currency pairs tend to be traded on multiple exchanges. The mean number of exchanges on which a pair is listed is 2.46, and the median is 1.81; BTC-ETH pair was listed on 19 exchanges at its peak. The mean Herfindahl index of trading volume and the number of trades in a given currency pair across exchanges is around 0.25, suggesting substantial degree of competition among exchanges on average. The typical age of a cryptocurrency pair is 12 months on any exchange and 9 months on a given exchange.

Panel C of Table 1 reports summary statistics at the level of a crypto exchange. A typical exchange in our sample is 5 months old. The mean share of an exchange's reported volume (number of trades) out of the crypto market aggregate volume (number of trades) is 9.4%. The mean (median) number of currency pairs listed on an exchange in a given month is 78 (12).

The next few rows provide statistics of various characteristics of crypto exchanges that describe their operating strategies. In 59% of exchange-months, an exchange has implemented anti-money-

[12]The frequency of exits may be understated, as Kaiko data focuses on a subset of most prominent exchanges, which have a lower likelihood of disappearance.

laundering measures (AML).[13] In 62% of exchange-months, an exchange has implemented know-your-customer (KYC) procedures.[14] 46% of exchanges are located in crypto-friendly countries.[15] In 25% of exchange-months, there have been news on hack attacks, scams, theft, or poor review results associated with the exchange (Bad News).[16] In 12% of exchange-months, an exchange operates multiple platforms (Multiplatform).[17]

The next four rows in Panel C describe measures of exchanges' popularity, their social media presence, technological advancement, and transparency. Alexa captures the mean popularity rank of an exchange's website (out of all contemporaneous sites on the world wide web), with the rank of one corresponding to the most popular website, available from www.Alexa.com.[18] The most popular exchange is Binance, whose website is ranked 230 on average. The mean (median) rank or a crypto exchange in our sample is 41,750 (9,470). For comparison, the average ranks of some of the main traditional exchanges' websites – NASDAQ, NYSE, and Euronext – are approximately 3,800, 27,000, and 62,000, respectively, as of November 2020. Reddit and Twitter measure social media activity related to the exchange – discussions on Reddit and Twitter posts under the exchange's official handle. The mean monthly numbers of Reddit posts and Twitter tweets by an exchange are 38 and 178, respectively, whereas a median exchange is not active on social networks. Github is the number of

[13] AML indicator equals one if the exchange has implemented an AML policy and provides detailed information about conformity with accepted international AML procedures. We use trust score from www.CoinGecko.com for all exchange characteristics discussed in this paragraph.

[14] KYC indicator equals one if there is evidence that the exchange provides clear guidelines as to the documents required for verification of the sources of clients' funds.

[15] The list of crypto friendly countries includes Singapore, Russia, Estonia, Malta, Luxembourg and Switzerland. A country is considered crypto-friendly if there is evidence that established exchanges and crypto-businesses move to it due to friendly regulatory environment, e.g., wide acceptance of cryptocurrencies, positive regulatory developments, and/or existing guidelines and easy registration with local financial authorities.

[16] News about hacks or crypto exchange misuse of funds are often reported in popular outlets, e.g., https://www.theguardian.com/technology/2019/jul/12/tokyo-cryptocurrency-exchange-hack-bitpoint-bitcoin. According to www.CoinTelegraph.com, the total amount of funds stolen from crypto exchanges as of November 2020 is $U.S. 2.8 billion.

[17] For example, Binance has a regular, centralized, platform, but also a decentralized platform, since April 2019 (see https://www.coindesk.com/binance-launches-decentralized-exchange-ahead-of-schedule). One reason exchanges provide users access to alternative platforms is an attempt to guard their market share in wake of the rise of decentralized exchanges (DEX), which reduce risks to users of misuse of funds and eliminate the need in a market maker.

[18] Alexa rank is computed using a methodology proprietary to www.Amazon.com that combines a site's estimated traffic and visitor engagement over the past three months.

commits (code reviews) of an exchange's platform, proxying for its technological advancement.[19] A median exchange sees 13 revisions to its code in a month, whereas the mean monthly number of code revisions is over 100. Since providing an open-source code is optional, code revision activity on an open-source platform is an indication of transparency of an exchange. The last few rows in Panel C present the distribution of exchange locations, aggregated into geographical regions.[20] Almost 40% of exchange-month observations are in Asia (including China) and only 20% of exchanges are in Western Europe or North America.

Panel D of Table 1 presents summary statistics at the level of a currency pair traded on a given exchange. The mean reported volume of trading of a currency pair on a single crypto exchange is $U.S. 46 million per month, whereas the median is lower than $U.S. one million. This skewness is driven by several abnormal volume numbers. For example, the highest reported monthly volume was $U.S. 49 billion in March 2019 for Peercoin-Bitcoin pair (PPC-BTC) at the BX.in.th exchange – once Thailand's largest crypto exchange, which by now has ceased operations. Similarly, the mean number of trades in a currency pair on a given exchange is over 120,000, whereas the median number is an order of magnitude lower. This difference is also driven by an unusual number of trades in some pairs on particular exchanges. For example, there were over 25 million trades in an unpopular Aeternity-Bitcoin pair (AE-BTC) at the ZB exchange in March 2019. As these examples suggest, there is a strong possibility that some of these outlier values of trading volume and the number of trades are driven by fake (wash) trading – a hypothesis we examine in detail below.

Trading on some exchanges is heavily concentrated in a given currency pair – the highest Herfindahl index of trading volume of currency pairs on a given exchange is one. However, some exchanges are well diversified – the lowest volume-based HHI is 0.02. The mean and median volume-based and number-of-trades-based Herfindahl indices on a given exchange equal 0.5, suggesting significant

[19] We only count commits in the main exchange repository when they are available.

[20] In many cases the precise location of an exchange is unclear and a region-level measure (as opposed to a country-level one) reduces the measurement error. For instance, Okex website states that the exchange is based in Belize, but its main operations are located in Hong Kong and the headquarters are in Malta. In cases involving discrepancies, we base the assignment of an exchange to a geographical region based on the location of its main operations.

reliance of exchanges on the most popular pairs traded on them.

4 Measuring fake trading

Measuring fake trading is difficult, and no direct measures exist. According to Gerald Chee, head of research at www.CoinMarketCap.com, “there is no way to tell if an exchange is inflating volume or not by merely looking at the volume they report. The only way to detect ‘wash trades’ would require access to ‘account-ID’ data... only exchanges have access to these [data]”. In the absence of direct fake trading measures, we use indirect, statistical measures. We rely both on measures used in existing papers examining wash trading (e.g., Aloosh and Li (2021) and Cong et al. (2021)), as well as measures novel to the finance literature.

4.1 Benford’s law

The first measure of irregular trading patterns that we use applies Benford’s Law (Benford (1938)), based on the likelihood of occurrences of first digits of a series. In many naturally observed series, which are not constrained to a certain range, 1 appears as the leading digit in 30.1% of cases. As the value of the first digit increases, its frequency decreases: 2 (3, 4, 5, 6, 7, 8 and 9) is the leading digit in 17.6% (12.5%, 9.7%, 7.9%, 6.7%, 5.8%, 5.1% and 4.6%) of the time. Deviations from Benford’s Law may indicate abnormalities in data series. We follow Cong et al. (2021) in using Benford’s Law to detect fake trading.[21] Aloosh and Li (2021), who, along with Gandal, Hamrick, Moore, and Oberman (2018) use an internal book of individual trader level records leaked from Mt. Gox exchange, show that Benford’s Law is useful in detecting fake trading.

To quantify the deviations from Benford’s Law, we calculate the mean absolute deviation (MAD) between the theoretical Benford’s Law-based fractions of leading digits and the proportions in the observed series. MAD is calculated as the equally-weighed average of the absolute distances between

[21] Panel A of Figure B.2 in Appendix B shows examples of observed series of first digits of trading volume.

the observed value and the Benford's Law-based value across the nine digits (e.g., Drake and Nigrini (2000)).[22] Summary statistics of MAD, reported in the first two rows of Panel A of Table 2, indicate that there is wide variation in MAD for both trading volume and the number of trades.

[Insert Table 2 here]

4.2 Distance from log-normal distribution

Empirically, in the absence of evident manipulation, trading volume tends to follow log-normal distribution (e.g., Richardson et al. (1986) and Ajinkya and Jain (1989)). Sizable deviations from log-normality may be indicative of irregularities in/manipulation of trading. A convenient measure that quantifies the distance between a sample's empirical cumulative distribution function (c.d.f.) and the c.d.f. of a reference distribution is Kolmogorov-Smirnov (KS) statistic. KS distance is given by the supremum of the distance between the c.d.f. of the theoretical distribution and that of the observed one over all realizations of the variable (e.g., Conover (1971)). Thus, we compute the KS distance between the c.d.f. of the empirical distribution of the natural logarithm of reported trading volume and the c.d.f. of a normal distribution with the same mean and variance. In particular, for each exchange-month-currency pair, we first compute the mean and standard deviation of log trading volume over ten-minute intervals. We then compute the maximum distance between the c.d.f. of the resulting empirical distribution and that of normal distribution with the same mean and variance. We perform this exercise for every exchange-month-currency pair and repeat the procedure while substituting trading volume by the number of trades.[23] Summary statistics of KS distance, found in the third and fourth rows of Table 2, indicate a roughly symmetrical distribution centered around 0.3.

[22] Our results are robust to employing another measure of deviations from Benford's Law – the standard absolute deviation (SAD) – which equals the standard deviation of the absolute differences between the theoretical, Benford-Law-implied, and observed series.

[23] Figure B.3 in Appendix B contains examples of deviations of trading volume and the number of trades from log-normal distribution.

4.3 E-divisive with medians

Another method that we use for flagging unusual patterns in trading is rooted in the computer science literature that focuses on detection of structural breaks, i.e. mean shifts or trend shifts in a series. One particular algorithm that is suitable for detecting structural breaks in trading volume and the number of trades is called EDM (E-Divisive with medians (e.g., James, Kejariwal, and Matteson (2016)). The algorithm attempts to determine whether a new chunk of time series data is considerably different from the previous chunk through comparisons of various permutations of the data.[24]

One important reason for the suitability of EDM in our setting is that it is robust to the presence of short-lived abnormalities in the series. This is particularly relevant because trading volume data tend to have occurrences of peaks, which, despite often being a result of a natural data generating process, may appear as anomalies when data series are aggregated into short intervals. In addition, EDM is non-parametric. This is important because trading volume that is partially a result of wash trading does not usually conform to a particular distribution. The trading volume and number of trades series often contain more than one structural break. Our EDM-based measure of fake trading is the number of breaks within a monthly series.[25] We calibrate the parameters of the algorithm, such as the minimum size of buckets, and penalization parameters.[26]

4.4 Aggregating fake trading measures

None of the three fake trading measures described above is perfect. Each measure is constructed to identify particular deviations from normal trading, frequently observed in the data. Thus, in order to construct a unified measure of fake trading, we extract principal components of the measures

[24] EDM is frequently used for detecting breakouts in data transmission in e.g., mobile internet applications.

[25] Figure B.4 in Appendix B presents examples of the performance of EDM algorithm in detecting structural breaks in the data.

[26] The minimum size of buckets is the lowest number of observations between structural breaks, where each observation is the trading volume or the number of trades within a ten-minute interval. We set the minimum bucket size at 6. We follow James et al. (2016) in choosing parameters of polynomial penalization, which determine the sensitivity of the model. In particular, degree of penalization is 1 and β equals 0.008. Our results are robust to various modifications of parameter values. For more details about the EDM algorithm see `https://github.com/twitter/BreakoutDetection`.

described above at the exchange-month-currency pair level.

Figure 2 presents fractions of variance explained by the first three principal components of the invividual fake trading measures – for principal components derived from the trading-volume-based measures in Panel A, for those derived from the number-of-trades-based measures in Panel B, and for those derived from both types of measures in Panel C.

[Insert Figure 2 here]

Since the first principal components explain significant fractions of variation in fake trading measures – 52-63%, we concentrate on the first principal components as aggregated measures of fake trading in the empirical analysis.[27]

Figure 3 presents mean principal-component-based fake trading measures over time. In particular, every quarter, we compute an equally-weighed average over all exchange-currency pair-months of the three versions of the first principal component of fake trading. The horizontal lines centered around point estimates depict confidence intervals of these estimates.

[Insert Figure 3 here]

Mean fake trading measures are generally increasing since 2017.[28] The temporal increase in fake trading – an interesting finding in its own right – is potentially consistent with the entry of less reputable exchanges, with fake trading being more prevalent in newer, less liquid currency pairs, and with the temporal increase in the intensity of competition among exchanges. We examine these conjectures below.

[27]The correlations between individual measures of fake trading and their first principal components range between 0.6 and 0.77. Figure B.5 in Appendix B presents biplots that show the orthogonalization of fake trading measures and their relation with the first two principal components.

[28]Figure B.6 in Appendix B depicts mean measures of fake trading over time, separated into five groups of currency-pair types: 1) ETH-BTC, 2) USDT-BTC, 3) BTC against other currencies, 4) ETH against other currencies, and 5) USTD against other currencies.

4.5 Validation of fake trading measures

As our fake trading measures are purely statistical and are partially based on machine learning, it is important to examine their validity. We do this in four ways, discussed in the following four subsections.

4.5.1 Fake trading, exchange size, age, and reputation

Figure 4 presents exchange-level averages of our three fake trading measures.

[Insert Figure 4 here]

Exchanges with the highest web popularity levels, among those covered in our data – Binance, Coinbase, and Upbit, as well as the oldest exchanges – Kraken, Bitfinex, and CEX.IO, all have below-sample-mean measures of fake trading. In addition, theree exchanges in our sample that are regulated by the New York State Department of Financial Services – Coinbase, Bitflyer, and Gemini – have some of the lowest fake trading measures. On the other hand, some of the exchanges with the highest estimated fake trading measures – CoinEx, Bibox, Okex, and Huobi – have been subject to coverage that may be indicative of subpar governance.[29]

4.5.2 Fake trading estimates and regulation/compliance/transparency

In Table 3 we compare our fake trading measures between groups of firms with relatively high and low levels of self-imposed and external regulation and compliance, as well as high and low levels of transparency. For each of the three principal-component-based fake trading measures as well as the individual fake trading measures, we report the mean measure for groups of exchanges with high/low values of characteristics potentially associated with regulation/compliance and the difference between

[29]See: https://www.trustpilot.com/review/coinex.com for examples of user complaints regarding CoinEx. See complaints about possible manipulation of Bibox and Okex trading volumes at https://medium.com/@pandahanda44/bibox-artificially-inflated-volume-in-pictures-ebf6cbe1ed2a and https://medium.com/@sylvainartplayribes/chasing-fake-volume-a-crypto-plague-ea1a3c1e0b5e, respectively. See complaints about funds disappearance on Huobi: https://medium.com/@revblc/hacked-at-huobi-or-an-inside-job-you-decide-7979553cae9f.

the two subsets. Most of the variables correlated with regulation/compliance are discrete. For continuous variables, groups are formed using the median of the variable values.

[Insert Table 3 here]

Exchanges with anti-money-laundering (AML) provisions in place have lower mean fake trading measures than those without such provisions, the difference in means being highly significant for all three principal-component-based measures and all the individual measures. Similarly, exchanges with know-your-customer (KYC) requirements have significantly lower fake trading measures than exchanges without such requirements. Exchanges located in countries with crypto-friendly regulations and exchanges subject to negative news coverage are characterized by significantly higher fake trading measures than exchanges located in countries with stricter regulation and those without bad publicity. Exchanges operating both centralized and decentralized platforms ("multiplatform") tend to have higher fake trading estimates (on their centralized platform). A possible reason is that washing trades on a decentralized platform would be easily detectable and, thus, if an exchange is interested in inflating volume, it would likely do so on its centralized platform. Finally, less popular exchanges (based on their Alexa rank), those that have relatively low social media presence (on Twitter and Reddit), and exchanges that are more technologically opaque (i.e. those without Github commits) tend to have higher fake trading estimates.

Given the strong correlation between the individual fake trading measures and principal-component-based aggregates, as well as the evidence in Table 3 that the relations between exchange characteristics and each of the individual measures are similar to the relations between exchange characteristics and principal-component-based measures, we will concentrate on the aggregate measures in the remainder of the analysis. All the qualitative results are robust to employing individual fake trading measures.

4.5.3 Alternative fake trading measures

Table 4 examines the relation between our principal-component-based measures of fake trading with alternative measures, which are based on correlations between either the number of trades or trading volume in a given currency pair within a ten-minute interval on a given exchange with the same variable aggregated for that currency pair on all exchanges. The idea behind the correlation-based measures is simple. Assume that on each exchange, trading consists of two components. The first is the legitimate one, driven by information/news, that is likely positively correlated with contemporaneous legitimate trading in the same currency pair on other exchanges. The second is fake trading, which, given its various shapes and frequencies, is generally uncorrelated across exchanges. Intuitively, trading volume and the number of trades within a given time interval on an exchange with a smaller fake trading component are likely to have a higher correlation with the aggregate contemporaneous trading volume or the number of trades than this correlation of an exchange with a larger fake trading component.[30]

To estimate the relation between our fake trading measures on one hand and correlations between trading volume or number of trades on an exchange and aggregate quantities on the other hand, we follow the following steps. First, each month for each exchange and currency pair that is traded on at least five exchanges, we compute the correlation between the volume of trading on that exchange during each ten-minute interval and the aggregate volume of trading on all exchanges during that interval. We repeat this procedure for the number of trades. Second, we regress the estimated monthly correlation for a given currency pair on a given exchange on the contemporaneous estimate of one of the three principal-component measures. Given that the correlation between trading volume on an exchange and aggregate volume is likely related to the popularity of the exchange – trading volume on more popular exchanges is likely to exhibit a more positive correlation with the aggregate volume – in some specifications we control for the exchange's web popularity and for its social media activity.

[30]Simulations in which we estimate these correlations while varying the proportion of fake trading on various exchanges are consistent with this intuitive argument.

[Insert Table 4 here]

The upper part of the first column in Table 4 shows that the correlation of trading volume on a given exchange with aggregate trading volume is significantly negatively related to our volume-based principal component measure of fake trading. The second column demonstrates that the negative relation remains significant, albeit weaker, when the exchange's web popularity and social media presence are controlled for. The third and fourth column show similar results when the correlation of trading volume is replaced by the correlation between the number of trades on an exchange and contemporaneous aggregate number of trades. Similar results are obtained when instead of volume-based principal component, we use number-of-trades-based principal component (in the middle part of the table) and the principal component based on both trading volume and the number of trades (in the bottom part of the table).

In the last two columns of Table 4, we perform a counterfactual analysis to ensure that the negative coefficients on principal-component-based measures of fake trading that we report in columns 1-4 are not mechanical. We use the correlation between the average exchange rate of a currency pair across all transactions on a given exchange within ten-minute intervals and the average exchange rate of that currency pair across all transactions on all exchanges during the same intervals. In other words, we replace the volume-based and number-of-trades-based correlations with the price-based correlation. The idea is that wash trades are typically not performed to systematically influence prices but rather to inflate trading volumes. Thus, we expect no relation between price-based correlation and principal-component-based fake trading measures. The results are consistent with this conjecture: This relation is small and statistically insignificant in all six specifications in columns 5-6 of Table 4. Overall, the results in Table 4 suggest that our statistical measures of fake trading are correlated with alternative, more intuitive, correlation-based measures, providing further evidence of the validity of our measures. Importantly, our results are robust to including these correlation-based measures into principal-component-based aggregates.

4.5.4 Fake trading estimates and the Chinese ban

In Table 5, we analyze the effects of a ban on crypto exchanges imposed by regulators in China in 2017 on fake trading estimates. In early 2017, leading Chinese exchanges at the time – Huobi, BTCC, and OkCoin – were responsible for over 90% of the total worldwide volume of Bitcoin trading. The regulatory action in September 2017 consisted of banning initial coin offerings, restricting any activity that involves crypto tokens, shutdown of exchanges' websites, and canceling exchange executives' business licenses.[31] As a result, several Chinese exchanges – BigONE, EXX, CoinEx, Gatecoin, Huobi, OkCoin and OkEx – moved operations outside of Mainland China, mainly to Hong Kong and the rest of Pacific Asia.

[Insert Table 5 here]

We use the Chinese ban as an exogenous shock to the propensity of inflating volume for (initially) Chinese exchanges. Relative to pre-ban China, the regulatory/compliance environments in Hong Kong and the rest of Pacific Asia were strict, making wash trading more difficult. Thus, we expect a reduction in the extent of fake trading in exchanges that moved from China to other Asian locations due to the ban. We use this event to further validate our fake trading measures by examining whether there are significant changes in estimated fake trading on these exchanges following the ban.

To examine the effects of the ban on fake trading estimates, we construct two samples. In the first one, the treated group includes seven aforementioned Chinese exchanges that relocated outside of China as a result of the ban. The control sample includes exchanges that were operating in Hong Kong, Singapore, Korea and Japan at the time of the ban – Binance, Bitfinex, ZB, Bit-Z and Ethfinex, Kucoin, BitForex, UPbit, BitBank, Quoine, and Zaif. In the second sample, we restrict the set of treated exchanges to those that moved from mainland China to Hong Kong – OkCoin, BigONE, CoinEX, EXX, and Gatecoin. The control sample includes five exchanges that were operating out

[31] See https://www.coindesk.com/chinas-ico-ban-a-full-translation-of-regulator-remarks for details of the regulation.

of Hong Kong at the time of the ban and remained there following the ban – Binance, Bitfinex, ZB, Bit-Z and Ethfinex.[32]

Our sample period for this analysis includes the first three quarters of 2017 (the "pre-ban period") and the first two quarters of 2018 (the "post-ban period"). We construct two indicator variables: the first takes the value of one for the treated exchanges ("Treated"); and the second indicator equals one for the post-ban period ("Post-ban"). We then estimate regressions of our three principal-component-based fake trading measures at the exchange-month-currency pair level on the treated indicator, the post-ban indicator, and the interaction between the two, while controlling for all exchange-level and currency-pair-level characteristics that we describe in detail below, in Table 6.

The coefficient on Treated is positive and is highly economically and statistically significant in all regressions – the level of fake trading on Chinese exchanges before the the ban was 0.8-2 standard deviations higher than on exchanges located in Pacific Asia/Hong Kong. (In all regressions here and below, all explanatory variables are normalized to have zero mean and unit standard deviation, to ease the interpretation of the coefficients' economic significance.) The negative coefficients on Post-ban are also large and significant, indicating that all exchanges reduced their fake trading in the first two quarters of 2018 relative to the first three quarters of 2017. Most importantly, the coefficients on the Treated $\times$ Post-ban interaction are negative and highly statistically significant and are economically large – Chinese exchanges that moved out of China following the ban reduced the extent of their fake trading by 0.7-1.3 standard deviations compared to their local peers. Figure 5 examines parallel trends of treatment and control exchanges and shows that the relative decrease in fake trading on exchanges that move out of China begins around the ban, consistent with the causal interpretation of the relation between the ban and change in the extent of fake trading.

[Insert Figure 5 here]

[32]We rely on www.CoinGecko.com and www.Cointelligence.com for obtaining historical locations of each exchange in our dataset.

4.5.5 Validation of fake trading measures: Summary

In this section, we present four types of suggestive evidence of the validity of our fake trading measures. First, we show that our estimates of fake trading are lower for most established and popular exchanges than for newer and less popular ones. Second, we demonstrate that exchanges that are subject to stricter regulation/compliance tend to have lower estimates of fake trading. Third, we show that our measures are correlated with more intuitive but less precise measures of fake trading. Fourth, we present evidence based on a quasi-natural experiment – the ban by China of some exchanges that used to be based there – that shows that our fake trading measures change in the expected direction following this policy shock. All these pieces of evidence suggest that the statistical measures of fake trading are likely to be correlated with true, unobservable wash trading.

5 Competition and fake trading

5.1 Static competition among exchanges and fake trading

In Table 6, we examine associations between exchange and currency pair characteristics on one hand and our fake trading measures on the other hand.

[Insert Table 6 here]

In odd columns, we include both exchange-level and currency-pair level characteristics, whereas in even columns, we focus on currency-pair-level ones, while including exchange fixed effects. In all regressions, we control for the base pair fixed effects (i.e. whether the base pair is BTC, ETH, or USDT) and for time (year-quarter) fixed effects. In all regressions here and below, standard errors are clustered at the exchange times currency pair level.

Exchanges do not fake trading equally in all trading pairs. There is a positive relation between the number of exchanges on which a pair is listed and the average level of fake trading in the pair. This is consistent with concerns about future reputation damages being lower in highly competitive markets. In line with this interpretation, the concentration of trading in a given pair across exchanges is negatively related to the average degree of fake trading in that pair: Lowering the Herfindahl index based on reported trading volume in a given currency pair in a given month across exchanges by one standard deviation is associated with a 0.12-0.22 standard-deviation increase in our fake trading estimates.[33]

Exchanges on which more currency pairs are traded tend to have higher fake trading measures: A one-standard-deviation increase in the log of the number of trading pairs is associated with 0.04-0.16 standard-deviation increase in fake trading. This is consistent with the results in Dana and Fong (2011), who show that maintaining reputation is easier in the presence of multimarket competition. Larger exchanges (measured by the overall share of an exchange's reported volume out of total aggregate volume) tend to have lower estimates of fake trading. Interestingly, this negative relation is observed despite the positive mechanical link between wash trading and volume, since the volume of wash trading is part of the overall reported volume. Exchange age, on the other hand, is not an important determinant of the extent of fake trading. While it is significantly negatively related to fake trading measures in two out of three specifications, the economic magnitude of this relation is quite small – a one-standard-deviation of log(age) is associated with 0-0.04 standard-deviation reduction in the extent of fake trading. Using exchanges located in North America as a benchmark, our results indicate that exchanges in Asia (and especially in China) and in European jurisdictions with lax regulatory oversight ("Europe: Islands"), as well as those in Central and South America and Africa tend to be characterized by high levels of fake trading.

Exchanges do not significantly change the extent of volume inflation as currency pairs mature, as evident from the largely insignificant relation between the age of a pair and fake trading measures. There is significantly less fake trading in currency pairs involving tokens issued in an ICO. A possible

[33]Similar results are obtained when the volume-based Herfindahl index is replaced by the number-of-trades-based Herfindahl index.

reason is the difference between exchanges' incentive structures for tokens and for coins. The bulk of compensation of an exchange from listing a token comes at the listing stage, in the form of fixed listing fee. On the contrary, most of an exchange's profits from listing pairs involving coins comes from trading commissions, which raises incentives to signal quality in coin-based pairs by inflating reported trading volume and the number of trades.

In Table C.1 in Appendix C, we split the sample of currency pairs into large and small quote currencies. The split is based on whether the market capitalization of the quote currency is above or below $US one billion. The relation between measures of static competition among exchanges in a given pair and fake trading in that pair are largely similar between the two subsamples and are consistent with the results in Table 6. This suggests that the positive relation between static competition and fake trading is not driven by cryptocurrency sizes.

5.2 Dynamic competition among exchanges and fake trading

The results in the previous subsection suggest that static measures of competition, such as the number of exchanges on which a currency pair is traded and concentration of trading in a given currency pair across exchanges are related to fake trading measures. We now examine how dynamic aspects of competition among exchanges influence the extent of volume inflation. In Table 7 we examine the effects of entry and exit of rival exchanges in a given currency pair on fake trading measures on a focal exchange, while controlling for all exchange-level and currency-pair-level characteristics highlighted in Table 6, as well as for base pair and time fixed effects.

[Insert Table 7 here]

Entry of an exchange into a given currency pair is a situation in which an exchange that has not previously listed the currency pair reports trading in it in a given month. Exit of an exchange is a situation in which the exchange that has listed the currency pair last month does not list it in a given month. We define three types of competitors. "General" competitors are a set of all exchanges in our dataset. "Geographical" competitors are a subset of exchanges that operate in the same geographical region as the focal exchange, where regions are defined as in Panel C of Table 1. The geographical dimension of competition is important in the crypto market. Shams (2020) shows that the clientele of investors on crypto exchanges is strongly related to their location. "Operational" competitor is one exchange belonging to the set of general competitors that has the largest overlap of pairs listed with the focal exchange.[34] Operating competitors' entry/exit may have especially pronounced effects on the focal exchanges.

We include two measures of static competition, captured by indicator variables – "Moderate competition", which equals one for a currency pair that is listed on at least two and at most seven exchanges, and "High competition", which equals one for currency pairs listed on at least eight exchanges. Consistent with the results of the effects of static competition on fake trading in Table 6, all three fake trading measures are monotonically increasing in the extent of competition. The coefficients on the moderate competition dummy are positive and significant and the coefficients on the high competition indicator are also highly significant and are larger in magnitude: Currency pairs that are traded on at least eight exchanges have 0.4-0.6 standard-deviation higher fake trading measures on average than currency pairs traded on a single exchange.

An (additional) exchange listing a currency pair ("competitor entry") is associated with a 0.14-0.22 standard-deviation increase in fake trading measures in that pair on the focal exchange. This increase tends to be somewhat larger if the rival exchange is operating in the same geographical region or if the rival exchange has a large overlap with the focal exchange in the set of currency pairs listed: in these cases, the increase in fake trading measures is 0.17-0.27 standard deviations and 0.20-0.29 standard deviations respectively. When a currency pair listed on an exchange is being delisted on another exchange ("competitor exit"), there is a reduction in fake trading estimates on the focal exchange. This result holds for the full set of competitors; however when subsets of competitors are restricted

[34]The overlap is computed as the ratio of the number of pairs listed on both exchanges to the number of distinct pairs listed on at least one of the two exchanges. Another possible way to define operational competitors is by performing textual analysis of crypto news, as in Schwenkler and Zheng (2019) and Schwenkler and Zheng (2020)).

based on geography or operational overlap, the relation between a competing exchange's exit and our fake trading measures becomes insignificant. In addition, the effects of competitor entry and exit tend to be more pronounced when the extent of competition is high (i.e. for currency pairs that are listed on many exchanges). The coefficient on the interaction of competitor entry and high competition is positive and significant in six specifications out of nine. The relation between the interaction of competitor exit and high competition on one hand and fake trading on the other hand is significantly negative in five specifications.

In Table C.2 in Appendix C we examine the relations between measures of dynamic competition and fake trading for subsamples of large and small currencies. The positive (negative) effects of competitor entry (exit) in a given currency pair on the focal exchange's fake trading in that currency pair are pronounced in both subsamples.

Overall, the results in Table 7 demonstrate that dynamic evolution of the competitive environment that an exchange is subject to leads to changes in the extent of fake trading that are consistent with competition affecting the quality of the exchange's product.

6 Consequences of fake trading

The results in the previous section suggest that fake trading may be partially driven by the competitive pressure, leading exchanges to inflate trading volume. In this section we examine short-term and long-term effects of fake trading.

6.1 Effects of fake trading on trading volume

We begin by asking whether fake trading is effective. In other words, while trading volume inflation mechanically increases overall contemporaneous volume, an interesting question is: Does volume inflation on an exchange in a given period have implications for the (legitimate) trading activity on that exchange in the future. To answer this question, we estimate regressions at the exchange-currency pair-month level of trading volume on lagged fake trading measures, while controlling for current fake trading and for exchange and currency pair characteristics as well as for base pair and time fixed effects, as in Tables 6 and 7.

[Insert Table 8 here]

Trading volume is mechanically positively related to contemporaneous volume-based measure of fake trading, as evident from the first column of Table 8. More interestingly, lagged measure of fake trading is positively related to current volume: A one-standard-deviation increase in last month's fake trading measure is associated with 0.11 standard-deviation increase in current volume. Similar results are obtained in columns 5 and 9, in which the volume-based fake trading measure is replaced by the number-of-trades-based measure and a measure based on both trading volume and the number of trades, respectively.

The likely mechanism behind the effect of lagged fake trading measures on contemporaneous trading volume is through inflated lagged volume that wash trading causes. Thus, in columns 2, 6, and 10, we augment the regressions by lagged trading volume. Lagged volume has a profound effect on current volume: A one-standard-deviation increase in last month's volume is associated with a 0.32 standard-deviation increase in current volume. This is consistent with strong autocorrelation in trading volume at the exchange-currency pair level that is present in the data. Importantly, after augmenting the regression by lagged trading volume, the coefficients on lagged fake trading measures flip sign and become negative. Conditional on overall (legitimate and fake) lagged trading volume, a one-standard-deviation increase in fake trading is associated with a 0.05-0.08 standard-deviation decline in current trading volume. The interpretation of this result is that market participants can, to a certain degree, distinguish between legitimate and fake trading volumes. However, they do not fully internalize the extent of fake trading, as inflating trading volume still has some positive impact on future volume, as evident from columns 1, 5, and 9.

Importantly, the estimates discussed above may be biased due to possible endogeneity. Lagged trading volume may be correlated with the error term of the regression in which the dependent variable is current volume due to the combination of two factors: positive autocorrelations of the fake trading measures and positive contemporaneous relations between fake trading measures and volume. To mitigate the endogeneity concern, we use an instrumental variable approach. In particular, we perform a two-stage estimation. In the first stage, reported in columns 3, 7, and 11 for the three fake trading measures, we regress lagged trading volume on a lagged fake trading measure and lagged price of Bitcoin (averaged over the course of the month) and its square.[35] Lagged Bitcoin price is unlikely to be correlated with lagged measure of fake trading at the exchange-currency pair level, i.e. it likely satisfies the exclusion restriction. Lagged volume is increasing in lagged Bitcoin price – the relation being concave, as evident from the negative coefficient on the squared Bitcoin price – suggesting that Bitcoin price satisfies the relevance restriction. Consistent with the results in the first two columns, lagged volume is positively related to lagged fake trading.

In the second stage, reported in columns 4, 8, and 12, we regress current trading volume on current and lagged volume-based fake trading measure, while replacing lagged volume by its fitted value from the first-stage regression. There are two interesting findings. First, the effect of past trading volume on current volume in columns 4, 8, and 12 tends to be substantially smaller than that in the OLS regression in columns 2, 6, and 10 respectively. Second, the negative effect of lagged fake trading on current volume decreases substantially. Controlling for the instrument for past trading volume, the negative effect of lagged fake trading on current volume is statistically significant in only one specification (in column 12), potentially overturning the conclusion that market participants can partially see through volume inflation by exchanges.

Overall, the takeaway from Table 8 is that fake trading is, to a certain extent, an effective way for exchanges to affect future legitimate trading volume. This finding supports the conjecture that exchanges use volume-inflating strategies to increase their short-term gains. In the next subsection, we examine the trade-off between these short-term gains and potential adverse longer-term consequences

[35]The results are similar when the squared term is omitted from the regressions.

of trading volume inflation.

6.2 Real short-term and long-term effects of fake trading on operating performance

In Table 9, we examine the effects of past fake trading on an exchange on measures of exchanges' operating performance at various horizons. One advantage of examining non-volume-based outcomes is that there is a possibility that the relation between past fake trading and current volume is due to the inability of our fake trading measures to perfectly control for current volume inflation. Non-volume-based outcomes are not subject to possible mechanical relation between volume inflation and reported trading volume.

[Insert Table 9 here]

In Table 9, we estimate regressions, at the exchange-month level, of two measures of an exchange's performance – its web popularity and its estimated revenue from trading commissions – on fake trading measured over periods of three to twelve months prior. Web popularity is measured as one minus the ratio of exchange's Alexa rank and the highest Alexa rank across exchanges (where the higher the rank the least popular the exchange). The relations between all three measures of fake trading on an exchange over the past three months and its current web popularity are positive, statistically significant, and economically large: A one-standard-deviation increase in lagged fake trading measures is associated with a 1.5-1.9 standard-deviation increase in the exchange's web popularity. An interpretation is that traders do pay attention to volume-based rankings of exchanges, which are based in large part on reported trading volume.

To estimate an exchange's revenue from trading commissions in a given month, we adopt the following procedure. We begin by assuming that all the trading volume on an exchange is legitimate, and that the exchange is compensated for the entire volume. The compensation takes the form of trading commission, which we assume to be equal to 0.1%. This is a conservative estimate. Crypto exchanges' trading commissions typically range from 0.1% to 5%, depending on currency pair and order size.[36] Since not all reported volume is legitimate, we attempt to estimate the proportion of reported volume that is fake and for which the exchange does not receive trading commissions.

In particular, we ask the question: What would the volume on the exchange be if volume inflation did not take place? To answer this question, we perform the following exercise. First, using the estimates of the coefficients in the fourth column in Table 8, we compute the fitted value of volume for each exchange-currency pair-month.[37] Second, we aggregate these fitted values to obtain the predicted value of overall volume on an exchange in a given month. Third, we replace the value of the fake trading measure of a given exchange-currency pair-month with the lowest value of that measure on any exchange for the same currency pair, and compute hypothetical exchange-pair trading volume without volume inflation. Under the assumption that the exchange with the lowest fake trading measure does not inflate trading volume at all, this calculation results in an estimate of what the trading volume in a given currency pair on a given exchange would have been had the exchange not engaged in trading volume inflation. Fourth, we aggregate hypothetical trading volumes in all currency pairs on a given exchange to compute the overall hypothetical trading volume on the exchange in a given month had it not inflated volume in any of the currency pairs listed on it. Fifth, we compute the ratio of hypothetical aggregate fitted volume to true aggregate fitted volume on an exchange in a given month to obtain the estimated proportion of (il)legitimate trading. Our estimates indicate that the mean proportion of fake trading on an exchange is 19%, and the maximum is 87%. Importantly, these are clearly downward-biased estimates of the extent of fake trading. The reason is the assumption that the exchange with the lowest level of fake trading measure does not inflate its trading volume, which is likely an overly optimistic view. Finally, we multiply the product of reported volume and assumed trading commission by the estimated proportion of legitimate trading to arrive at an estimate

[36]According to `https://www.Bitdegree.org/crypto`, the cheapest exchanges and their respective fees are: Binance - up to 0.1%, Kraken - up to 0.26%, Cex - up to 0.25%, Bittrex - fixed at 0.25%, Coinbase - from 1.49% to 3.99%, Bitstamp - From 0.05% to 5%, and Poloniex - up to 0.125%.

[37]The results are similar when we use estimates from other regression specifications, such as those in columns 8 and 12 in Table 8.

of overall trading commissions on an exchange in a given month.

The effect of fake trading over the past three months on estimated exchange revenue, reported in Panel A of Table 9, is positive and significant both statistically and economically. A one-standard-deviation increase in lagged fake trading measures is associated with 0.4-0.5 standard-deviation increase in the estimated revenue of the exchange over the next three months. Combining this result with the positive relation between lagged fake trading and web popularity suggests that fake trading is effective in the short term. These findings complement Cong et al. (2021), who report that wash trading has a positive impact on an exchange's rank on aggregator websites, such as `www.CoinMarketCap.com`.

In Panel B of Table 9, we estimate longer-term effects of fake trading on non-volume-based measures of exchange performance. In particular, we measure past fake trading over a period of six months. The findings in Panel B indicate that the effect of past fake trading on measures of operating performance are substantially weaker over the six-month horizon than over the three-month horizon, albeit still significantly positive. In Panel C, we repeat the estimation over the period of nine months. The relation between past fake trading and web traffic becomes significantly negative, whereas the relation between past fake trading and estimated revenues becomes insignificant. Finally, in Panel D, we extend the estimation period to twelve months. Both web popularity of an exchange and its estimated revenue from trading commissions are significantly negatively associated with all three measures of fake trading over the past year. In particular, an increase in a measure of past fake trading by one standard deviation is associated with a 2.7-3.4 standard-deviation reduction in web popularity and with a 0.2-0.3 standard-deviation reduction in estimated trading commissions.

The finding that fake trading has positive short-term effects – on both legitimate trading volume (in Table 8) and non-volume-based performance indicators (in Panel A of Table 9), which gradually decrease in the medium term and become significantly negative in the long term (in Panel D of Table 9) suggests that volume inflation has short-term benefits and long-term costs. This result is consistent with exchanges choosing the degree of volume inflation while trading off the near-term increase in operating performance against longer-term adverse reputation effects of fake trading.

7 Conclusion

We examine the effects of competition among crypto exchanges on their incentives to engage in an opportunistic strategy of inflating (faking) trading volume. The benefit of this strategy is that an exchange with (seemingly) large trading volume is attractive to potential traders, as larger volume is likely to be associated with lower direct and indirect trading costs. The cost of volume inflation is reputation damages, which occur once investors realize that not all reported trading volume is legitimate. Theoretical effects of competition among exchanges on this tradeoff are ambiguous. On one hand, reputation is more valuable when future rents are higher, i.e. when there is less competition. On the other hand, competition creates outside options for consumers, increases the importance of reputation.

Our main findings consistently point to the positive relation between competition and fake trading. Measures of static competition, such as the number of exchanges trading in a given currency pair and the Herfindahl index of exchanges, indicate that trading volume inflation is increasing in competition. An analysis of effects of entry and exit by various types of competitor exchanges – general, geographical, and operational – in a particular currency pair suggests that fake trading intensifies upon competitor exchange entry into that currency pair and declines upon competitor exchange exit from that pair, especially when the ex-ante landscape is highly competitive.

Our analysis of the effectiveness of fake trading, i.e. its ability to generate short-term rents, shows that exchanges are generally successful in misleading traders in the short run. Fake trading raises future trading volume, exchange's web popularity, and estimated trading commissions over relatively short horizons. However, the strategy of inflating trading volume has its long-term costs. The effects of fake trading on longer-run operating performance are negative: Both the web popularity and estimated trading commissions are significantly negatively related to fake trading over longer horizons.

We use the crypto exchange industry as a convenient laboratory for examining the effects of competition on firms' product quality choices that extend beyond this industry. In addition to the general implications, however, our analysis has particular implications for future regulation of crypto exchanges. Our finding of pervasive volume inflation complements nascent empirical literature on crypto exchanges (e.g., Amiram et al. (2022), Cong et al. (2021), and Cong et al. (2022)) in illustrating the consequences of generally lax regulation of and low compliance by exchanges, and in highlighting the importance of regulation of the crypto exchange industry, which is one of the cornerstones of the crypto market.

References

Abbott, L. (1955). Quality and competition: an essay in economic theory. *Columbia University Press*.

Ajinkya, B. and P. Jain (1989). A test of dividend irrelevance using volume reactions to a change in dividend policy. *Journal of Accounting and Economics 4*(11), 331–359.

Allen, F. (1984). Reputation and product quality. *RAND Journal of Economics 15*(3), 311–327.

Aloosh, A. and J. Li (2021). Direct evidence of bitcoin wash trading. *George Mason University working paper*.

Amiram, D., Z. Bozanic, and E. Rouen (2015). Financial statement errors: Evidence from the distributional properties of financial statement numbers. *Review of Accounting Studies 20*(4), 1540–1593.

Amiram, D., B. N. Jørgensen, and D. Rabetti (2022). Coins for bombs: The predictability of on-chain transfers for terrorist attacks. *Journal of Accounting Research 60*(2), 427–466.

Bar-Isaac, H. and J. Shapiro (2013). Ratings quality over the business cycle. *Journal of Financial Economics 108*(1), 62–78.

Becker, B. and T. Milbourn (2011). How did increased competition affect credit ratings? *Journal of Financial Economics 101*(3), 493–514.

Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American Philosophical Society 78*(4), 551–72.

Bennett, V. M., L. Pierce, J. A. Snyder, and M. W. Toffel (2013). Customer-driven misconduct: How competition corrupts business practices. *Management Science 59*(8), 1725–1742.

Bolton, P., X. Freixas, and J. Shapiro (2012). The credit ratings game. *Journal of Finance 67*(1), 85–111.

Chamberlin, E. (1933). The theory of monopolistic competition. *The Economic Journal 43*(1), 661–666.

Chemmanur, T. J. and P. Fulghieri (1994). Investment bank reputation, information production, and financial intermediation. *Journal of Finance 49*(1), 57–79.

Cong, L. W., W. R. Landsman, E. L. Maydew, and D. Rabetti (2022). Tax-loss harvesting with cryptocurrencies. Working paper. Available at https://dx.doi.org/10.2139/ssrn.4033617.

Cong, W., X. Li, K. Tang, and Y. Yang (2021). Crypto wash trading. *Cornell University working paper*.

Conover, W. (1971). Practical nonparametric statistics. new york: John wiley & sons. pp. 295–301.

Cooper, R. and T. W. Ross (1984). Prices, product qualities and asymmetric information: The competitive case. *Review of Economic Studies 51*(2), 197–207.

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

Dana, J. J. D. and Y. F. Fong (2011). Product quality, reputation, and market structure. *International Economic Review 52*(4), 1059–1076.

Domberger, S. and A. Sherr (1989). The impact of competition on pricing and quality of legal services. *International Review of Law and Economics 1*(9), 41–56.

Drake, P. D. and M. J. Nigrini (2000). Computer assisted analytical procedures using benford's law. *Journal of Accounting Education 18*, 127–146.

Gandal, N., J. T. Hamrick, T. Moore, and T. Oberman (2018). Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics 95*, 86–96.

Gervais, S., R. Kaniel, and D. H. Mingelgrin (2001). The high-volume return premium. *Journal of Financial Economics 56*(3), 877–919.

Griffin, J. M. and A. Shams (2020). Is bitcoin really untethered? *Journal of Finance 75*(4), 1913–1964.

Grinblatt, M. and M. Keloharju (2004). Tax-loss trading and wash sales. *Journal of Financial Economics 71*(1), 51–76.

Horner, J. (2002). Reputation and competition. *American Economic Review 92*(3), 644–663.

James, N. A., A. Kejariwal, and D. S. Matteson (2016). Leveraging cloud data to mitigate user experience from 'breaking bad'. *IEEE International Conference on Big Data*, 3499–3508.

Karpoff, J. M., D. S. Lee, and G. S. Martin (2008). The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis 43*(3), 581–611.

Klein, B. and K. B. Leffler (1981). The role of market forces in assuring contractual performance. *Journal of Political Economy 89*(4), 615–641.

Luca, M. and G. Zervas (2016). Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science 62*(12), 3412–3427.

Lyandres, E., D. Palazzo, and D. Rabetti (2021). Ico success and post-ico performance. *Tel Aviv University working paper*.

Mailath, G. J. and L. Samuelson (2001). Who wants a good reputation? *Review of Economic Studies 68*(2), 415–441.

Mathis, J., J. McAndrews, and J. C. Rochet (2009). Rating the raters: are reputation concerns powerful enough to discipline rating agencies? *Journal of Monetary Economics 56*(5), 657–674.

Matsa, D. (2011). Competition and product quality in the supermarket industry. *Quarterly Journal of Economics 3*(126), 1539–1591.

Mazzeo, M. (2003). Competition and service quality in the us airline industry. *Review of Industrial Organization 4*(22), 275–296.

Michalski, T. and G. Stoltz (2013). Financial statement errors: Evidence from the distributional properties of financial statement numbers. *Review of Economics and Statistics 2*(95), 591–616.

Richardson, G., S. Sefcik, and R. Thompson (1986). A test of dividend irrelevance using volume reactions to a change in dividend policy. *Journal of Financial Economics 2*(17), 313–333.

Schwenkler, G. and H. Zheng (2019). The network of firms implied by the news. *Santa Clara University working paper*.

Schwenkler, G. and H. Zheng (2020). Competition or contagion? evidence from cryptocurrency peers. *Santa Clara University working paper*.

Shams, A. (2020). The structure of cryptocurrency returns. *Ohio State University working paper*.

Shapiro, C. (1983). Premiums for high quality products as returns to reputations. *Quarterly Journal of Economics 98*(4), 659–679.

Shleifer, A. (2004). Does competition destroy ethical behavior? *American Economic Review 2*(94), 414–418.

Figure 1. Evolution of exchange market concentration. The plot shows the evolution of Herfindahl index across exchanges based on the number of currency pairs (solid black), trading volume (dashed blue), and number of trades (dotted red). Currency-pair-based Herfindahl index is computed as the ratio of the sum of squared number of currency pairs traded on each exchange to the squared sum of all numbers of currency pairs traded on all exchanges. Trading-volume-based and number-of-trades-based Herfindahl indices are computed similarly. The grey bars show the total number of distinct currency pairs. The measures are computed monthly during the period from January 2016 to September 2019.

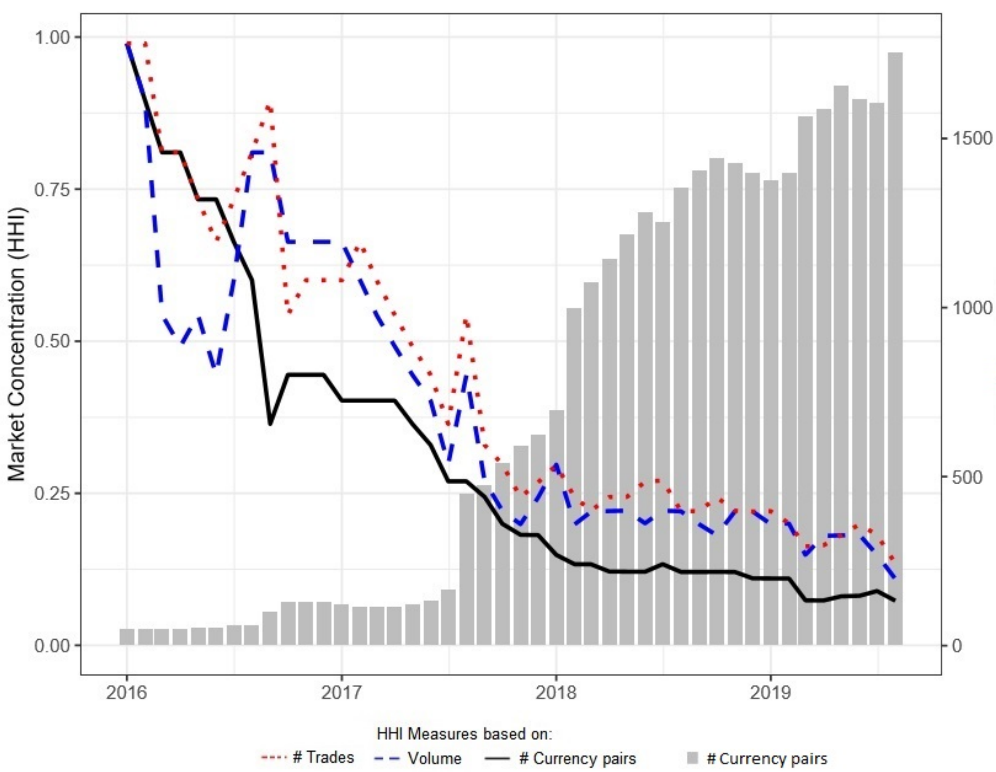


Figure 2. Principle components - Scree plots. The three plots show the percentages of variation in the fake trading measures explained by the first three principal components. In Panel A, FT(Volume), is the principal component of volume-based fake trading measures (MAD: Volume, KS: Volume, and EDM: Volume). In Panel B, FT(Trades) is the principal component of number-of-trades-based fake trading measures (MAD: # Trades, KS: # Trades, and EDM: # Trades). In Panel C, FT(Both), is the principal component of both volume-based and number-of-trades-based fake trading measures.

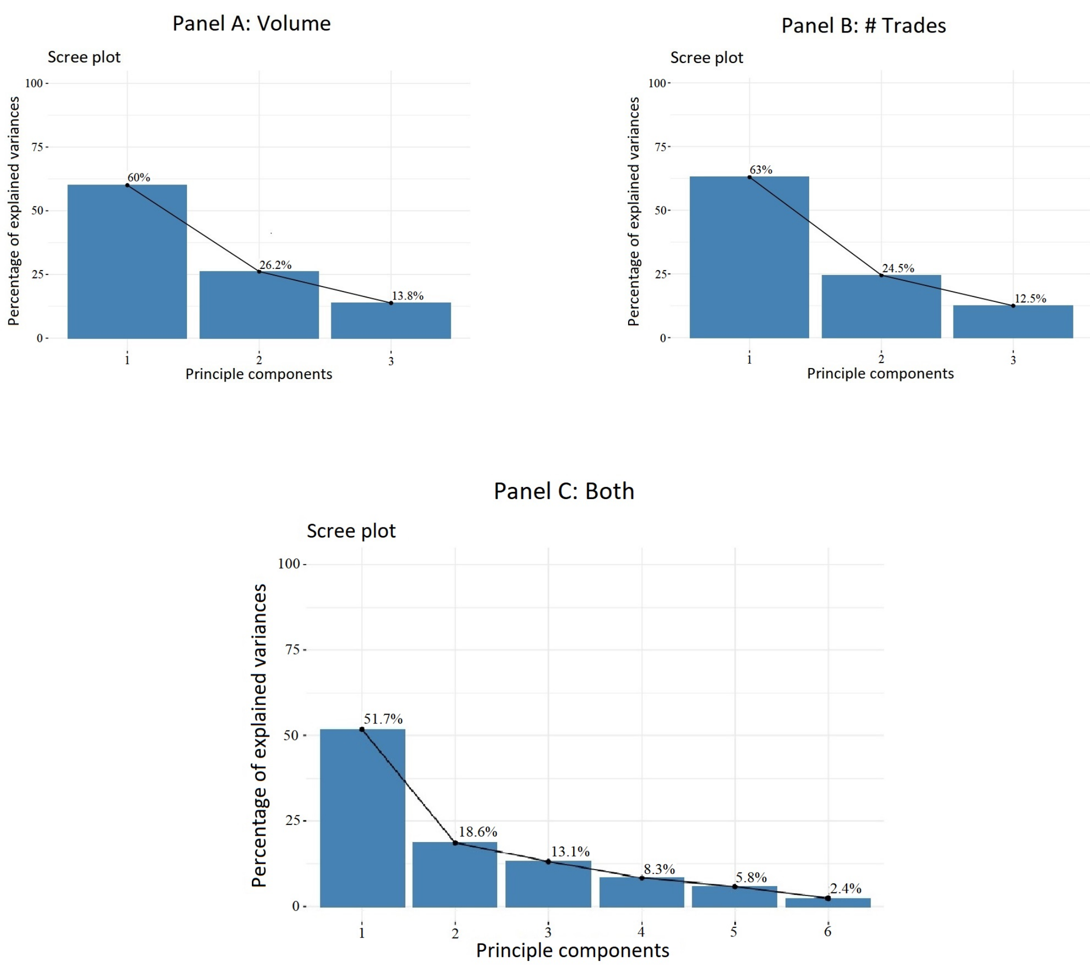


Figure 3. Mean fake trading measures over time. The plot shows equally-weighed (across exchange-currency pair-month) means of the three principle-component-based fake trading measures – PC1: Volume (blue squares), PC1: # Trades (orange triangles), and PC1: Both (green circles) – for each quarter in our sample period between 2013-Q2 to 2019-Q3. The lines around point estimates indicate confidence intervals.

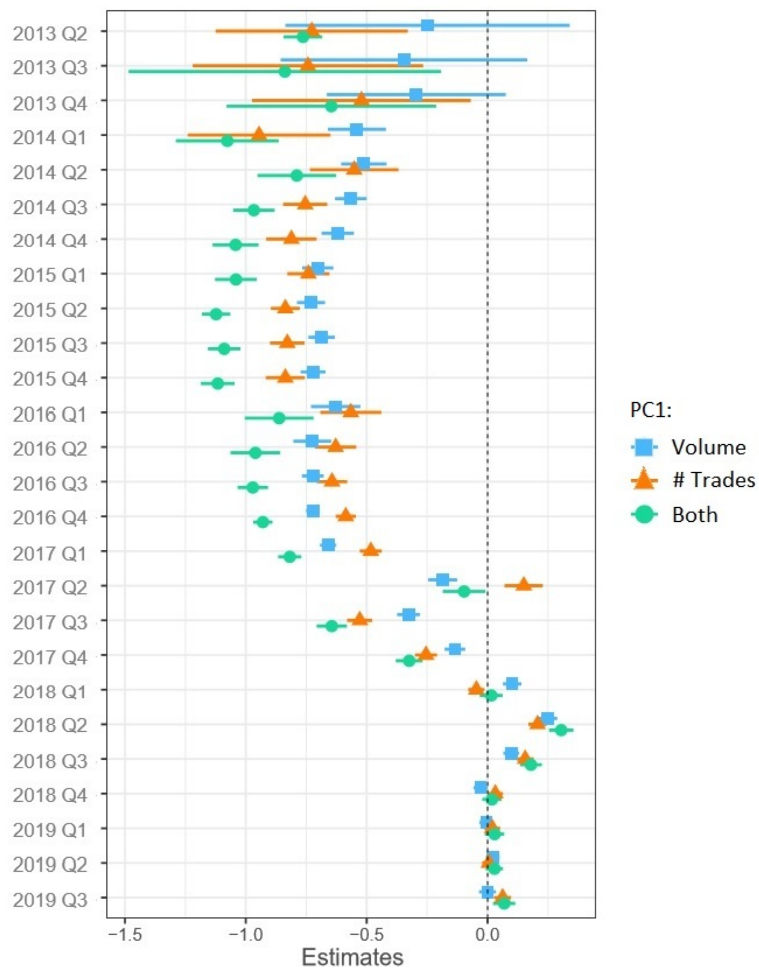


Figure 4. Mean fake trading measures by exchange. The plot shows equally-weighed (across currency pair-month) means of the three principle-component-based fake trading measures – PC1: Volume (blue squares), PC1: # Trades (orange triangles), and PC1: Both (green circles) – for each exchange in our sample period between 2013-Q2 to 2019-Q3. The lines around point estimates indicate confidence intervals.

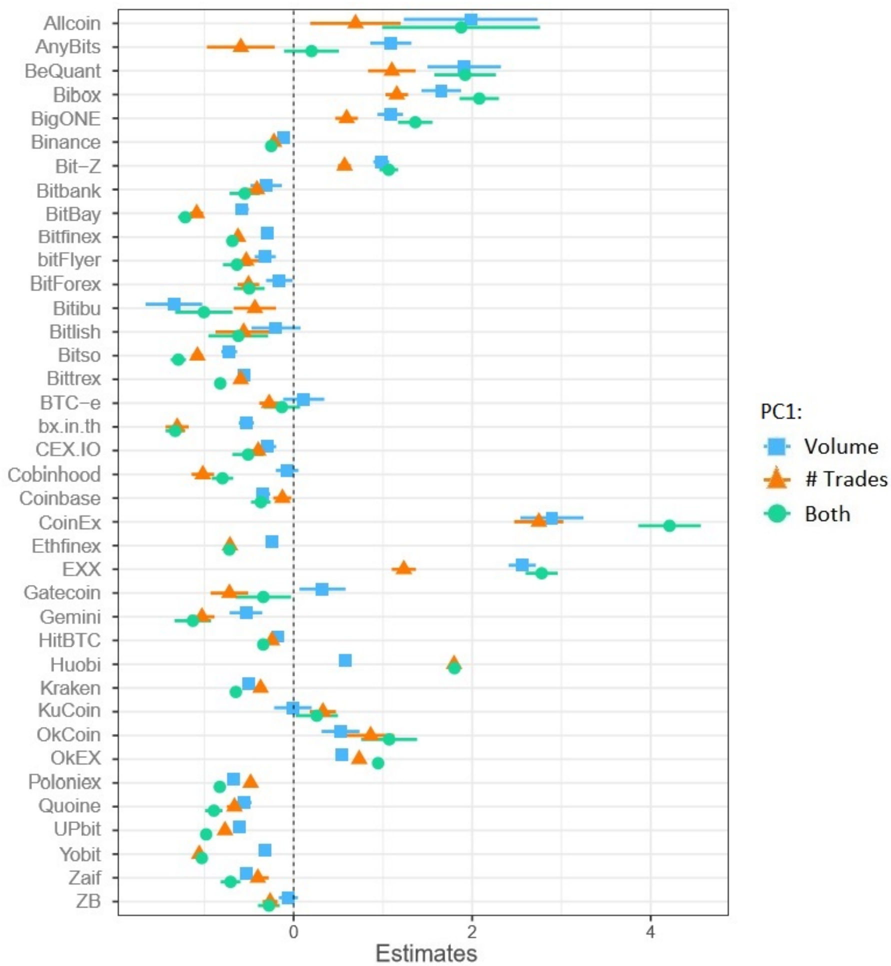


Figure 5. Chinese Ban - Parallel Trends. The plot shows the trend lines of fake trading for exchanges that migrated from China to Pacific Asia following the Chinese ban (Treated) and exchanges that operated in Pacific Asia prior to the ban (Control). Fake trading measure is FT(Both), the first principal-component-based measure based on both trading volume and the number of trades. This figure complements the analysis in Table 5.

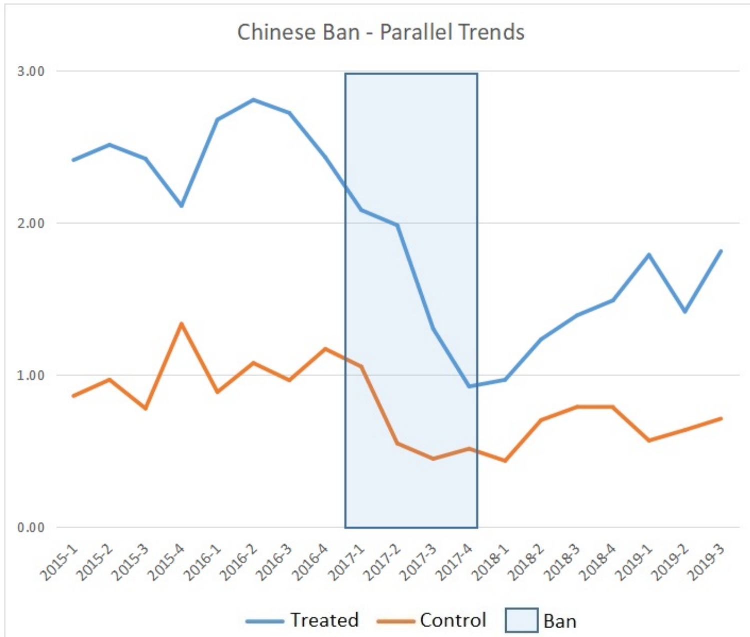


Table 1. Summary statistics. The table reports summary statistics for market-level (in Panel A), currency-pair-level (in Panel B), exchange-level (in Panel C), and exchange-currency-pair level (in Panel D) of the variables used in the empirical analysis. The sample period is May 2013 – September 2019. All variables are defined in Table D.1 in Appendix D.

Panel A: Market

	Min	Max	Median	Mean	SD	Obs.
Market cap: CoinMarketCap (CMC)	0.18	1,046.85	12.13	184.73	342.97	76
Market cap: Kaiko	0.01	1,003.16	10.05	178.58	287.06	76
Market cap Kaiko / Market cap CMC	0.05	0.96	0.82	0.87	0.21	76
Currencies: All	1.00	967.00	54.50	262.41	326.03	76
Currencies: Tokens	0.00	626.00	21.50	148.91	205.22	76
Currencies: Coins	1.00	348.00	33.00	113.76	123.32	76
Currencies: Entry	0.00	380.00	2.50	33.03	68.81	76
Currencies: Exit	0.00	80.00	0.00	7.62	16.25	76
Currency pairs: All	1.00	1,753.00	56.50	428.01	590.13	76
Currency pairs: Tokens	0.00	1,221.00	22.50	274.32	405.77	76
Currency pairs: Coins	1.00	532.00	34.00	153.70	185.96	76
Currency pairs: Entry	0.00	593.00	2.50	53.72	117.99	76
Currency pairs: Exit	0.00	91.00	0.00	9.67	20.98	76
Volume: $U.S. (MM)	0.00	267.59	0.54	37.87	68.66	76
Volume: BTC (M)	0.00	43.14	0.76	5.63	9.29	76
# Trades (M)	0.00	642.66	5.06	99.4	166.4	76
Exchanges	1.00	41.00	9.50	10.86	10.29	76
Exchanges: Entry	0.00	14.00	0.00	0.53	1.73	76
Exchanges: Exit	0.00	1.00	0.00	0.05	0.22	76
HHI Exchanges: # Currencies	0.07	1.00	0.12	0.14	0.13	76
HHI Exchanges: Volume	0.11	1.00	0.20	0.22	0.11	76
HHI Exchanges: # Trades	0.13	1.00	0.22	0.24	0.12	76

Panel B: Currency pairs

	Min	Max	Median	Mean	SD	Obs.
Listed on # exchanges	1.00	19.00	1.81	2.46	0.93	32,529
HHI: Currency pair across exchanges: Volume	0.11	1.00	0.20	0.23	0.13	32,529
HHI: Currency pair across exchanges: # Trades	0.13	1.00	0.22	0.26	0.14	32,529
Age of listing on any exchange	0.00	75.00	9.00	11.63	10.56	32,529
Age of listing on a given exchange	0.00	61.00	8.00	8.92	6.94	32,529
Time to listing	0.00	36.00	4.22	5.87	4.55	32,529
Token	0.00	1.00	0.51	0.64	0.48	32,529

Table 1. Summary statistics – continued

Panel C: Exchanges

	Min	Max	Median	Mean	SD	Obs.
Age	1.00	8.00	5.00	4.95	1.69	807
Market share: Volume	0.00	1.00	0.006	0.094	0.20	807
Market share: # trades	0.00	1.00	0.007	0.094	0.19	807
Market share: Currency pairs	0.00	1.00	0.006	0.094	0.20	807
Currency pairs	1.00	581.00	12.00	77.67	122.14	807
Currency pairs: Entry	0.00	419.00	0.00	5.99	27.09	807
Currency pairs: Exit	0.00	62.00	0.00	0.95	4.16	807
AML	0.00	1.00	1.00	0.59	0.49	807
KYC	0.00	1.00	1.00	0.62	0.49	807
Crypto-friendly location	0.00	1.00	0.00	0.46	0.50	807
Bad news	0.00	1.00	0.00	0.25	0.43	807
Multiplatform	0.00	1.00	0.00	0.12	0.32	807
Alexa (K)	0.23	735.99	9.47	41.75	98.02	342
Reddit	0.00	2,228.00	0.00	37.85	156.51	418
Twitter	0.00	21,002.00	0.00	178.45	1,133.73	442
Github	0.00	695.00	13.00	103.36	159.94	237
Africa	0.00	1.00	0.00	0.02	0.15	807
Asia	0.00	1.00	0.00	0.25	0.43	807
China	0.00	1.00	0.00	0.14	0.35	807
Central and South America	0.00	1.00	0.00	0.12	0.33	807
Eastern Europe	0.00	1.00	0.00	0.09	0.28	807
Western Europe	0.00	1.00	0.00	0.12	0.33	807
Europe: Islands	0.00	1.00	0.00	0.18	0.38	807
North America	0.00	1.00	0.00	0.08	0.26	807

Panel D: Exchange-Currency pairs

	Min	Max	Median	Mean	SD	Obs.
Volume: $U.S. (M)	0.00	49,374.67	0.78	45.92	413.00	62,676
Volume: BTC (K)	0.00	27,260	6.94	9.33	7.24	62,676
# Trades (K)	1.00	25,593.80	12.32	120.53	447.24	62,676
HHI Currency pairs within exchange: Volume	0.02	1.00	0.50	0.51	0.36	62,676
HHI Currency pairs within exchange: # Trades	0.02	1.00	0.50	0.51	0.36	62,676

Table 2. Fake trading measures and principal components. Panel A reports summary statistics of three volume-based and three number-of-trades-based measures of fake trading (MAD, KS, and EDM). Fake trading measures and principal components are at the exchange-currency pair-month level. All measures are described in Section 4 and Table D.1 in Appendix D. Panel B reports summary statistics of the first principal components of the fake trading measures.

Panel A: Fake trading measures

	Min	Max	Median	Mean	SD	Obs.
MAD: Volume	0.38	463.80	12.43	31.63	42.64	55,242
MAD: # Trades	0.34	241.99	7.56	17.57	26.82	55,242
KS: Volume	0.00	0.53	0.33	0.31	0.08	55,228
KS: # Trades	0.00	0.56	0.29	0.27	0.08	55,228
EDM: Volume	0.00	1239.00	8.00	18.73	43.60	57,004
EDM: # Trades	0.00	885.00	3.00	11.47	33.93	57,004

Panel B: Principle components

	Min	Max	Median	Mean	SD	Obs.
PC1: Volume	-2.30	15.63	-0.44	0	1.34	55,228
PC1: # Trades	-2.84	22.97	-0.52	0	1.37	55,228
PC1: Both	-3.09	16.14	-0.73	0	1.76	55,228

Table 3. Fake trading and exchange characteristics. This table reports the differences in mean values of principal-component-based measures of fake trading associated with regulation/compliance/transparency between High and Low subsamples. In case of discrete variables, High and Low correspond to indicator variables equaling one and zero. In case of continuous variables, High and Low are defined based on whether the value of the variable is higher or lower than its in-sample median. See Table D.1 in Appendix D for variable definitions. In column 1, FT(Volume) is the first principal component based on trading-volume-based measures. In column 2, FT(# Trades) is the first principal component based on number-of-trades-based measures. In column 3, FT(Both) is the first principal component based on both trading-volume-based and number-of-trades-based measures. In column 4, MAD is the Mean-Adjusted Deviations from Benford rule. In column 5, KS is Kolmogorov-Smirnov distance between the cumulative distribution function (c.d.f.) of the natural logarithm of the volume or number of trades in a currency pair and the c.d.f. of normal distribution with the same mean and standard deviation. In column 6, EDM is the number of breakouts obtained with E-Divisive with Medians algorithm. The sample is all exchange-months with non-missing values of the characteristics being compared. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Fake trading measure	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**	**MAD**	**KS**	**EDM**
AML	-0.281 ***	-0.419 ***	-0.537 ***	-20.374 ***	-0.014 ***	-3.225 **
	(0.033)	(0.042)	(0.048)	(1.417)	(0.002)	(1.425)
KYC	-0.212 ***	-0.045	-0.0857	-6.587 ***	-0.005 *	-3.770
	(0.030)	(0.041)	(0.048)	(1.338)	(0.002)	(1.372)
Crypto-friendly location	0.725 ***	0.734 ***	1.048 ***	21.373 ***	0.039 ***	17.664 ***
	(0.028)	(0.031)	(0.038)	(0.871)	(0.002)	(1.079)
Bad news	0.568 ***	0.743 ***	0.955 ***	23.253 ***	0.034 ***	20.635 ***
	(0.032)	(0.032)	(0.040)	(1.030)	(0.002)	(1.215)
Multiplatform	0.581 ***	1.209 ***	1.344 ***	35.223 ***	0.072***	24.913 ***
	(0.033)	(0.036)	(0.046)	(1.177)	(0.002)	(1.529)
Web popularity	-0.420 ***	-0.232 ***	-0.459 ***	-8.972 ***	-0.005 ***	-7.599 ***
	(0.031)	(0.030)	(0.041)	(1.043)	(0.001)	(1.324)
Twitter	-0.627 ***	-0.796 ***	-1.058 ***	-28.716 ***	-0.036 ***	-15.387 ***
	(0.034)	(0.037)	(0.046)	(1.227)	(0.002)	(1.357)
Reddit	-0.499 ***	-0.706 ***	-0.909 ***	-26.098 ***	-0.035 ***	-11.094 ***
	(0.030)	(0.035)	(0.042)	(1.080)	(0.002)	(1.321)
Github	-0.212 ***	-0.459 ***	-0.506 ***	-16.123 ***	-0.015 ***	-16.817 ***
	(0.032)	(0.031)	(0.042)	(0.984)	(0.002)	(1.068)
Obs.	55,228	55,228	55,228	55,228	55,228	55,228

Table 4. Alternative fake trading measures. This table reports estimates of regressions of alternative, correlation-based measures of fake trading on the three principal-component-based measures of fake trading. The dependent variable in columns 1 and 2 is trading-volume correlation-based measures. To compute it, each month for each exchange and currency pair that is traded on at least five exchanges, we calculate the correlation between the volume of trading on that exchange during ten-minute intervals and contemporaneous aggregate trading volume in that pair on all exchanges. Number-of-trades correlation-based measure, used as the dependent variable in columns 3 and 4, and price correlation-based measure, used as the dependent variable in columns 5 and 6, are computed similarly. In the upper part of the table, the main independent variable is FT(Volume), the first principal component based on trading-volume-based measures. In the middle part of the table, the main independent variable is FT(# Trades), the first principal component based on number-of-trades-based measures. In the lower part of the table, the main independent variable is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. In even columns we control for Web popularity of the exchange, measured as one minus the ratio of the highest Alexa rank of exchanges in the sample divided by the exchange's Alexa rank, and for the exchange's social media presence, proxied by the natural logarithm of the number of Twitter tweets. See Table D.1 in Appendix D for variable definitions. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable	**Corr (Volume)**		**Corr (# Trades)**		**Corr (Price)**	
FT(Volume)	-0.007 ***	-0.006 ***	-0.009 ***	-0.003 *	-0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Web popularity	No	Yes	No	Yes	No	Yes
Social media	No	Yes	No	Yes	No	Yes
Obs.	26,630	16,537	26,630	16,537	26,630	16,537
Adj. R^2	0.083	0.142	0.092	0.186	0.054	0.060
FT(# Trades)	-0.018 ***	-0.007 **	-0.015 ***	-0.005 *	0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Web popularity	No	Yes	No	Yes	No	Yes
Social media	No	Yes	No	Yes	No	Yes
Obs.	26,630	16,537	26,630	16,537	26,630	16,537
Adj. R^2	0.091	0.141	0.095	0.186	0.050	0.060
FT(Both)	-0.011 ***	-0.004 *	-0.010 ***	-0.006 *	-0.001	-0.000
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Web popularity	No	Yes	No	Yes	No	Yes
Social media	No	Yes	No	Yes	No	Yes
Obs.	26,630	16,537	26,630	16,537	26,630	16,537
Adj. R^2	0.087	0.141	0.094	0.186	0.052	0.061

Table 5. Chinese Ban. This table reports estimates of regressions of the three principal-component-based measures of fake trading around the ban in China of crypto exchanges in September 2017 on the Treated exchange indicator, Post-ban indicator, and their interaction. The sample in columns 1-3 includes all exchanges that operated in China prior to the ban and moved to Pacific Asia as a result of the ban (treated exchanges) and exchanges that operated in Pacific Asia prior to the ban (control exchanges). The sample in columns 4-6 includes all exchanges that operated in China prior to the ban and moved to Hong Kong as a result of the ban (treated exchanges) and exchanges that operated in Hong Kong prior to the ban (control exchanges). The sample period is the first three quarters of 2017 and the first two quarters of 2018. In columns 1 and 4, the dependent variable is Volume, the first principal component based on trading-volume-based measures. In columns 2 and 5, the dependent variable is # Trades, the first principal component based on number-of-trades-based measures. In columns 3 and 6, the dependent variable is Both, the first principal component based on both trading-volume-based and number-of-trades-based measures. Treated is an indicator variable equaling one for treated firms. Post-ban equals one for the first two quarters of 2018. Treated × Post ban is the interaction between these two variables. We control for exchange characteristics and currency pair characteristics described in detail in Table 6. See Table D.1 in Appendix D for variable definitions. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample	**Pacific Asia (Treated exchanges: 7) (Control exchanges: 11)**			**Hong Kong (Treated exchanges: 5) (Control exchanges: 5)**		
Fake trading measure	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**
Treated	1.679 ***	1.379 ***	1.596 ***	1.662 ***	0.833 *	1.956 ***
	(0.161)	(0.150)	(0.168)	(0.402)	(0.336)	(0.490)
Post-ban	-0.378 *	-0.420 **	-0.594 **	-0.356 ***	-0.306 **	-0.473 **
	(0.168)	(0.156)	(0.204)	(0.098)	(0.107)	(0.183)
Treated × Post-ban	-1.342 ***	-1.297 ***	-1.146 ***	-0.791 ***	-0.745 ***	-1.154 ***
	(0.185)	(0.161)	(0.193)	(0.259)	(0.232)	(0.311)
Exchange characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Currency pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,554	6,554	6,554	3,524	3,524	3,524
Adj. R^2	0.180	0.213	0.224	0.182	0.226	0.213

Table 6. Static competition and fake trading. This table reports estimates of regressions of three principal components-based measures of fake trading on exchange-level and currency-pair-level characteristics. In columns 1 and 2, the dependent variable is FT(Volume), the first principal component based on trading-volume-based measures. In columns 3 and 4, the dependent variable is FT(# Trades), the first principal component based on number-of-trades-based measures. In columns 5 and 6, the dependent variable is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. See Table D.1 in Appendix D for definitions of exchange and currency-pair characteristics. The set of independent variables includes base pair (BTC, ETH, USDT) fixed effects and year-quarter fixed effects. In odd columns, the regressions include the geographical region of the exchange location. In even columns, exchange fixed effects are included. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	(2)	(3)	(4)	(5)	(6)
Fake trading measure	**FT(Volume)**		**FT(# Trades)**		**FT(Both)**	
Static competition measures						
log (Listed on # exchanges)	0.044 ***	0.048 ***	0.025 ***	0.022 ***	0.046 ***	0.048 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HHI pair: Volume	-0.040	-0.116 ***	-0.125 ***	-0.204 ***	-0.117 ***	-0.218 ***
	(0.023)	(0.022)	(0.020)	(0.020)	(0.027)	(0.026)
Exchange characteristics						
log (# Currency pair)	-0.053 ***		0.149 ***		0.068 ***	
	(0.011)		(0.010)		(0.013)	
Market share: Volume	-0.033 ***		-0.048 ***		-0.057 ***	
	(0.005)		(0.004)		(0.006)	
log (Age)	-0.049 ***		-0.023 **		-0.010	
	(0.009)		(0.008)		(0.011)	
Exchange location						
Africa	1.065 ***		0.701 ***		1.324 ***	
	(0.054)		(0.049)		(0.066)	
Asia (Other than China)	0.813 ***		0.263 ***		0.730 ***	
	(0.033)		(0.030)		(0.039)	
China	1.571 ***		2.051 ***		2.686 ***	
	(0.035)		(0.032)		(0.043)	
Central and South America	1.381 ***		1.217 ***		1.918 ***	
	(0.038)		(0.034)		(0.046)	
Eastern Europe	0.508 ***		-0.630 ***		-0.129 ***	
	(0.031)		(0.028)		(0.038)	
Western Europe	0.330 ***		-0.150 ***		0.125 ***	
	(0.029)		(0.026)		(0.035)	
Europe: Islands	0.600 ***		0.017		0.416 ***	
	(0.030)		(0.028)		(0.037)	
Currency-pair characteristics						
log (Age of listing on exchange)	0.032	0.050	-0.093 **	-0.038	-0.066	-0.013
	(0.035)	(0.033)	(0.031)	(0.030)	(0.042)	(0.040)
Token	-0.089 ***	-0.060 ***	-0.124 ***	-0.101 ***	-0.150 ***	-0.112 ***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.013)	(0.013)
Exchange FE	no	yes	no	yes	no	yes
Base pair FE	yes	yes	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes	yes	yes
Obs.	55,220	55,228	55,220	55,228	55,220	55,228
Adj. R^2	0.145	0.221	0.333	0.389	0.281	0.347

Table 7. Dynamic competition and fake trading. This table reports estimates of regressions of three principal components-based measures of fake trading on measures of competition, indicators of entry and exit by competitor exchanges, and the interaction of these entry/exit indicators with high competition indicator. In columns 1, 4, and 7, the dependent variable is FT(Volume), the first principal component based on trading-volume-based measures. In columns 2, 6, and 8, the dependent variable is FT(# Trades), the first principal component based on number-of-trades-based measures. In columns 3, 6, and 9, the dependent variable is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. In columns 1-3, "general" competitors are a set of all exchanges in our dataset. In columns 4-6, "geographical" competitors are a subset of exchanges that operate in the same geographical region as the focal exchange, where regions are defined as in Panel C of Table 1. In columns 7-9, "operational" competitor is the exchange belonging to the set of general competitors that has the largest overlap of pairs listed with the focal exchange. Moderate competition is an indicator equaling one if a currency pair is listed on at least two and at most seven exchanges. High competition is an indicator equaling one if a currency pair is listed on at least eight exchanges. Competitor entry is an indicator equaling one if there exists at least one exchange that has not previously listed a currency pair starts listing it in a given month. Competitor exit is an indicator equaling one if there is at least one exchange that has listed a currency pair last month and does not list it in a given month. We control for exchange characteristics and currency pair characteristics described in detail in Table 6. See Table D.1 in Appendix D for definitions of exchange and currency pair characteristics. The set of independent variables also includes base pair (BTC, ETH, USDT) fixed effects and year-quarter fixed effects. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Competitor type	**General**			**Geographical**			**Operational**		
Fake trading measure	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**
Moderate competition	0.046 *	0.024	0.070 **	0.054 **	0.036	0.064 **	0.058 **	0.045 *	0.084 ***
	(0.019)	(0.019)	(0.024)	(0.019)	(0.019)	(0.024)	(0.019)	(0.019)	(0.024)
High competition	0.107 ***	0.171 ***	0.203 ***	0.104 ***	0.158 ***	0.191 ***	0.124 **	0.192 ***	0.229 ***
	(0.025)	(0.026)	(0.033)	(0.025)	(0.026)	(0.033)	(0.025)	(0.025)	(0.032)
Competitor entry	0.125 ***	0.184 ***	0.208 ***	0.166 ***	0.185 ***	0.255 ***	0.215 ***	0.209 ***	0.313 ***
	(0.025)	(0.025)	(0.032)	(0.029)	(0.029)	(0.037)	(0.036)	(0.036)	(0.046)
Competitor exit	-0.159 ***	-0.286 ***	-0.328 ***	0.012	-0.066	-0.044	-0.018	0.126	0.100
	(0.039)	(0.040)	(0.051)	(0.052)	(0.052)	(0.067)	(0.068)	(0.068)	(0.087)
Competitor entry	0.080 *	0.035	0.074	0.088 *	0.132 **	0.151 **	0.168 **	0.172**	0.181 *
× High competition	(0.039)	(0.039)	(0.050)	(0.042)	(0.042)	(0.054)	(0.064)	(0.065)	(0.083)
Competitor exit	-0.170 **	-0.187 **	-0.261 ***	-0.157 *	0.022	-0.108	-0.211	-0.545 ***	-0.601 ***
× High competition	(0.058)	(0.058)	(0.074)	(0.069)	(0.069)	(0.089)	(0.126)	(0.126)	(0.162)
Exchange characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency-pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	55,220	55,220	55,220	55,220	55,220	55,220	55,220	55,220	55,220
Adj. R^2	0.082	0.114	0.116	0.082	0.114	0.116	0.082	0.113	0.115

Table 8. Effects of fake trading on trading volume. This table reports estimates of regressions of trading volume on lagged trading volume, as well as contemporaneous and lagged principal components-based measures of fake trading. In columns 1-2, 5-6, and 7-8 the dependent variable is trading volume and the regressions are estimated using OLS. Columns 4, 8, and 12 present estimates of the second stage of 2SLS regressions, in which the dependent variable is trading volume, and lagged volume is replaced a fitted value from the first-stage regressions, whose estimates are reported in columns 3, 7, and 11 respectively. The dependent variable in the first-stage regressions is lagged volume and the independent variables are lagged fake trading measure, lagged average Bitcoin price throughout the month of the observation and lagged squared Bitcoin price. In columns 1-4, the fake trading measure FT(Volume), is the first principal component based on trading-volume-based measures. In columns 5-8, the fake trading measure FT(# Trades), is the first principal component based on trading-volume-based measures. In columns 9-12, the fake trading measure is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. We control for exchange characteristics and currency pair characteristics described in detail in Table 6. See Table D.1 in Appendix D for definitions of exchange and currency pair characteristics. The set of independent variables also includes base pair (BTC, ETH, USDT) fixed effects and year-quarter fixed effects. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Estimation Method:	**OLS**	**OLS**	**2SLS 1st stage**	**2SLS 2nd stage**	**OLS**	**OLS**	**2SLS 1st stage**	**2SLS 2nd stage**	**OLS**	**OLS**	**2SLS 1st stage**	**2SLS 2nd stage**
Dependent Variable:	**Volume**	**Volume**	**Lag (Volume)**	**Volume**	**Volume**	**Volume**	**Lag (Volume)**	**Volume**	**Volume**	**Volume**	**Lag (Volume)**	**Volume**
Fake trading measure	**FT(Vol.)**	**FT(Vol.)**	**FT(Vol.)**	**FT(Vol.)**	**FT(# Tr.)**	**FT(# Tr.)**	**FT(# Tr.)**	**FT(# Tr.)**	**FT(Both)**	**FT(Both)**	**FT(Both)**	**FT(Both)**
PC1	0.154 ***	0.081 ***		0.151 ***	0.206 ***	0.133 ***		0.222 ***	0.191 ***	0.117 ***		0.192 ***
	(0.021)	(0.019)		(0.017)	(0.026)	(0.023)		(0.019)	(0.015)	(0.012)		(0.015)
Lag (PC1)	0.106 ***	-0.052 **	0.310 ***	-0.036	0.156 ***	-0.083 ***	0.403 ***	-0.028	0.121 ***	-0.077 ***	0.352 ***	-0.060 **
	(0.015)	(0.017)	(0.027)	(0.022)	(0.017)	(0.013)	(0.033)	(0.022)	(0.016)	(0.022)	(0.023)	(0.020)
Lag (Volume)		0.317 ***		0.271 ***		0.425 ***		0.326 ***		0.581 ***		0.452 ***
		(0.042)		(0.054)		(0.061)		(0.057)		(0.062)		(0.076)
Lag (BTC Price)			0.028 ***				0.029 ***				0.025 ***	
			(0.004)				(0.004)				(0.005)	
Lag (BTC Price$2̂$)			-0.001 ***				-0.001 ***				-0.001 ***	
			(0.000)				(0.000)				(0.000)	
Exchange characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency-pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	49,861	49,861	49,861	49,861	49,861	49,861	49,861	49,861	49,861	49,861	49,861	49,861
Adj. R^2	0.361	0.863	0.174	0.365	0.448	0.870	0.287	0.445	0.431	0.869	0.271	0.432

Table 9. Real effects of fake trading on web popularity and estimated exchange revenue. This table reports estimates of regressions of a measure of web popularity and of estimated revenue of the exchange on trading volume over the past three months (in Panel A), past six months (in Panel B), past nine months (in Panel C), and past twelve months (in Panel D). Web popularity is measured as one minus the ratio of the highest Alexa rank of exchanges in the sample divided by the exchange's Alexa rank. See Section 6.2 for details of estimation of exchange's revenue. In columns 1 and 4, the fake trading measure, FT(Volume), is the first principal component based on trading-volume-based measures. In columns 2 and 5, the fake trading measure, FT(# Trades), is the first principal component based on trading-volume-based measures. In columns 3 and 6, the fake trading measure, FT(Both), is the first principal component based on both trading-volume-based and number-of-trades-based measures. We control for exchange characteristics, described in detail in Table 6 and defined in Table D.1 in Appendix D. The set of independent variables also includes year-quarter fixed effects. The sample is all exchange-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**Web popularity**			**Estimated exchange revenue**		
Fake trading measure	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**	**FT(Volume)**	**FT(# Trades)**	**FT(Both)**
Panel A: 3 months						
Lag3 (PC1)	1.778 **	1.892 **	1.481 **	0.496 ***	0.511 ***	0.414 ***
	(0.624)	(0.632)	(0.483)	(0.028)	(0.028)	(0.020)
Obs.	722	722	722	724	724	724
Adj. R^2	0.467	0.480	0.511	0.475	0.498	0.497
Panel B: 6 months						
Lag6 (PC1)	0.253 ***	0.139 ***	0.207 ***	0.390 ***	0.354 ***	0.321 ***
	(0.024)	(0.024)	(0.018)	(0.095)	(0.096)	(0.094)
Obs.	624	624	624	624	624	624
Adj. R^2	0.166	0.164	0.165	0.395	0.382	0.403
Panel C: 9 months						
Lag9 (PC1)	-0.301 ***	-0.286 ***	-0.254 ***	0.102	0.094	0.053
	(0.046)	(0.056)	(0.055)	(0.076)	(0.056)	(0.041)
Obs.	532	532	523	522	532	532
Adj. R^2	0.424	0.418	0.429	0.211	0.223	0.229
Panel D: 12 months						
Lag12 (PC1)	-3.115 ***	-3.425 ***	-2.700 ***	-0.210 ***	-0.259 ***	-0.201 ***
	(0.822)	(0.808)	(0.630)	(0.037)	(0.036)	(0.028)
Obs.	428	428	428	430	430	430
Adj. R^2	0.649	0.646	0.646	0.717	0.719	0.719
Exchange characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Currency-pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Base pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A : Evolution of the crypto market

Figure A.1 presents the evolution of the crypto market capitalization over time.[38]

[Insert Figure A.1 here]

The solid black line in Figure 1 depicts the market cap of Bitcoin, the dashed blue line refers to Ether, and the dotted red line represents the combined market cap of all other cryptocurrencies ("alt coins"). The cryptocurrency market has grown tremendously between 2013 and 2019 – from 0.18 billion $US to over 800 billion $US at its peak, in January 2018, but since then saw a significant decline, which was mainly due to the decline in Bitcoin price and to "ICO winter", i.e. a sharp reduction in the volume of initial coin offerings since the middle of 2018.[39]

Figure A.2 shows the evolution of entries of new currency pairs (solid blue line), exits of currency pairs (dashed red line) and the net monthly change in the number of traded pairs across all exchanges (grey bars).[40]

[Insert Figure A.2 here]

Panel A of Figure A.3 presents the evolution over time of combined reported volume on all exchanges (in billion $U.S.), separated into the following subgroups of currency pairs: 1) ETH-BTC, 2) USDT-BTC, 3) BTC against other currencies, 4) ETH against other currencies, and 5) USTD against other currencies.

[Insert Figure A.3 here]

The volume of trading in USDT saw a rapid rise since its inception in late 2017, whereas the volume of trading in pairs involving ETH has been declining since its peak in the beginning of 2018. The peak of trading in BTC pairs preceded slightly the peak, during our sample period, of the crypto market capitalization in January 2018. Panel B of Figure A.3 presents the evolution of the number of trades (in million) across all exchanges for the same subgroups of currency pairs. The main patterns are similar to those evident in the evolution of trading volume. One interesting difference is that the reported number of trades in USDT pairs is low relative to reported volume, suggesting a relatively large average trade size.

[38] For visualization purposes, in this and other figures, we omit data prior to 2016, when the rapid development of the crypto market started.

[39] Since the end of our sample period, the crypto market capitalization has rebounded and currently exceeds $US 2 trillion.

[40] In Figure A.2, every appearance (disappearance) of a currency pair on (from) an exchange is counted, regardless of whether the currency pair is listed on other exchanges.

Figure A.1. Evolution of crypto market capitalization. The plot shows the evolution of market capitalisation in billions of US Dollars for Bitcoin (BTH, black solid), Ether (ETH, dashed blue) and remaining coins and tokens (dotted red). Market capitalizations are aggregated monthly in the period from January 2016 to September 2019.

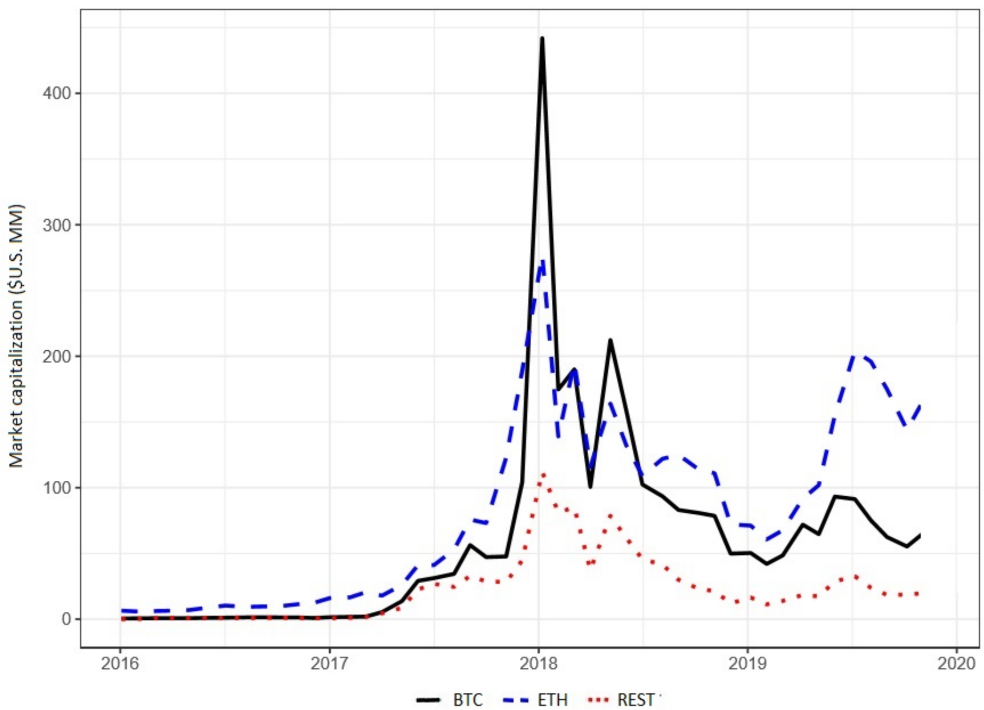


Figure A.2. Dynamics of entry and exit of currency pairs. The plot depicts the number of entries (solid blue), the number of exits (dashed red) and entries net of exits (grey bars) of currency pairs on crypto exchanges. The numbers of entries and exists are computed at the currency pair-exchange level and are aggregated monthly in the period from January 2016 to September 2019.

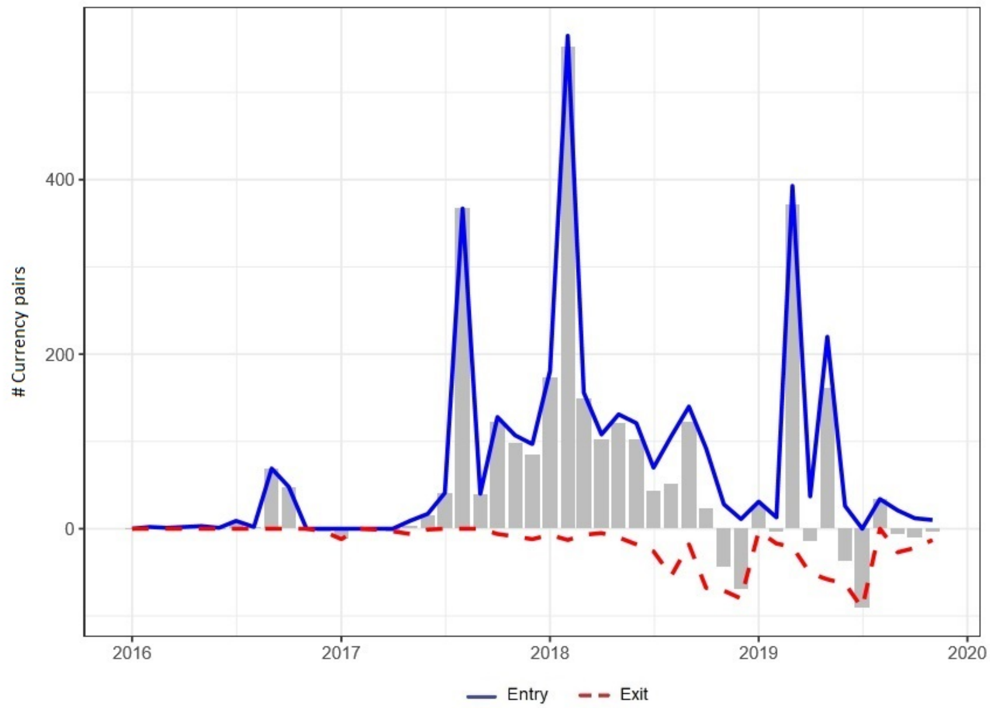
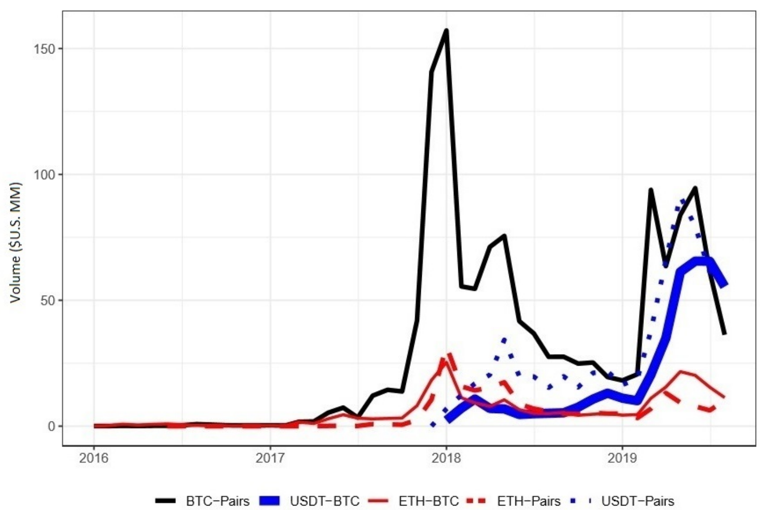
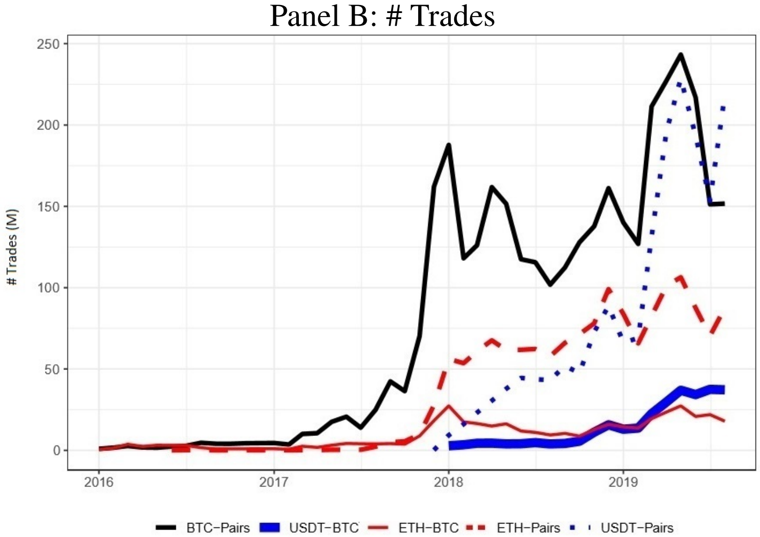


Figure A.3. Evolution of trading volume and number of trades. The plot shows the evolution of reported trading volume (in Panel A) and number of trades (in Panel B) for ETH-BTC pair (solid red), USDT-BTC pair (solid blue), other BTC pairs (solid black), other ETH pairs (dashed red), and other USDT pairs (dotted blue). Trading volume is aggregated monthly in the period from January 2016 to September 2019 and reported in billions of $U.S. Number of trades is aggregated monthly and reported in millions.

Panel A: Volume



Panel B: # Trades



Appendix B : Examples of methods for detecting fake trading

Figure B.1 presents examples of trading activity that may be indicative of fake trading.

[Insert Figure B.1 here]

Panel A depicts the evolution of trading volume (in the upper two figures) and the number of trades (in the lower two figures) in the OmiseGo-Bitcoin pair (OMG-BTC) during 4,464 ten-minute intervals in January 2019 on two exchanges – Okex and Binance. The upper two figures suggest that while trading volume on Binance follows an arguably random pattern, there seem to be several structural breaks in trading volume on Okex. Similar structural breaks are evident in the number of trades on Okex, whereas they do not seem to be present on Binance.

Panel B presents trading volume and number of trades in one of the most important cryptocurrency pairs – ETH-BTC – on two exchanges: ZB (on the left) and Binance (on the right) in April, 2019. While the plots of both trading volume and the number of trades on Binance do not reveal unusual patterns, there are numerous spikes of trading activity on ZB, which are often two orders of magnitude larger than typical trading volume and occur with a roughly constant frequency.

Panel C depicts trading volume and number of trades in Time New Bank-Bitcoin pair (TNB-BTC) pair on Huobi and Binance. Once again, the trading volume on Binance does not suggest specific patterns. In contrast, there are several peculiarities in the graphs of trading volume and the number of trades on Huobi. First, both trading volume and the number of trades are constant for prolonged periods of time. Second, there are clear structural breaks in the number of trades plot. Finally, the average trade size on Huobi is about three orders of magnitude smaller than that on Binance.

Panel A of Figure B.2 shows examples of observed series of first digits of trading volume during ten-minute intervals over the course of one month (March 2019) in the ETH-BTC pair on four crypto exchanges – Binance, ZB, Okex, and Bibox.

[Insert Figure B.2 here]

In each of the four figures, the solid line depicts the actual distribution of leading digits of the number of trades, whereas the dashed line depicts the theoretical, Benford's-Law-based distribution. The observed series for Binance seems to roughly approximate the theoretical Benford's Law. However, the other plots indicate frequencies of leading digits that deviate substantially from Benford's Law. For instance, the plot for ZB shows that the frequencies of digits 7-9 are over twice as large as those predicted by Benford's Law; the same is true for digit 5 on Okex and digits 2 and 3 on Bibox. The deviations from Bedford's Law are even more striking in Panel B of Figure B.2, which presents examples of frequencies of first digits of the number of trades series.

Figure B.3 illustrates the c.d.f. of the natural logarithm of trading volume (solid line) on four exchanges – Binance, Okex, ZB, and Bibox and the c.d.f. of a normal distribution with the same mean and variance (dotted line) – for ETH-BTC pair in March, 2019 – for trading volume in Panel A and for the number of trades in Panel B.

[Insert Figure B.3 here]

The c.d.f. of the volume of the log of trading on Binance and Okex are the closest to normal: the Kolmogorov-Smirnov distances are 0.15 and 0.19, respectively. On the other end of the spectrum is ZB, with KS statistic of 0.60, whereas Bibox is in between (KS statistic of 0.31). Similar results are obtained for number-of-trades-based KS distances: The lowest are those for Binance and Okex (0.14 and 0.20, respectively), whereas the highest is for ZB (0.52).

Figure B.4 presents two examples of the performance of EDM algorithm in detecting structural breaks in the data.

[Insert Figure B.4 here]

The first example, presented in Panel A, is the number of trades within ten-minute intervals in the OMG-BTC pair on the Okex exchange in January 2019. The series is characterised by a step-like shape. The EDM algorithm is able to correctly detect four structural breaks, highlighted by dashed vertical lines (where the timing of the breaks is identified by the algorithm). Importantly, due to its reliance on comparisons of medians (and not means), the algorithm also correctly ignores a temporary spike in trading around bin 3,800. The second example, depicted in Panel B, is the number of trades in the ETH-BTC pair on the Binance exchange in May 2019. The EDM algorithm does not identify any breakouts in this case, consistent with no visible structural breaks in the trading volume plot.

Figure B.5 presents biplots that show the orthogonalization of fake trading measures and their relation with the first two principal components (for trading-volume-based, number-of-trades-based and both volume-based and number-of-trades-based measures in Panels A, B, and C, respectively). The length of each vector (squared cosine) represents the respective variable in the first two principal components. The horizontal and vertical projections of a vector represent the variable in the first and second principal components, respectively.

[Insert Figure B.5 here]

Figure B.6 depicts mean measures of fake trading over time, separated into five groups of currency-pair types: 1) ETH-BTC, 2) USDT-BTC, 3) BTC against other currencies, 4) ETH against other currencies, and 5) USTD against other currencies.

[Insert Figure B.6 here]

The measure depicted in this Figure is the first principal component of both volume-based and number-of-trades-based measures.[41] The lowest level of fake trading is observed in pairs involving BTC and ETH on one side and alt coins on the other side, perhaps because these pairs tend to be rather illiquid on average and detecting fake trading in such pairs is the easiest. Most fake trading occurs in the USDT-BTC pair, followed by the ETH-BTC pair, which are, as of late, the pairs with the highest volume of trading.

[41] The results are similar for the volume-based principal component measure and for the number-of-trades-based one.

Figure B.1. Examples of trading volume and number of trades series. The plot shows trading volume (in upper figures of Panels A, B, and C) and number of trades (in the lower figures of Panels A, B, and C), aggregated into 4,032-4,464 ten-minute bins. Panel A displays data for OMG-BTC pair on Okex (left panels) and Binance (right panels) in January 2019. Panel B displays data for ETH-BTC pair on ZB (left panels) and Binance (right panels) in March 2019. Panel C displays data for TNB-BTC pair on Huobi (left panels) and Binance (right panels) in February 2019.

Panel A

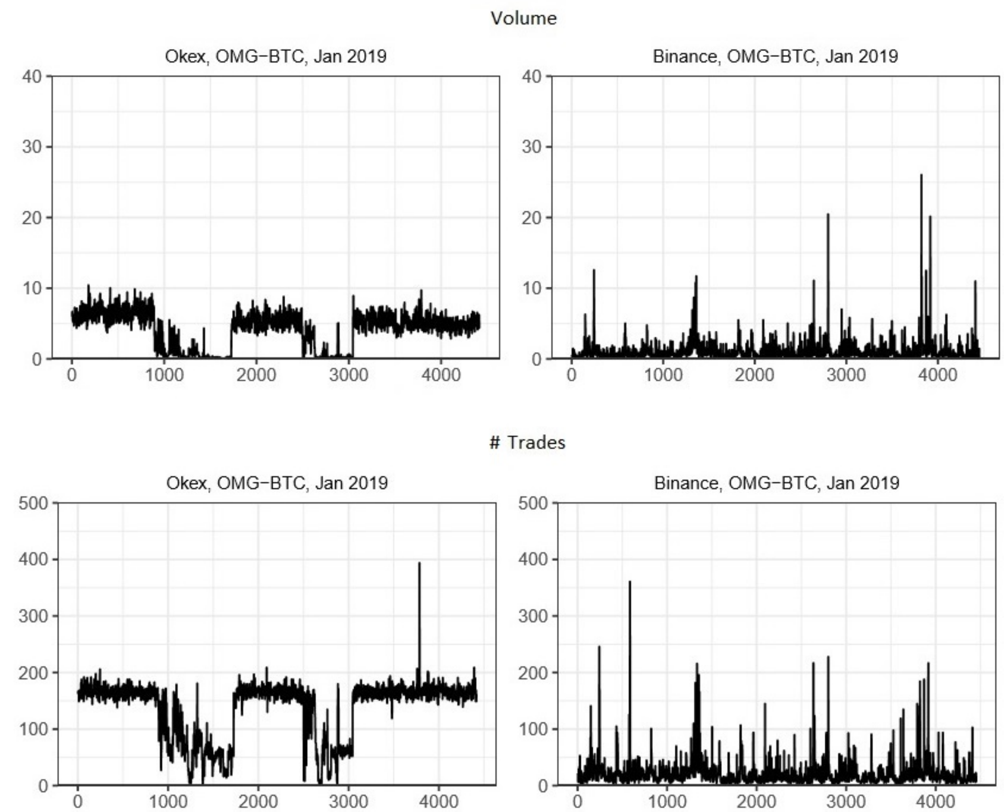


Figure B.1. Examples of trading volume and number of trades series – continued

Panel B

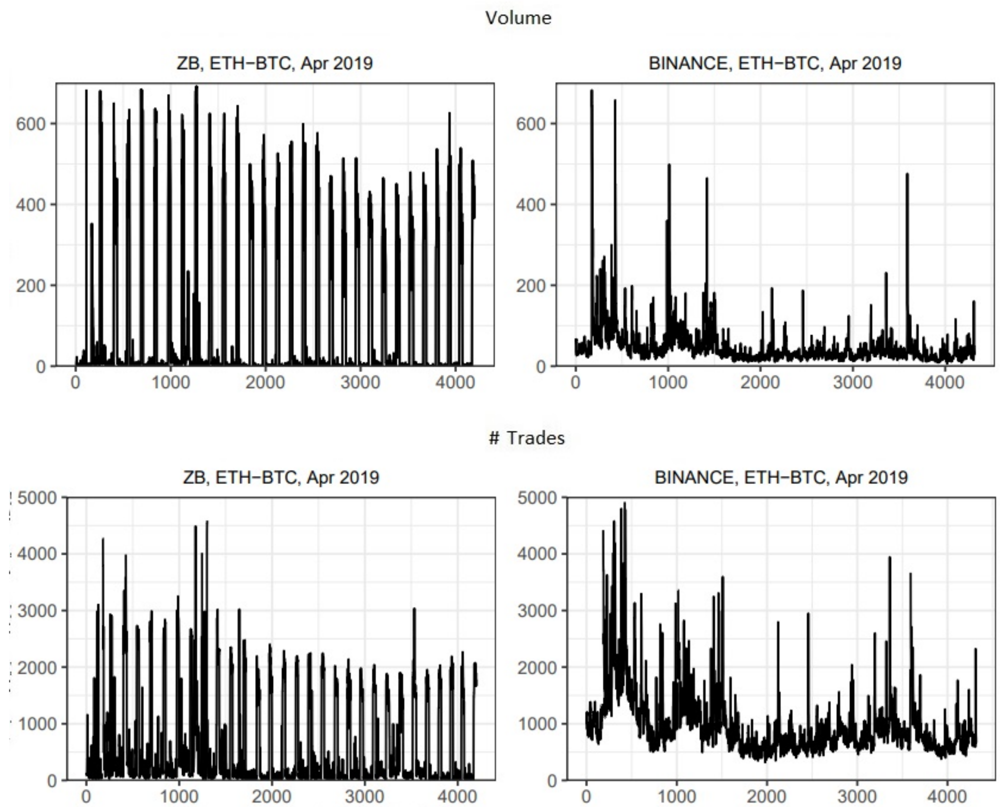


Figure B.1. Examples of trading volume and number of trades series – continued

Panel C

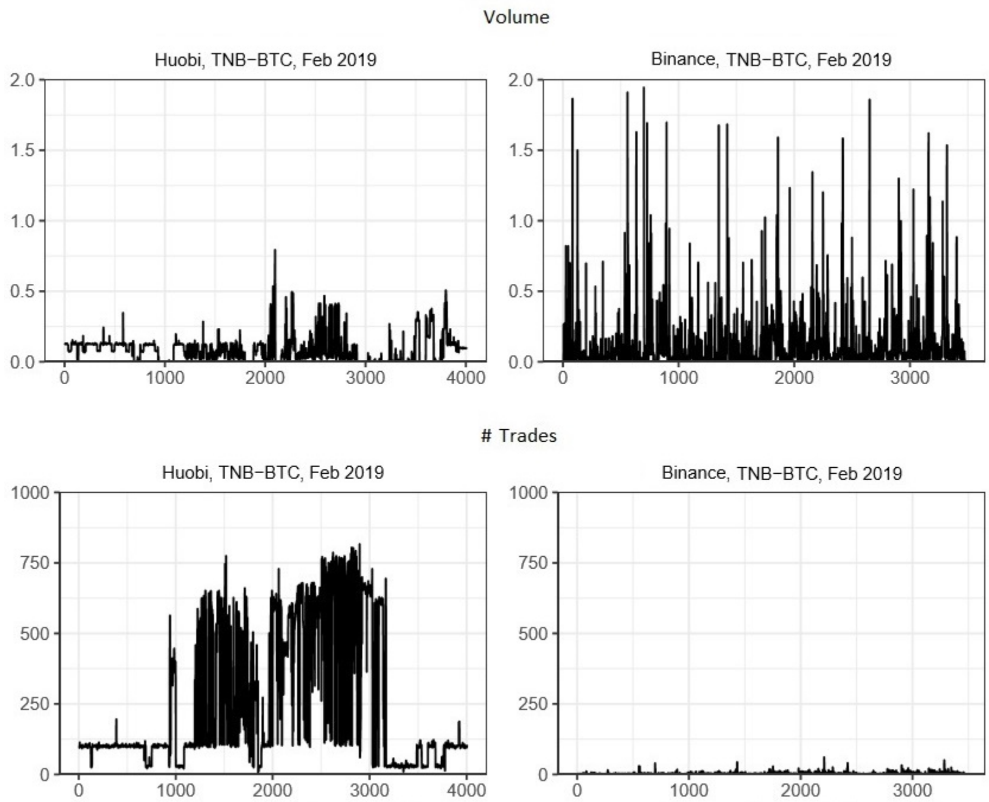


Figure B.2. Examples of deviations from Benford's Law. The plot shows empirical frequencies of leading digits of trading volume (in Panel A, blue blue curve) and number of trades (in Panel B, blue solid line) aggregated into ten-minute bins within a month. Dotted red curve represents frequencies of leading digits under Benford's Law. The frequencies are computed for ETH-BTC pair in March 2019 on four exchanges: Binance, ZB, Okex, and Bibox.

Panel A: Trading volume

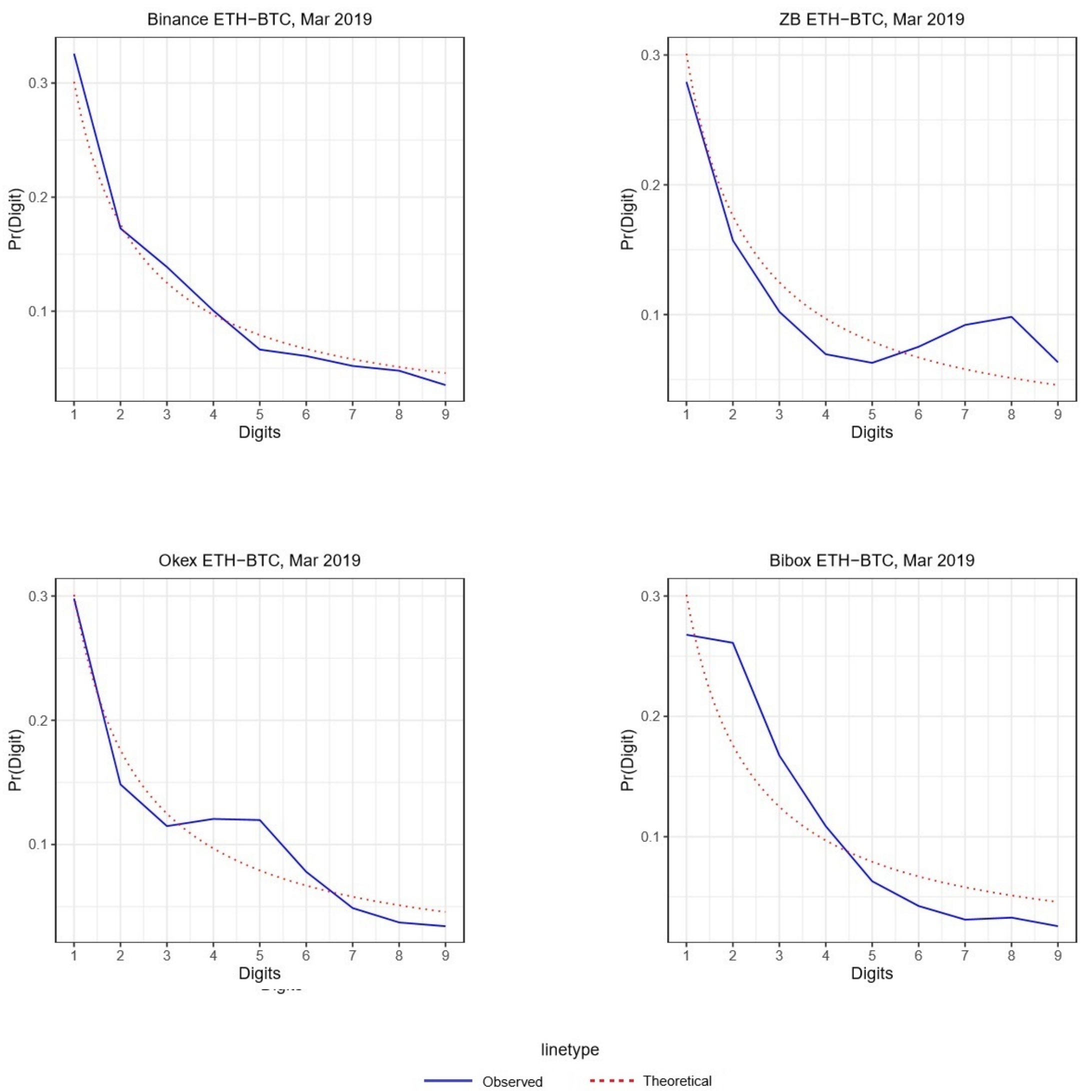


Figure B.2. Examples of deviations from Benford's Law – continued

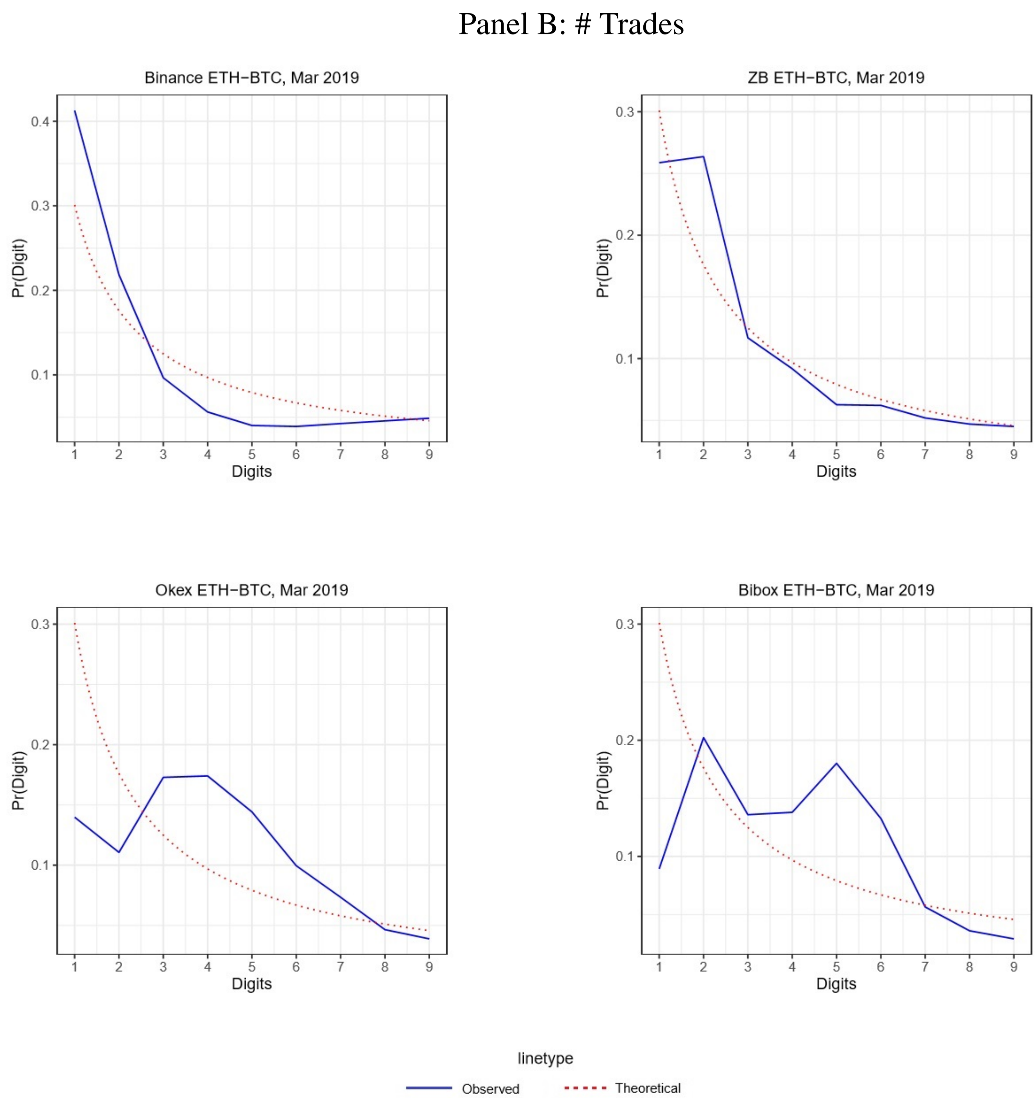


Figure B.3. Examples of deviations from log-normal distribution. The plot shows empirical cumulative density function (solid blue curve) of the natural logarithm of trading volume (in Panel A) and number of trades (Panel B) aggregated into ten-minute bins within a month, and c.d.f. of normal distribution with the same mean and variance (dotted red curve). The c.d.f.'s are computed for ETH-BTC pair in March 2019 on four exchanges: Binance, ZB, Okex, and Bibox.

Panel A: Trading volume

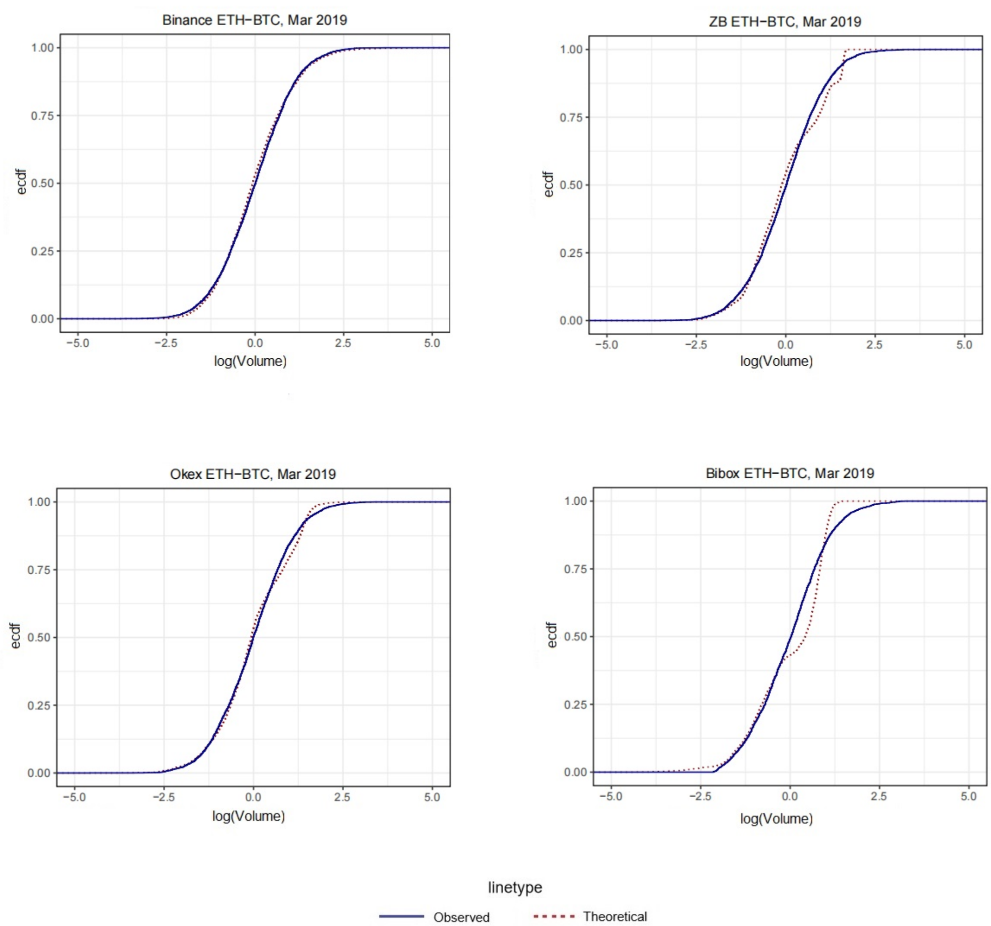


Figure B.3. Examples of deviations from log-normal distribution – continued

Panel B: # Trades

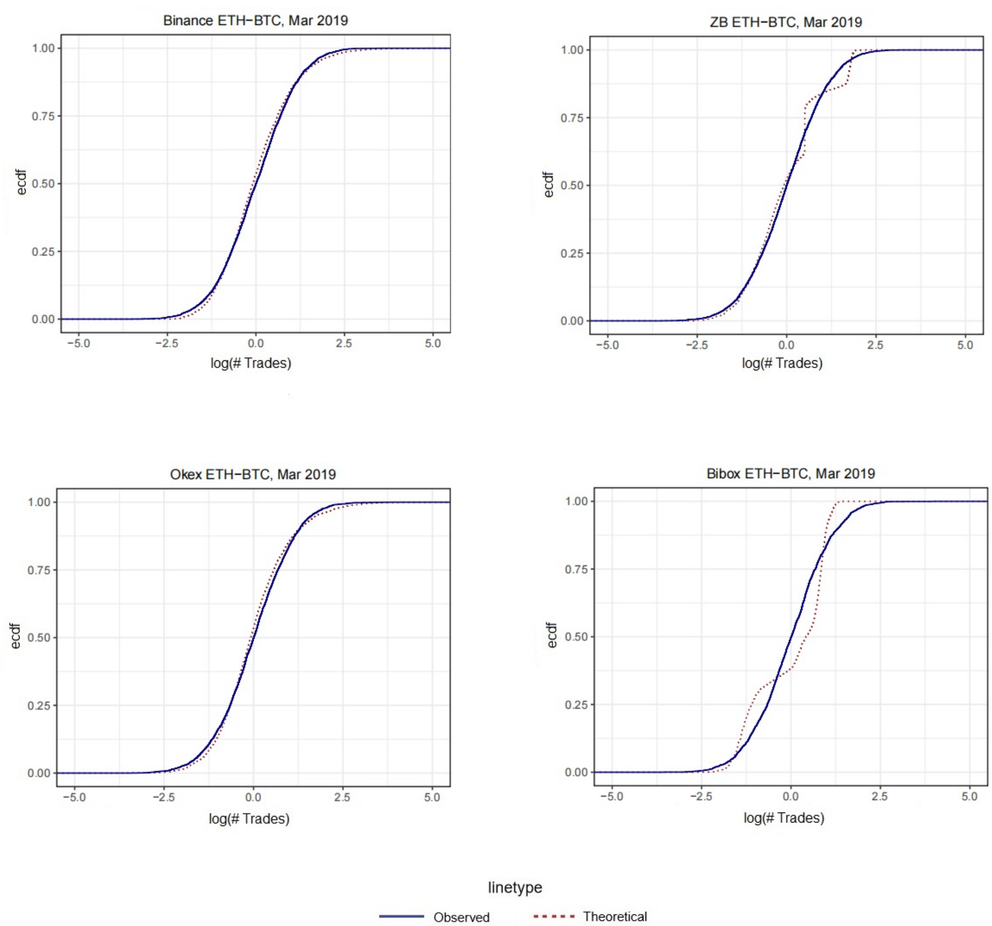
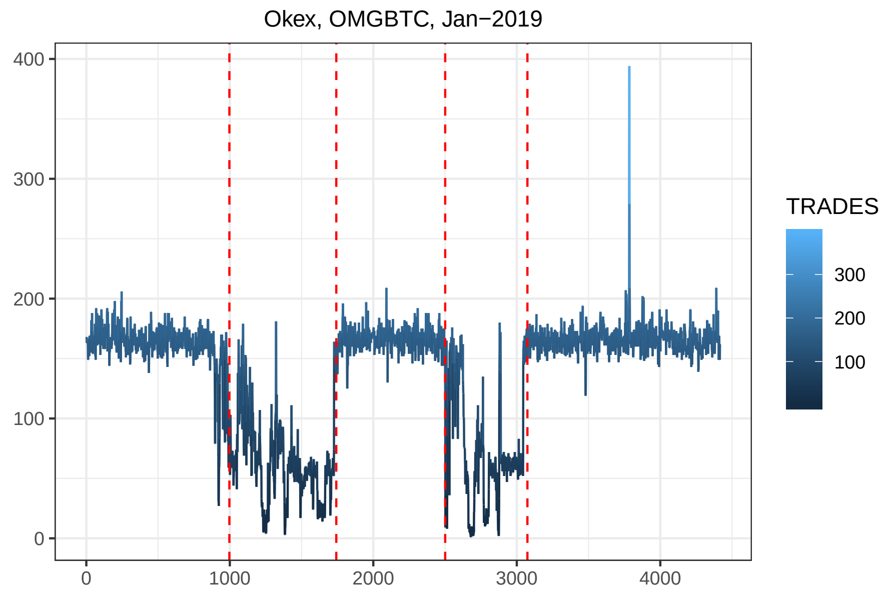


Figure B.4. Examples of application of EDM measure. The plot in Panel A shows structural breaks (dashed red lines) in the number of trades series, aggregated into ten-minutes bins within a month, on Okex exchange in OMG-BTC pair in January 2019. The plot in Panel B depicts the number of trades series, aggregated into ten-minutes bins within a month, on Binance exchange in ETH-BTC pair in May 2019, in which EDM algorithm did not detect any structural breaks.

Panel A



Panel B

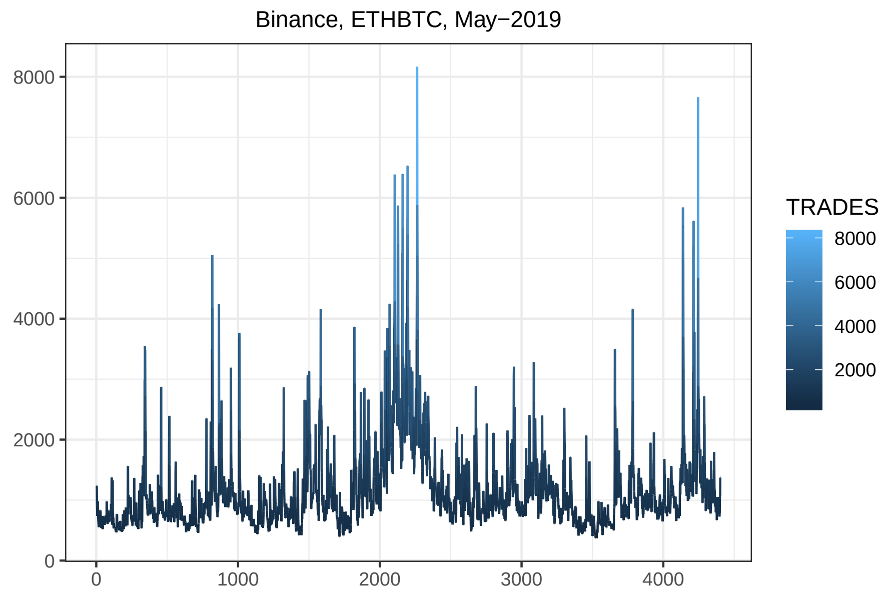


Figure B.5. Principle components - Biplots. The three plots depict the proportion of variation in the first principal component explained by measures of fake trading. The length of each vector (squared cosine) represents the respective variable in the first two principal components. The horizontal and vertical projections of a vector represent the variable in the first and second principal component respectively. In Panel A, FT(Volume), is the principal component of volume-based fake trading measures (MAD: Volume, KS: Volume, and EDM: Volume). In Panel B, FT(Trades) is the principal component of number-of-trades-based fake trading measures (MAD: # Trades, KS: # Trades, and EDM: # Trades). In Panel C, FT(Both), is the principal component of both volume-based and number-of-trades-based fake trading measures.

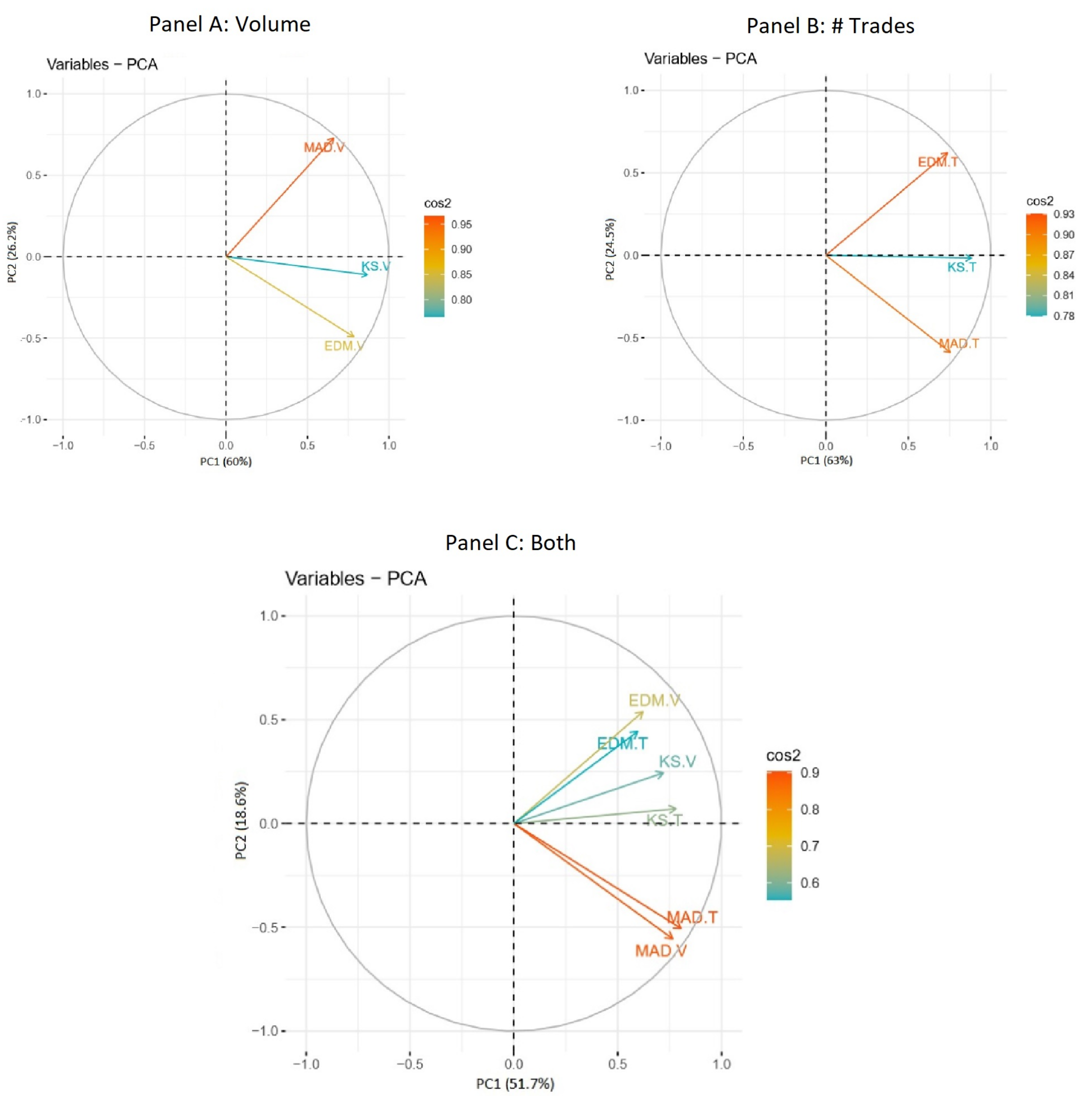
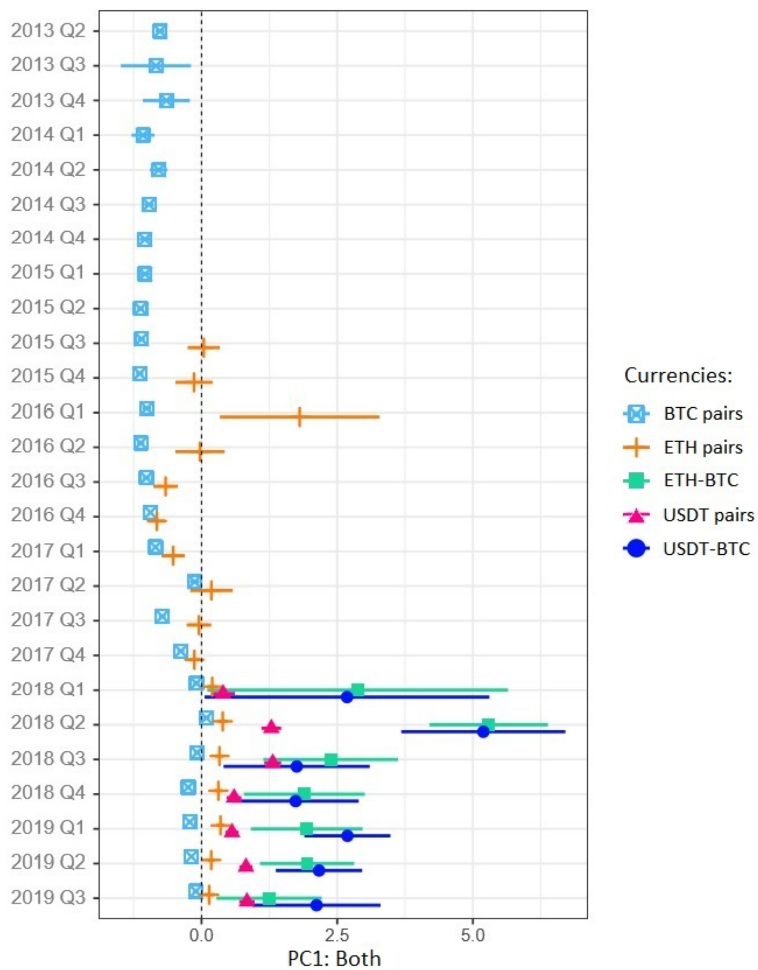


Figure B.6. Fake by pair types. The plot shows equally-weighed (across exchange-currency pair-month) means of combined principle-component-based fake trading measure – FT(Both) – for each quarter in our sample period between 2013-Q2 to 2019-Q3, and for each of the five groups of currency pairs: ETH-BTC (green squares), USDT-BTC (dark blue circles), other BTC pairs (light blue squares), other ETH pairs (orange crosses), and other USDT pairs (pink triangles). The lines around point estimates indicate confidence intervals.



Appendix C : Robustness Tests by Size

Table C.1. Static competition and fake trading by size. This table reports estimates of regressions of the principal-component-based measure of fake trading on exchange-level and currency-pair-level characteristics. The dependent variable is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. See Table D.1 in Appendix D for definitions of exchange and currency-pair characteristics. The set of independent variables includes base pair (BTC, ETH, USDT) fixed effects and year-quarter fixed effects. In the first two columns, the results are reported for a subsample of currency pairs in which the quote currency has a market cap exceeding $U.S. one billion. Columns 3 and 4 report the results for a subsample of pairs in which the quote currency has a market cap below $U.S. one billion. In odd columns, the regressions include the geographical region of the exchange location. In even columns, exchange fixed effects are included. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	High market Cap		**Low market Cap**	
Fake trading measure	**FT(Both)**			
Static competition measures:				
log (Listed on # exchanges)	0.049 ***	0.054 ***	0.044 ***	0.050 ***
	(0.004)	(0.004)	(0.004)	(0.004)
HHI pair: Volume	-0.155 **	-0.097 *	-0.138 **	-0.125 *
	(0.049)	(0.047)	(0.052)	(0.050)
Exchange characteristics				
log (# Currency pair)	-0.124 ***		-0.065 **	
	(0.017)		(0.023)	
Marke share: Volume	-0.141 ***		-0.047 ***	
	(0.017)		(0.008)	
log (Age)	-0.054 **		-0.021	
	(0.019)		(0.019)	
Exchange location				
Africa	0.983 ***		1.326 ***	
	(0.132)		(0.128)	
Asia (Other than China)	1.155 ***		0.798 ***	
	(0.078)		(0.072)	
China	1.866 ***		1.567 ***	
	(0.082)		(0.077)	
Central and South America	1.691 ***		1.398 ***	
	(0.089)		(0.082)	
Eastern Europe	-0.784 ***		0.472 ***	
	(0.072)		(0.070)	
Western Europe	0.512 ***		0.293 ***	
	(0.070)		(0.064)	
Europe: Islands	0.817 ***		0.591 ***	
	(0.071)		(0.066)	
Currency-pair characteristics				
log (Age of listing on exchange)	0.028	-0.037	0.044	-0.048
	(0.024)	(0.024)	(0.086)	(0.082)
Token	-0.098 ***	-0.067 **	-0.048 *	-0.049 *
	(0.024)	(0.024)	(0.020)	(0.021)
Exchange FE	no	yes	no	yes
Base pair FE	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes
Obs.	12,417	12,417	10,565	10,573
Adj. R^2	0.156	0.219	0.148	0.231

Table C.2. Dynamic competition and fake trading by size. This table reports estimates of regressions of the principal-component-based measures of fake trading on measures of competition, indicators of entry and exit by competitor exchanges, and the interaction of these entry/exit indicators with high competition indicator. The dependent variable is FT(Both), the first principal component based on both trading-volume-based and number-of-trades-based measures. In columns 1 and 4, "general" competitors are a set of all exchanges in our dataset. In columns 2 and 5, "geographical" competitors are a subset of exchanges that operate in the same geographical region as the focal exchange, where regions are defined as in Panel C of Table 1. In columns 3 and 6, "operational" competitor is the exchange belonging to the set of general competitors that has the largest overlap of pairs listed with the focal exchange. In the first three columns, the results are reported for a subsample of currency pairs in which the quote currency has a market cap exceeding #U.S. one billion. Columns 4-6 report the results for a subsample of pairs in which the quote currency has a market cap below #U.S. one billion. Moderate competition is an indicator equaling one if a currency pair is listed on at least two and at most seven exchanges. High competition is an indicator equaling one if a currency pair is listed on at least eight exchanges. Competitor entry is an indicator equaling one if there exists at least one exchange that has not previously listed a currency pair starts listing it in a given month. Competitor exit is an indicator equaling one if there is at least one exchange that has listed a currency pair last month and does not list it in a given month. We control for exchange characteristics and currency pair characteristics described in detail in Table 6. See Table D.1 in Appendix D for definitions of exchange and currency pair characteristics. The set of independent variables also includes base pair (BTC, ETH, USDT) fixed effects and year-quarter fixed effects. The sample is all exchange-currency pair-month observations with non-missing values of dependent and independent variables. The regressions are estimated at the exchange-currency pair-month level. * Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent. Standard errors (reported in parentheses) are heteroskedasticity consistent and clustered at the exchange × currency level.

	High market Cap			Low market Cap		
Competitor type	**General**	**Geographical**	**Operational**	**General**	**Geographical**	**Operational**
Fake trading measure	**FT(Both)**					
Moderate competition	0.21 **	0.199 *	0.173 *	0.226 **	0.217 **	0.201 *
	(0.080)	(0.080)	(0.080)	(0.084)	(0.084)	(0.084)
High competition	0.638 ***	0.535 ***	0.587 ***	0.584 ***	0.555 ***	0.562 ***
	(0.120)	(0.120)	(0.118)	(0.124)	(0.126)	(0.123)
Competitor entry	0.223 ***	0.206 **	0.282 **	0.312 ***	0.182 *	0.140 *
	(0.064)	(0.070)	(0.092)	(0.071)	(0.073)	(0.067)
Competitor exit	-0.503 ***	0.036	0.095	-0.312 **	0.11	-0.093
	(0.102)	(0.145)	(0.190)	(0.111)	(0.133)	(0.183)
Competitor entry	0.225 *	0.331 **	0.308 **	0.265 *	0.356**	0.566 **
× High competition	(0.112)	(0.111)	(0.103)	(0.128)	(0.113)	(0.187)
Competitor exit	-0.563 ***	-0.404 *	-1.379 **	-0.591 **	-0.391 *	-0.914 *
× High competition	(0.170)	(0.192)	(0.447)	(0.183)	(0.184)	(0.438)
Exchange characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Currency-pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Base pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,417	12,417	12,417	10,565	10,565	10,565
Adj. R^2	0.128	0.128	0.128	0.114	0.111	0.111

Appendix D : Variable definitions

Table D.1. Variable description

Variable	Type	Description
Market		
Market cap: CMC	Continuous $(0, \infty)$	Aggregate monthly market capitalization at the end of a month in millions of $U.S. Dollars as per www.CoinMarketCap.com
MarketCap: Kaiko	Continuous $(0, \infty)$	Aggregate monthly market capitalization at the end of a month in millions of $U.S. Dollars as per www.Kaiko.com
Market cap CMC / Market Cap Kaiko	Continuous $(0, 1]$	The ratio of Market cap CMC and Market cap Kaiko
Currencies: All	Integer	Total number of crypto currencies (tokens and coins) listed on at least one exchange in a given month
Currencies: Tokens	Integer	Total number of crypto tokens listed on at least one exchange in a given month
Currencies: Coins	Integer	Total number of crypto coins listed on at least one exchange in a given month
Currencies: Entry	Integer	Total number of crypto currencies listed on at least one exchange in a given month and not listed on any exchange in the previous month
Currencies: Exit	Integer	Total number of crypto currencies not listed on any exchange in a given month and listed on at least one exchange in the previous month
Currency pairs: All	Integer	Total number of distinct currency pairs listed on at least one exchange in a given month
Currency pairs: Tokens	Integer	Total number of distinct currency pairs involving a token as a quote currency listed on at least one exchange in a given month
Currency pairs: Coins	Integer	Total number of distinct currency pairs involving a coin as a quote currency listed on at least one exchange in a given month
Currency pairs: Entry	Integer	Total number of currency pairs listed on at least one exchange in a given month and not listed on any exchange in the previous month
Currency pairs: Exit	Integer	Total number of currency pairs not listed on any exchange in a given month and listed on at least one exchange in the previous month
Volume: $U.S. (MM)	Continuous $(0, \infty)$	Aggregate reported volume of trading in all currency pairs on all exchanges in a given month in billions of $U.S.
Volume: BTC (M)	Continuous $(0, \infty)$	Aggregate reported volume of trading in all currency pairs on all exchanges in a given month in millions of BTC
# Trades (M)	Integer	Aggregate reported number of trades in all currency pairs on all exchanges in a given month in millions
Exchanges	Integer	Number of exchanges listing at least one currency pair in a given month
Exchanges: Entry	Integer	Number of exchanges listing at least one currency pair in a given month and not listing any currency pairs in the previous month
Exchanges: Exit	Integer	Number of exchanges not listing any currency pairs in a given month and listing at least one currency pair in the previous month
HHI Exchanges: # Currencies	Continuous $(0, 1]$	Sum of squared number of currencies listed on each exchange divided by the squared sum of number of currencies listed on all exchanges in a given month
HHI Exchanges: Volume	Continuous $(0, 1]$	Sum of squared reported trading volume on each exchange divided by the squared sum of reported trading volume on all exchanges in a given month
HHI Exchanges: # Trades	Continuous $(0, 1]$	Sum of squared reported number of trades on each exchange divided by the squared sum of reported number of trades on all exchanges in a given month

Table D.1. Variable description – continued

Variable	Type	Description
Currency pairs		
Listed on # exchanges:	Integer	The number of exchanges on which a currency pair is listed in a given month
log (Listed on # exchanges):	Continuous $(0, \infty)$	Natural logarithm of the number of exchanges on which a currency pair is listed in a given month
HHI: Currency pair across exchanges: Volume	Continuous $(0, 1]$	Squared reported volume of trading in a currency pair on each exchange divided by the squared sum of total reported volume of trading in the currency pair on all exchange in a given month
HHI: Currency pair across exchanges: # Trades	Continuous $(0, 1]$	Squared reported number of trades involving a currency pair on each exchange divided by the squared sum of total reported number of trades involving the currency pair on all exchange in a given month
Age of listing on any exchange	Integer	Difference in months between current month and the first month a currency pair was listed on any exchange
Age of listing on a given exchange	Integer	Difference in months between current month and the first month a currency pair was listed on a particular exchange
Time to listing	Integer	Difference in months between the first month a currency pair was listed on a particular exchange and the first month the currency pair was listed on any exchange
Token	Indicator	Equals one for tokens issued in an ICO

Table D.1. Variable description – continued

Variable	Type	Description
Exchanges		
Age	Integer	The difference in month between current month and the first month any currency pair was listed on an exchange
Market share: Volume	Continuous (0, 1]	Ratio of reported aggregate trading volume on a given exchange and total reported trading volume on all exchanges in a given month
Market share: # Trades	Continuous (0, 1]	Ratio of reported aggregate number of trades on a given exchange and total reported number of trades on all exchanges in a given month
Market share: Currency pairs	Continuous (0, 1]	Ratio of the number of currency pairs listed on a given exchange and the sum across all exchanges of the numbers of currency pairs listed on them in a given month
Currency pairs	Integer	Number of currency pairs listed on an exchange in a given month
Currency pairs: Entry	Integer	Number of currency pairs that are listed on an exchange in a given month that were not listed on the exchange in the previous month
Currency pairs: Exit	Integer	Number of currency pairs that are not listed on an exchange in a given month that were listed on the exchange in the previous month
AML	Indicator	Equals one if an exchange implemented an AML policy and provides detailed information about conformity with accepted international AML procedures
KYC	Indicator	Equals one if there are evidence that the exchange provides clear guidelines, requires documents, and verifies sources of clients' funds
Crypto-friendly location	Indicator	Equals one if an exchange is located in Singapore, Russia, Estonia, Malta, Luxembourg or Switzerland
Bad news	Indicator	Equals one if an exchange has negative news in the current quarter. News are considered bad if it is related to hack attacks, poor review results, scams or theft.
Multiplatform	Indicator	Equals one if an exchange has both a regular platform and a decentralized platform
Alexa (K)	Integer	Rank in thousands of an exchange's website, as reported by www.Alexa.com
Reddit	Integer	Number of Reddit posts from an exchange's official Reddit account in a given month
Twitter	Integer	Number of Twitter tweets from an exchange's official Twitter account in a given month
Github	Integer	The amount of code reviews (commits) at the exchange main Github repository in a given month
Exchange-currency pairs		
Volume: \$U.S. (M)	Continuous $(0, \infty)$	Aggregate reported volume of trading in all currency pairs on a given exchange in a given month in millions of \$U.S.
Volume: BTC (K)	Continuous $(0, \infty)$	Aggregate reported volume of trading in all currency pairs on a given exchange in a given month in thousands of BTC
# Trades	Integer	Aggregate reported number of trades involving all currency pairs on a given exchange in a given month in thousands
HHI Currency pairs within exchange: Volume	Continuous (0, 1]	Sum of squared reported trading volume of all currency pairs listed on a given exchange divided by the squared sum of aggregate reported trading volume of all currency pairs in the exchange in a given month
HHI Currency pairs within exchange: # Trades	Continuous (0, 1]	Sum of squared reported number of trades involving all currency pairs listed on a given exchange divided by the squared sum of aggregate reported number of trades involving all currency pairs in the exchange in a given month

Table D.1. Variable description – continued

Variable	Type	Description
Quality measures		
MAD: Volume	Continuous $(0, 1)$	Mean absolute distance between the frequency of leading digits of the trading volume series in a currency pair on a given exchange in a given month and the frequency of leading digits given by Benford's Law
MAD: # Trades	Continuous $(0, 1)$	Mean absolute distance between the frequency of leading digits of the number of trades series in a currency pair on a given exchange in a given month and the frequency of leading digits given by Benford's Law
KS: Volume	Continuous $[0, 1]$	Kolmogorov-Smirnov distance between the cumulative distribution function (c.d.f.) of the natural logarithm of trading volume in a currency pair on a given exchange in a given month and the c.d.f. of standard normal distribution
KS: # Trades	Continuous $[0, 1]$	Kolmogorov-Smirnov distance between the cumulative distribution function (c.d.f.) of the natural logarithm of the number of trades involving a currency pair on a given exchange in a given month and the c.d.f. of standard normal distribution
EDM: Volume	Integer	The number of structural breaks in series of trading volume within ten-minutes intervals of a currency pair on a given exchange in a given month identified by E-Divisive with Medians algorithm
EDM: # Trades	Integer	The number of structural breaks in series of number of trades within ten-minutes intervals involving a currency pair on a given exchange in a given month identified by E-Divisive with Medians algorithm
Principal components		
PC1: Volume	Continuous	The first principle component of Mad: Volume, KS: Volume, and EDM: Volume
PC1: # Trades	Continuous	The first principle component of Mad: # Trades, KS: # Trades, and EDM: # Trades
PC1: Both	Continuous	The first principle component of Mad: Volume, KS: Volume, EDM: Volume, Mad: # Trades, KS: # Trades, and EDM: # Trades