Detecting Fake Trading Volume

on Cryptocurrency Exchange

by

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1 Introduction

To date, there are more than 500 cryptocurrency exchanges that support active trading of
cryptocurrencies and the combined 24-hour volume of the whole market is up to billions of
dollars. However, most exchanges were founded within the last five years and can be founded by
anybody without any inspection, regulation, or warranty. About 120 new crypto exchanges were
created in 2018 and also made themselves known to the public, but the estimated total number of
new exchanges exceeds 200. In fact, getting the total count of cryptocurrency exchanges around
the world is nearly impossible. Many exchanges have failed or bailed, and some exchanges are
created just to scam investors.

The only channel for customers to compare and know exchanges is through exchange
ranking websites, and CoinMarketCap is the most popular one which ranks exchanges by their
daily trading volume. As a higher trading volume means better liquidity, popularity, and
recognition from the public, for these exchanges, a higher ranking can serve as a better
propaganda than any advertisement or social media campaign. As CoinMarketCap takes data
directly from exchange's website, the trading volume is completely self-reported. Therefore,
many exchanges start using bots to fake trades and create fraudulent high volume to get better
ranking and exposure to the public.

2 Overview of Cryptocurrency Exchange Market

2.1 Role of Exchanges in the Cryptocurrency World

1 https://blog.cer.live/education/year-trends-review-for-crypto-exchanges/
Similar to stock exchanges, cryptocurrency exchanges are online platforms that provide exchange or trade of cryptocurrencies for other digital currency based on current listed price on each exchange. Cryptocurrency exchanges are derivatives of the zeal of cryptocurrency investing and numerous success of initial coin offerings (ICO). On one hand, as Bitcoin price surges to nearly $20,000 at its peak and people all of a sudden rise to billionaires by investing in cryptocurrencies, the need for buying cryptocurrencies grows more and more imminent. On the other hand, many ICO projects have raised millions of dollars to develop their own digital tokens, and the first step of their project is to get their coins to be listed on an exchange for trade. Cryptocurrency exchanges has become a crucial part in the development of the crypto ecosystem.

There was a time when the whole bitcoin ecosystem was beholden to one exchange². Launched in 2010, Mt. Gox was the largest bitcoin exchange by 2013 handling over 70% of all bitcoin transactions worldwide, but in February 2014, Mt. Gox suspended trading and closed down website to file for bankruptcy due to a hack.³ Since then, the number of exchanges exploded and is still growing with every passing week.⁴

2.1.1 Types of Exchange: Fiat or Digital

Exchange platforms usually provide two forms of transactions: local fiat-to-cryptocurrency, and cryptocurrency-to-cryptocurrency transactions⁵. Some exchanges focus more on fiat-to-cryptocurrency transactions, and they have much fewer currency pairs including only the most popular and reputable digital tokens. For example, Luno only provide transactions

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² [https://news.bitcoin.com/the-number-of-cryptocurrency-exchanges-has-exploded/](https://news.bitcoin.com/the-number-of-cryptocurrency-exchanges-has-exploded/)
³ [https://blockonomi.com/mt-gox-hack/](https://blockonomi.com/mt-gox-hack/)
⁴ [https://news.bitcoin.com/the-number-of-cryptocurrency-exchanges-has-exploded/](https://news.bitcoin.com/the-number-of-cryptocurrency-exchanges-has-exploded/)
⁵ [https://www.coininsider.com/different-cryptocurrency-exchanges/](https://www.coininsider.com/different-cryptocurrency-exchanges/)
of 2 digital currencies, Bitcoin and Ethereum, and five fiat currency including Nigerian naira, South African rand, Euro, Indonesian Rupiah, and Malaysian Ringgit\(^6\). Some other exchanges are cryptocurrency-only that provide trading among a wide range of alternative coins. For example, Poloniex lists 63 coins and 124 trading pairs. The rest of exchanges have a mix of two types transactions, for example, Kraken provides 21 coins and 78 trading pairs but also accepts five fiat currency including Euros, US dollars, Canadian Dollars, British Pounds and Japanese Yen.

### 2.1.2 Types of Exchange: Centralized vs Decentralized

There are two types of cryptocurrency exchanges: centralized exchanges (CEX) and decentralized exchanges (DEX). Centralized exchanges are trading platforms that function like traditional brokerage or stock markets and are controlled and operated by a company. Users do not have access to the private keys of their exchange account’s wallets and the exchanges hold and have full control of all users’ digital coins and transactions on their platforms\(^7\). Most exchanges with high trade volume like Coinbase, Binance, and Kraken are centralized exchanges. Decentralized exchanges do not hold any information or assets of their customers and all transactions are controlled by automated process under smart contracts\(^8\).

Whether an exchange is truly decentralized remains questionable. Bancor, the world’s largest decentralized liquidity network, got hacked and the hacker transferred out $13 million in ETH and $10 million in BNT, Bancor’s own coin. According to definition, decentralized exchanges do not have control over any assets going through the platform, so they cannot lose

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\(^6\) [https://www.luno.com/](https://www.luno.com/)

\(^7\) [https://blog.cer.live/education/which-exchange-is-better-2/](https://blog.cer.live/education/which-exchange-is-better-2/)

\(^8\) [https://www.coininsider.com/different-cryptocurrency-exchanges/](https://www.coininsider.com/different-cryptocurrency-exchanges/)
customer funds or cannot freeze funds during transactions\(^9\). However, Bancor was able to freeze BNT and prevent them from being cashed out, which reveals their centralized control over the exchange\(^10\). Since whether an exchange is decentralized is hard to distinguish, I will not separate my samples to centralized or decentralized.

### 2.2 Motivation of Inflating Reported Trading Volume

#### 2.2.1 High Profitability of Famous Exchanges

Just like other parts of crypto ecosystem, cryptocurrency exchanges provide the similar meteoric rise for newcomers and the myth of “overnight fortune” has drawn many people swarming into the exchange business. To some extent, the myth is true: Binance, launched in July 2017, grew from nothing to the top three exchange in less than a year and its founder, Changpeng Zhao, has ranked number three in Forbes 2018 list of richest people in the crypto space\(^11\). Moreover, as Bitcoin price plunged to under $3,700 in December 2018, Binance still stayed profitable with an estimated annual profit around $446 million\(^12\). According to Bloomberg estimation, the top ten cryptocurrency exchanges are bringing in $3 million profit per day and for a newly emerged industry, this profit is astonishingly high compared to historical development of other industries\(^13\).

Exchanges have many sources of income. Besides profiting from the trading fees per transaction, exchanges also gained significantly from listing fees, withdrawal and deposit fees,
dark pool trading, airdrops, and other promotional activities\textsuperscript{14}. If digital coins are not on any exchanges, they are equal to not existing at all, so all ICO projects will strive to get listed on any exchange. Well aware of this fact, exchanges profit greatly from listing fees: small exchanges require $6,000 to $30,000, medium-sized exchanges require $60,000 to $300,000, and large exchanges will charge $1 to $2.5 million for a token listing\textsuperscript{15}. While some well-known exchanges do not charge a listing fee, for many exchanges, listing fee can become their major source of income. Therefore, to charge a higher listing fee, exchanges are motivated to expand their market shares. As cryptocurrency exchange market is highly concentrated, with the top 30 exchanges taking most of the market share, to gain greater profits, all exchanges want to become the top exchanges. However, one crucial problem lies in the center: how to determine the size of the exchange?

### 2.2.2 Lack of Disclosure Channel

Due to lack of transparency and asymmetric information of many exchanges, customers do not have proper channels to gain information about these exchanges. Most people get to know and compare exchanges through exchange ranking websites like CoinMarketCap and CoinGecko. CoinMarketCap ranks #478 globally by Alexa website traffic and is the most popular website in the cryptocurrency industry\textsuperscript{16}. There is research showing that for new and aspiring exchanges, up to 90% of website traffic comes from rankings pages with up to 83% from CoinMarketCap alone\textsuperscript{17}. Since CoinMarketCap ranks exchanges by self-reported trading

\textsuperscript{14} https://coincodex.com/article/2044/besides-trading-fees-how-do-exchanges-make-money/
\textsuperscript{15} https://www.bitcoinmarketjournal.com/crypto-exchange/
\textsuperscript{16} https://www.alexa.com/siteinfo/coinmarketcap.com
\textsuperscript{17} https://www.bti.live/report-august2018/
volume, exchanges have enough motive and convenience to use trading bots to inflate their volume and gain more exposure to the public.

2.3 Issues arising from Lack of Regulation

In most countries except China, cryptocurrency exchanges are legal but in an uncertain territory. In US, the SEC considered cryptocurrencies to be securities and was looking to apply securities laws for digital wallets and exchanges. In contrary, the Commodities Futures Trading Commission adopted a friendlier, “do no harm” approach, and considered bitcoin as a commodity and allowed cryptocurrency derivatives to trade publicly. In Australia, Japan, South Korea, UK, Switzerland, and some member states in EU, exchanges are required to register with their respective regulators before operation. While most countries are planning to implement tighter regulations, how and what to regulate exactly remains unclear and varies by district. Only a few leading exchanges are under regulation: for example, Coinbase is the first fully regulated exchange monitored by the Financial Industry Regulatory Authority and the SEC. The exchange is capable of offering blockchain based securities and can operate as a broker-dealer, an alternative trading system and a registered investment adviser. Because of the insufficiency in regulation, many issues arise in the cryptocurrency exchange market.

2.3.1 Lack of Security in Digital Assets

Similar to banks, users store digital assets in their accounts on cryptocurrency exchanges, but cryptocurrency exchanges do not have to follow and comply with the FDIC reporting

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18 [https://complyadvantage.com/blog/cryptocurrency-regulations-around-world/](https://complyadvantage.com/blog/cryptocurrency-regulations-around-world/)
19 [https://www.coindesk.com/coinbase-claims-it-now-has-regulatory-approval-to-list-security-tokens](https://www.coindesk.com/coinbase-claims-it-now-has-regulatory-approval-to-list-security-tokens)
regulations, neither with the Investor Protection Corporation procedures\textsuperscript{20}. Coinbase has the best insurance in the industry, but their insurance only covers the company against hacks, and the individual user account is not insured. Although Coinbase claims that it has FDIC insurance, the insurance only applies to fiat money stored on the exchange and all digital assets including Bitcoin are still not insured. Exchanges also do not have the same reserve requirements as banks, and for most exchanges, the assets are completely unprotected. Whenever the exchanges get hacked or go bankrupt, customers lose all money in their accounts.

What makes things even worse is that most exchanges are in total control of user’s assets, and when these online platforms fall apart, there is no way for users to trace their money. Moreover, many less legit exchanges are just scams: sometimes users have trouble withdrawing their digital assets stored on the exchange. For example, with HitBTC, when some users tried to withdraw their bitcoin, they received messages like “withdrawals are temporarily disabled on your account”\textsuperscript{21}.

\subsection*{2.3.2 Ease of Relocating and Rebranding}

Regulations based on geographical jurisdiction have limited power on exchanges. For example, right after China completely banned cryptocurrency exchanges, all exchanges in China has quickly moved their operations offshore to other countries. Binance moved to Malta, OKEx moved to Belize, and Huobi planned to launch two exchanges in Japan\textsuperscript{22}. While some exchanges

\begin{footnotesize}
\begin{enumerate}
\item \textsuperscript{20} https://flagshipcrypto.com/which-cryptocurrency-exchanges-are-insured/
\item \textsuperscript{21} https://hackernoon.com/top-10-decentralized-crypto-exchanges-for-a-successful-proofofkeys-in-2019-478dc38cff7a
\item \textsuperscript{22} https://qz.com/1149678/chinas-huobi-will-launch-two-bitcoin-exchanges-in-japan-after-beijings-crackdown-on-domestic-trading/
\end{enumerate}
\end{footnotesize}
moved their operations to different jurisdictions, their physical offices remain at the same place. As the exchange business is based completely online, the cost of relocating is rather low.

For some troubled exchanges, rebranding is also easy because of the lack of disclosure of exchanges. The website domain of BTC-e was seized by the FBI after the arrest of alleged owner of the exchange for money laundering charges including laundering bitcoins stolen in the Mt. Gox hack. However, the platform relaunched under the Wex name and gained a lot of users again. When the new Wex.nz domain got seized again, Wex changed its web address several times and now hosted on another domain, wex1.in. It was again out of service and many users reported they are unable to withdraw their funds from the platform. Recently Wex is sold to another new owner who promised to restore the funds lost by Wex users, but the reopen date of the exchange remains uncertain.23

2.3.3 Wash Trade

Wash trade is defined as a market manipulation method where either individual user or the institution itself simultaneously sells and buys the same financial instruments to create misleading, artificial activity in the market.24 Wash trading has been illegal on financial market in US under the Commodity Exchange Act since 1936, but this regulation does not apply to the cryptocurrency market. Therefore, besides many other forms of fraudulent activities, using trading bots to wash trade and manipulate reported volume has been one of the most common operations in cryptocurrency market. A guide on “how to start a bitcoin exchange” lists the number 4 step as following:

24 https://en.wikipedia.org/wiki/Wash_trade
"Establish a transaction history and liquidity on the exchange: Customers are hesitant to place orders or even deposit funds unless they see a full order book and trading activity. There are three established ways of kick-starting your liquidity:
You can simulate trading activity within your exchange by buying and selling between two artificial accounts within your own exchange.
You can implement an API interface which connects your bitcoin exchange to another existing exchange.
You can join a whole network of cryptocurrency exchanges." 

Arguably, not all exchanges start out by faking their trading volume, but there is research suggesting that over 67% of daily volume on CoinMarketCap is wash traded. Another research team also found that on some exchanges, the total daily trading volume of a particular coin sometimes exceeds the market capitalization of that coin. Take Coinbit, a Korean exchange founded in 2018, as an example: on November 26, Groestlcoin’s 24-hours trade volume was 5.25 times larger than its capitalization and on November 19, Qtum’s daily volume was twice of its overall market capitalization. Similarly, another Chinese exchange ZB, founded in 2017, traded one of the most well-known coin, DASH, of more than $288 million in one day, which accounts for 80.5% of Dash’s global total volume. Clearly, these exchanges are manipulating their trading volume and they do not even bother to do it in an elaborate way.

2.3.4 Levels of Difficulty of Faking

As it turns out, it is rather easy to start your own exchange. Just as the ICO boom has fueled the rapid growth of cryptocurrency exchanges, the growth in exchange market has spawned yet another business, “ICO or cryptocurrency exchange development”, which provides services to build digital coins, ICO projects, and cryptocurrency exchange websites by requests.

26 https://www.skalex.io/how-to-start-your-bitcoin-exchange/
In fact, searching only “cryptocurrency exchange development” on Google results in 16 million results. Based on my inquiry with “Coinsclone”, building a fully functional exchange like Coinbase that can trade bitcoin, ethereum, ripple, usdt, and eos and accept dollars as payments only costs $5500 and 5 working days\(^{30}\). In general, obtaining a customized trading platform with technical support costs between $8,000 to $35,000\(^{31}\).

It is even easier to start a fraudulent exchange. Research has shown that many exchanges with 99% fake volume share the same trading engine and design\(^ {32}\). Fiverr, an online marketplace for freelancing, have countless providers for building exchange website services starting from as low as $200\(^ {33}\). To build “an exchange like Binance” and then use trading bots to wash trade to top 10 on CoinMarketCap only costs $850\(^ {34}\).

Additionally, “adding real active users Telegram groups” only costs $15 for 500 members\(^ {35}\). However, inflating the number of Twitter followers seem to be more technically difficult, as there are only a few providers on Fiverr with failing reviews. The distinction of difficulty of faking social media popularity is evident because many exchanges have only thousands of Twitter followers, but their Telegram groups are 10 times larger. For example, ZB exchange only has 2900 followers on Twitter by September 2018, but their Telegram group had 99,000 members. However, such a large chat group only produced less than 58 messages on September 24, 2018\(^ {36}\). Nonetheless, buying Twitter followers is still possible through other channels and on some websites, it only costs $12 per 1000 followers\(^ {37}\). As of February 2019, ZB

\(^{30}\) www.coinsclone.com


\(^{32}\) https://www.bti.live/reports-april2019/

\(^{33}\) https://www.fiverr.com/queensophia75/develop-exchange-website-like-binance

\(^{34}\) https://www.bti.live/reports-april2019/

\(^{35}\) https://www.fiverr.com/proquestpostseo/add-real-active-users-to-the-telegram-group-and-channel


\(^{37}\) https://buytwitterfollowersreview.org/
exchange still only had 3501 followers, but in three months, on May 2, 2019, it has gained 32,797 followers, with many presumably fake accounts that have 1 post, no follower, but follow many exchange accounts. Despite the increase in the number of followers, most of the bought accounts are inactive, so the statistics of average number of Likes or Retweets stays at the normal level. ZB exchange only has an average of 5 Likes and 1 Retweet each post, which reflects the real popularity of the exchange.

Lastly, website traffic can also be bought from Fiverr to improve Alexa ranking, but most of the website visits are created by bots, which cannot constantly generate traffic and inflate the traffic over a long period of time. As I have collected the website traffic of the past three years, and the data shows that only 10 exchange websites have an average daily global ranking smaller than 20,000, the website traffic can serve as a relatively impartial indicator of the exchanges’ real popularity.

3 Data Analysis
3.1 Data Sources and Collection

I collect trading volume data mainly from CoinMarketCap and create a list of 269 cryptocurrency exchanges. The first exchange within the sample is founded in 2009 and the last in November 2018. Figure 1 shows the distribution of founding time of the exchanges and the surge in 2014 and 2017 is distinct. CoinMarketCap has total daily trading volume at the exchange level of 233 exchanges for 288 data points starting from April 26, 2018 to February 7, 2019. There are 20 exchanges that are no longer active. Since CoinMarketCap does not have the

38 https://www.quora.com/10-000-visits-for-5-Should-I-buy-traffic-from-Fiverr-com
right to distribute data of some important exchanges like Coinbase, I seek alternative source to include them.

3.2 Methodology

3.2.1 Former Research

Sylvain Ribes first pointed out that large exchanges are inflating their volume and tested order book liquidity by measuring how badly market selling $50k USD worth of each cryptocurrency would crash the price\(^\text{39}\). He identified a list of exchanges that seem to be accurately reporting trading volume. Blockchain Transparency Institute found that the list is highly correlated with the number of website unique visitors reported by SimilarWeb. Therefore, using the number of unique daily visitors and daily trading volume, BTI got the per visitor volume figure. With a base set of accurate reporting websites from Ribes’ research, BTI established the normal level of per visitor trading volume, and then applied it to other suspicious exchanges to calculate their real trading volume.

BTI’s research has studied the top 130 exchanges and estimated that over 67% of daily volume is wash trading with over 70% of the CoinMarketCap top 100 exchanges wash trading by at least 3 times their stated volume\(^\text{40}\). BTI collected data directly from each exchange’s website and their website traffic data comes from SimilarWeb, which provides more accurate data but costs much more than Alexa. Additionally, they are in contact with many exchanges directly and are able to include data specific to the transaction level.

My research intends to only use easily attainable data including website traffic data from Alexa, reported trading volume from CoinMarketCap, and Twitter to create a simpler model. Our

\(^{39}\) https://medium.com/@sylvainartplayribes/chasing-fake-volume-a-crypto-plague-ea1a3c1e0b5e

\(^{40}\) https://www.bti.live/report-august2018/
methodologies different in two aspects: BTI is using current monthly unique website visitor data while I use time series data of daily website pageview from the past year. They created a list of legit exchanges, calculated a normal level of trading volume per website visitor, and then used it as reference to compare with all other exchanges. I run a regression including all exchanges. My method could be better in terms of including time series and all exchanges. However, as BTI could achieve more accurate results with better data, I will compare my results with theirs to check the accuracy of my model.

3.2.2 Naïve Regression Model

To identify fraudulent exchanges that are faking volume using bots, I decide to use website traffic as indicator of their popularity. For each exchange, more website traffic means the exchange is more popular, and that exchange should have more trading volume. Therefore, my hypothesis is the website traffic should be positively correlated with the reported trading volume. Exchanges that have high trading volume but low website traffic is considered as fraudulent. Because they have low website traffic coefficients, they will have a really low predicted trading volume. After subtracted the predicted value from the high reported volume, they will have positive residuals. By regressing daily reported trading volume on website traffic and looking at the distribution of residuals for each exchange, I intend to create a simple model to find these fraudulent exchanges.

The following coefficient estimates are needed for the model: global daily pageviews, bounce rate, pageviews per user, time spend on site, and the number of trading pairs on each exchange. As bounce rate shows the percentage of daily visits that consist of only a single pageview, I discounted the bounce rate from global pageview to use as the website traffic
indicator. Both the log of pageviews per user and time spend on site are included as additional indicators for the website popularity. If the user browses more pages during each visit or spend more time on the site, website is more popular. I also include a dummy variable to mark the days that have Twitter posts, which normally suggests big announcement or changes. The above coefficients should all be positively correlated with reported volume. Lastly, fixed factors like the day of week and month are also included as dummy variables.

\[
\log(\text{Trading Volume}) = \log(\text{Pageview} \times (1 - \text{Bounce})) + \log\left(\frac{\text{Pageviews}}{\text{user}}\right) + \log(\text{Time}) \\
+ \text{Pageviews} + C(\text{Tweet}) + C(\text{Weekday}) + C(\text{Month}) + \text{Constant}
\]

For the sample size, I have collected daily website traffic data from Alexa starting from 2/23/2016-2/20/2019 for the coefficient estimates. From CoinMarketCap, I’ve collected reported trading volume of 233 exchanges starting from 04/26/2018-02/07/2019, and the full time period has 288 days. Since some exchanges are founded recently, the data is only available for less than half of the duration, so I choose 170 exchanges with more than 200 days to run the regression and there are in total 48225 observations.

3.3 Summary Statistics

3.3.1 Monthly Exchange Volume

Combining CoinMarketCap one month of daily trading volume from January 08 to February 07 of 2019, we have a total reported trading volume of 380.1 billion dollars across the whole market. 96 of 211 exchanges have only less than 0.01% of market share, and 140 exchanges have less than 0.1% volume summing up to 1.8% of the whole market trading volume. The top 30 exchanges account for 76% of the market trading volume and Bithumb reported volume accounts for 10.6% volume. On average, each exchange has daily trading
volume of 58.7 million dollars and 71 currency pairs. Figure 2 shows the pie chart of market
share and Table 1 shows the summary statistics.

3.3.2 Twitter

Social media is the central channel for these online exchanges to communicate with their
users, so I collect their Twitter account data to serve as an indicator of their popularity. Out of
269 exchanges, there are 250 exchanges that have official accounts, and a small number of
leading exchanges like Coinbase even have multiple technical support accounts that interact with
users. In fact, most of these online communities are rather small. 25% of exchanges has less than
1000 followers or no account, 67% of exchanges has less than 10000 followers, and 90% of
exchanges has less than 50000 followers. The top five Twitter accounts are for Coinbase,
Binance, Bittrex, Bitfinex, and Kraken, with Coinbase as the only account that exceeds 1 million
followers.

For all accounts, although Twitter API only provides the most recent 3200 Tweets, 53.2%
of exchanges have posted less than 500 Tweets and 87.6% of accounts have posted less than
3200 Tweets before February 24, 2019, so only 30 exchanges have incomplete data as shown in
the histogram 1. I have split the Tweets into three types: Original Tweets created by the account,
Retweets, and Replies to other accounts. Since Original Tweets are often used for making
updates or announcement, and Retweets show not only less effort but also cannot provide more
information about the exchange, I subtracted the Retweets from the total number of Tweets and
calculated the share of Retweets comparing to all Tweets for each exchange, with distribution
shown in histogram 2. The maximum percentage is 94.49% and the account has a total of 15.3K
Tweets but only 259 followers, which suggests the exchange “FYBSE” is using bots to send
Tweets. From the histogram, we can see that 84% of exchange have less than 20% Retweets, which shows that most exchanges are devoted into communication with users. For each account, I calculate the mean of Likes and Retweet each Tweet gets and use the average of each exchange account to get the summary statistics for the whole sample, shown in Table 2.

Across the whole sample, on average, each Tweet gets 37 Likes and 117 Retweets, which seems rather small, but the histogram 3 and 4 of both counts of average Retweets and Likes suggest that 80% of Twitter account only receive less than 50 Likes and Retweets. There are only a few leading exchanges on average have hundreds of Likes and Retweets each Tweet. Ranking by maximum Likes and Retweets, Binance had reached 88.4K Retweets, OKEx 1.3K Likes, and Coinbase 9184 Likes.

3.3.3 Website Traffic

One important indicator of the online crypto exchanges is the website traffic since most trading need to be accessed through their official site. From Amazon Alexa I’ve gathered three-year daily website traffic data starting from February 23, 2016 to February 20, 2019 for 263 exchanges. I’ve taken the average of each exchange website and then calculate the summary statistics shown in Table 3 for the whole sample. For Alexa Ranking, the data is available for the whole sample, but the other metrics are only available for 165 websites that are ranked within the top 100,000.

For Alexa Ranking, histogram 5 shows the distribution of average global daily ranking for each site, and we can see that the data is positively skewed and as the rankings get lower, there are fewer number of exchanges. For 62% of exchanges that are in top 100,000, histogram 6 shows a bimodal distribution peaked at around 50,000 and 80,000. Ranking by average of daily
rankings, the top 5 exchanges are Coinbase (2076), Poloniex (3797), Bittrex (6314), Yobit (8471), and Kraken (11414) and only 10 exchanges are in top 20,000 ranked websites. If summarizing all exchanges by the minimum of daily rankings, although the histogram across all sites looks the same as the one by average, in histogram 7 of first 100,000 sites, we see a positively skewed shape that looks completely different from the one ranked by average daily rankings. From the histogram we can see that during the best days of cryptocurrency, 19% websites ranked in top 10,000 globally and the leading 19 exchanges have ranked within top 3000, for example, Binance ranked 196, Coinbase 218, Bittrex 299, and Poloniex 596.

For reach, the estimated percentage of the daily global internet audience that visited the site reflect the popularity of each site. The histogram 8 shows severely positively skewed distribution and 77% of exchanges have less than 42 ppm average daily global visitors. Getting summary statistics using the maximum for each exchange instead of using the average, the mean for all exchanges change from 48.65 ppm to 310 ppm but the shape in histogram 9 is basically the same. As shown in histogram 10, the data distribution is similar for pageview, the estimated percentage of daily pageviews over the internet. Both variables show that more than half of the sites have rather low visitor volume, even during the most popular time of cryptocurrency, and there are a small portion of popular leading sites. Since the histograms are so skewed, the mean or median across the whole sample is not representative for each site.

Bounce rate, the percentage of refusals, shows the estimated percentage of daily visits that consist of a single pageview, which means the better the website, the lower the bounce rate. As in histogram 11, the distribution of average daily bounce rate has a normal distribution centered at 41.67% and the largest bounce rate is 75.89%. The 75% quantile is 48.5%, which suggests that for most websites, the visits half of the time might not lead to actual trading on the
website. If summarizing the exchange data with their minimum bounce rate, the 75% quantile is reduced to 20% but the max is still 69.2%, which again shows that while some sites stay unpopular or popular for the whole time, many other sites have large spreads within their own distribution over the three year.

Histogram 12 and 13 shows that both average daily unique pageviews per user and average browsing time on site in seconds are normal distribution with a very long right tail, which again shows that most sites catch fewer attention from users while only a small number of leading websites have more pageviews and more time spend on site by one user.

Overall, the website traffic shows a similar distribution like the reported exchange trading volume: a large number of small players combine with a few leading exchanges.

3.4 Grouped by Social Media Popularity

As shown in Table 4, I group the exchanges by their counts of Twitter Followers, as the conditions of small exchanges differ from the popular ones in an order of magnitude. Calculating the average of each group shows a clear picture of the irregularities in the market. Monthly website visitors, the number of links to the website, and average Likes or Retweets per Tweet increase with the number of followers, but for the monthly reported trading volume, the trend is completely in reverse. While the top exchanges with the most followers have only trading volume of 3077, 20169, and 764 million dollars, the average reported volume for exchanges between 50K and 100K Followers have reached 487 billion dollars, which is 150 times of Coinbase trading volume.

Dividing the reported volume by the number of Twitter Followers, from this ratio we can see that for the large and more legit exchanges, the ratio is smaller, and for exchanges with less
than 10K followers, the ratio is significantly larger, which suggests that these exchanges are inflating their trades with fake trades. Same with website traffic, dividing the monthly reported trading volume with monthly website visitors, large exchanges only have trading volume of 465 dollars, 1196 dollars, and 6822 dollars per visitor, but for small exchanges, like the group with followers between 1K and 10K, their reported volume per visitor has an average of 6 billion dollars, which is 13 billion times over Coinbase. Clearly, these exchanges are using bots to fake trades and inflate trading volume.

4 Relationship between website traffic volume and trading volume

4.1 Regression Results

Table 5 shows the regression results and the model has a R-Squared of 19.6%. For coefficients, we can find that all website traffic and social media metrics including site traffic, page/user, time on site, and twitter posts are positively correlated with reported volume and they all have large T-Values that show statistical significance. Number of trading pairs on exchanges also positively correlated with trading volume and is statistically significant.

4.2 Residual Analysis

Figure 3 shows the residual plot including all observations and each exchange is differentiated with a different color. Table 6 shows the summary statistics of residuals of each exchange ranked by the average. Comparing to earlier findings of BTI, I mark the possibly fraudulent exchanges with 0 (yellow) and the legit exchanges with 1 (blue). The table shows a rather distinctive split between the fraudulent exchanges and the legit ones. Most fraudulent exchanges have large positive residuals, which shows that the actual reported volume for these
exchanges is much higher than the predicted trading volume. The residuals for legit exchanges are mostly close to 0 or negative. Figure 4 plots the marked 44 fraudulent and 35 legit exchanges, and their residuals grouped by each exchange rank from large to small by their average.

There are some exchanges inconsistent with the model, which could be resulted from the inaccuracy of the data source or other activities engaged by the exchange. Only famous exchanges like Kraken, Bitfinex, UPbit, and Bitstamp have shown false positive and have positive residuals. These positive residuals show that the reported trading volume of these exchanges are higher than the model predicated trading volume for the same amount of website traffic, which on one hand could suggest that these exchanges are inflating their volume, but on the other hand could suggest that people might invest and trade more with each website visit. This explains why only famous exchanges have shown false positive: because it is possible that people will invest more on more popular exchanges, which leads to higher trading volume per visitor and higher trading volume per website traffic. Despite a few exceptions, the separation of most fraudulent exchanges and legit exchanges can be seen clearly on Figure 4, which shows that this simple model can serve as a preliminary separation of exchanges.

5 Conclusion

For the 269 cryptocurrency exchanges, I’ve summarized their reported trading volume, website traffic data, and current Twitter status, and the condition is similar across all three sectors. A few leading exchanges are far ahead taking most of the market share and attention, while the recent of smaller exchanges taking a small market share. However, since all data on in
the internet can be fabricated, some small exchanges use trading bots to inflate their reported volume and quickly rise to the top on crypto exchange rankings to gain more recognition.

From my analysis, we can see that the website traffic data and Twitter follower data can serve as a valid indicator for detecting fake trades. Although Twitter follower can be bought and some well-known exchanges, whose websites have rather high website volume, are still faking trading volume, in general, exchanges with a rather active Twitter account and a highly ranked website is less likely to fake their trading volume. Considering that only a small number of exchanges have large website traffic and active Twitter accounts, these indicators are sufficient for preliminary distinction of whether exchanges are faking their trading volume.
Histogram 1: Count of Exchanges Account by Number of Twitter Followers

Histogram 2: Counts of Exchange Account by Share of Retweets over all Tweets
Histogram 3: Counts of Exchange Account by Average Number of Retweets per Tweet

Histogram 4: Counts of Exchange Account by Average Number of Likes per Tweet
Histogram 5: Counts of All Sites by Average Global Daily Ranking

Histogram 6: Counts of Top 100,000 Sites by Average Global Daily Ranking per Exchange
Histogram 7: Counts of Top 100,000 Sites by Minimum Global Daily Ranking per Exchange

Histogram 8: Counts of Top 100,000 Sites by Average Global Reach per Exchange
Histogram 9: Counts of Top 100,000 Sites by Maximum Global Reach per Exchange

Histogram 10: Counts of Top 100,000 Sites by Average Global Pageview Percentage
Histogram 11: Counts of Top 100,000 Sites by Average Bounce Rate

Histogram 12: Counts of Top 100,000 Sites by Average Daily Unique Pageviews/User
Histogram 13: Counts of Top 100,000 Sites by Average Time on Site

Figure 1: Number of Exchanges Founded by Year
Figure 2: Share of Reported Trading Volume of Exchanges

Figure 3: Residual Plot of all Observations of 170 Exchanges
Figure 4: Residual Plot Separated by Exchange
Table 1: Monthly Reported Trading Volume Summary Statistics (Jan 8 - Feb 7, 2019)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0.01%</td>
<td>96</td>
<td>7.87</td>
<td>9.00</td>
<td>0.00</td>
<td>0.59</td>
<td>4.24</td>
<td>12.53</td>
<td>37.40</td>
</tr>
<tr>
<td>&gt;0.01%</td>
<td>43</td>
<td>142.76</td>
<td>92.35</td>
<td>41.27</td>
<td>67.28</td>
<td>119.67</td>
<td>184.76</td>
<td>374.54</td>
</tr>
<tr>
<td>&gt;=0.1%</td>
<td>35</td>
<td>1688.96</td>
<td>1095.51</td>
<td>387.51</td>
<td>778.76</td>
<td>1352.12</td>
<td>2702.08</td>
<td>3513.85</td>
</tr>
<tr>
<td>&gt;1%</td>
<td>30</td>
<td>6730.33</td>
<td>2101.72</td>
<td>3884.39</td>
<td>5003.97</td>
<td>6578.02</td>
<td>8386.39</td>
<td>10474.7</td>
</tr>
<tr>
<td>&gt;3%</td>
<td>6</td>
<td>18699.3</td>
<td>11164.8</td>
<td>11476.1</td>
<td>12781.2</td>
<td>14226.7</td>
<td>17901.2</td>
<td>40840.8</td>
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</table>

Table 2: Summary Statistics of Official Twitter Account of Exchange

Panel 1: Current Twitter Account

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Follower</td>
<td>250</td>
<td>34603</td>
<td>114872</td>
<td>2</td>
<td>1347</td>
<td>4710</td>
<td>17823</td>
<td>1054945</td>
</tr>
<tr>
<td>Liked</td>
<td>250</td>
<td>583</td>
<td>1145</td>
<td>0</td>
<td>29</td>
<td>170</td>
<td>592</td>
<td>8257</td>
</tr>
<tr>
<td>Following</td>
<td>250</td>
<td>1378</td>
<td>13570</td>
<td>0</td>
<td>33</td>
<td>108</td>
<td>393</td>
<td>213857</td>
</tr>
<tr>
<td>Listed</td>
<td>250</td>
<td>323</td>
<td>870</td>
<td>0</td>
<td>16</td>
<td>64</td>
<td>225</td>
<td>7861</td>
</tr>
<tr>
<td>Tweets</td>
<td>250</td>
<td>1916</td>
<td>7709</td>
<td>0</td>
<td>198</td>
<td>486</td>
<td>1624</td>
<td>115388</td>
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</tbody>
</table>

Panel 2: Recent 3200 Tweets

<table>
<thead>
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<th></th>
<th>N</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>N of Tweets</td>
<td>247</td>
<td>889.1</td>
<td>967.7</td>
<td>1.0</td>
<td>173.5</td>
<td>446.0</td>
<td>1221.5</td>
<td>3229.0</td>
</tr>
<tr>
<td>Average Likes/Tweet</td>
<td>247</td>
<td>37.7</td>
<td>91.8</td>
<td>0.1</td>
<td>3.1</td>
<td>10.4</td>
<td>32.9</td>
<td>679.9</td>
</tr>
<tr>
<td>Account Retweets</td>
<td>247</td>
<td>117.6</td>
<td>283.9</td>
<td>0.0</td>
<td>5.0</td>
<td>24.0</td>
<td>106.5</td>
<td>2914.0</td>
</tr>
<tr>
<td>Average Retweets/Tweet</td>
<td>247</td>
<td>25.8</td>
<td>87.2</td>
<td>0.0</td>
<td>1.3</td>
<td>4.4</td>
<td>15.4</td>
<td>700.7</td>
</tr>
<tr>
<td>Retweets/Original Tweets</td>
<td>247</td>
<td>10.06%</td>
<td>12.47%</td>
<td>0.00%</td>
<td>1.77%</td>
<td>6.52%</td>
<td>13.38%</td>
<td>94.49%</td>
</tr>
</tbody>
</table>
Table 3: Website Traffic Summary Statistics

Panel 1: By Average of each Exchange

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reach (ppm)</td>
<td>165</td>
<td>48.65</td>
<td>48.65</td>
<td>2.16</td>
<td>10.28</td>
<td>21.09</td>
<td>40.57</td>
<td>1028.74</td>
</tr>
<tr>
<td>Bounce</td>
<td>164</td>
<td>42.18%</td>
<td>12.19%</td>
<td>5.82</td>
<td>34.86</td>
<td>41.67%</td>
<td>48.59%</td>
<td>75.89%</td>
</tr>
<tr>
<td>Pageview (ppm)</td>
<td>165</td>
<td>5.70</td>
<td>13.15</td>
<td>0.12</td>
<td>0.76</td>
<td>1.91</td>
<td>4.77</td>
<td>131.25</td>
</tr>
<tr>
<td>Page/User</td>
<td>165</td>
<td>4.08</td>
<td>2.54</td>
<td>1.11</td>
<td>2.61</td>
<td>3.56</td>
<td>4.41</td>
<td>17.58</td>
</tr>
<tr>
<td>Time/Sec</td>
<td>165</td>
<td>420</td>
<td>209</td>
<td>137</td>
<td>289</td>
<td>361</td>
<td>496</td>
<td>1444</td>
</tr>
<tr>
<td>Rank</td>
<td>263</td>
<td>268574</td>
<td>213048</td>
<td>2076</td>
<td>94554</td>
<td>223692</td>
<td>395870</td>
<td>959781</td>
</tr>
</tbody>
</table>

Panel 2: By Best Status (Maximum or Minimum) of each Exchange

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reach (ppm)</td>
<td>165</td>
<td>310</td>
<td>888</td>
<td>6</td>
<td>38</td>
<td>99</td>
<td>200</td>
<td>7930</td>
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<tr>
<td>Bounce</td>
<td>164</td>
<td>15.61%</td>
<td>12.14%</td>
<td>2.10</td>
<td>6.70</td>
<td>12.00%</td>
<td>20.00%</td>
<td>69.20%</td>
</tr>
<tr>
<td>Pageview (ppm)</td>
<td>165</td>
<td>42.19</td>
<td>117.53</td>
<td>0.22</td>
<td>3.8</td>
<td>13</td>
<td>29.2</td>
<td>1160</td>
</tr>
<tr>
<td>Page/User</td>
<td>165</td>
<td>12.82</td>
<td>8.91</td>
<td>2</td>
<td>7.8</td>
<td>10</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>Time</td>
<td>165</td>
<td>3</td>
<td>5</td>
<td>137</td>
<td>887</td>
<td>1332</td>
<td>1932</td>
<td>14543</td>
</tr>
<tr>
<td>Rank</td>
<td>263</td>
<td>125017</td>
<td>172255</td>
<td>196</td>
<td>13887</td>
<td>63000</td>
<td>154860</td>
<td>913079</td>
</tr>
</tbody>
</table>
Table 4: Summary Statistics Grouped by Magnitude of Twitter Follower

Panel 1: Trading Volume Comparison

<table>
<thead>
<tr>
<th>No Account</th>
<th>N</th>
<th>Trading Volume (MM in $)</th>
<th>Vol/Follower (K)</th>
<th>Vol/Visitor (MM in $)</th>
<th>N of Trading Pairs</th>
<th>Website Visitor</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Account</td>
<td>19</td>
<td>635.6</td>
<td></td>
<td>635.6</td>
<td>27</td>
<td>0</td>
</tr>
<tr>
<td>&lt;100</td>
<td>9</td>
<td>9.7</td>
<td>244.4</td>
<td>9.7</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>&lt;1K</td>
<td>38</td>
<td>787.3</td>
<td>2187.4</td>
<td>725.3</td>
<td>38</td>
<td>4047</td>
</tr>
<tr>
<td>&lt;10K</td>
<td>115</td>
<td>6759.5</td>
<td>1377.1</td>
<td>6365.2</td>
<td>71</td>
<td>52325</td>
</tr>
<tr>
<td>&lt;50K</td>
<td>60</td>
<td>1446.2</td>
<td>75.0</td>
<td>831.1</td>
<td>88</td>
<td>61656</td>
</tr>
<tr>
<td>&lt;100K</td>
<td>12</td>
<td>486866.2</td>
<td>8694.7</td>
<td>3233.3</td>
<td>124</td>
<td>48798</td>
</tr>
<tr>
<td>&lt;250K</td>
<td>8</td>
<td>4003.3</td>
<td>20.9</td>
<td>552.4</td>
<td>243</td>
<td>104902</td>
</tr>
<tr>
<td>&lt;500K</td>
<td>5</td>
<td>2256.0</td>
<td>5.9</td>
<td>629.1</td>
<td>122</td>
<td>266632</td>
</tr>
<tr>
<td>&lt;750K</td>
<td>1</td>
<td>764.8</td>
<td>1.0</td>
<td>0.0012</td>
<td>326</td>
<td>639355</td>
</tr>
<tr>
<td>&lt;1M</td>
<td>1</td>
<td>20169.8</td>
<td>21.9</td>
<td>0.0068</td>
<td>439</td>
<td>2956323</td>
</tr>
<tr>
<td>&gt;1M</td>
<td>1</td>
<td>3077.7</td>
<td>2.9</td>
<td>0.0005</td>
<td>35</td>
<td>6609425</td>
</tr>
</tbody>
</table>

Panel 2: Tweet and Website Popularity

<table>
<thead>
<tr>
<th>No Account</th>
<th>Repute /Tweet</th>
<th>Likes /Tweet</th>
<th>Retweets /Tweet</th>
<th>N of Tweets</th>
<th>Direct</th>
<th>Social</th>
<th>Search</th>
<th>Links</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Account</td>
<td>45</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20.4%</td>
<td>0.0%</td>
<td>1.8%</td>
<td>14.6%</td>
</tr>
<tr>
<td>&lt;100</td>
<td>11</td>
<td>1</td>
<td>0</td>
<td>60</td>
<td>7.2%</td>
<td>0.0%</td>
<td>0.7%</td>
<td>3.3%</td>
</tr>
<tr>
<td>&lt;1K</td>
<td>31</td>
<td>6</td>
<td>2</td>
<td>564</td>
<td>37.0%</td>
<td>0.5%</td>
<td>11.7%</td>
<td>21.9%</td>
</tr>
<tr>
<td>&lt;10K</td>
<td>51</td>
<td>19</td>
<td>12</td>
<td>921</td>
<td>54.5%</td>
<td>0.9%</td>
<td>10.0%</td>
<td>23.2%</td>
</tr>
<tr>
<td>&lt;50K</td>
<td>145</td>
<td>47</td>
<td>31</td>
<td>2503</td>
<td>62.7%</td>
<td>0.9%</td>
<td>11.2%</td>
<td>20.2%</td>
</tr>
<tr>
<td>&lt;100K</td>
<td>99</td>
<td>35</td>
<td>19</td>
<td>2882</td>
<td>60.7%</td>
<td>1.1%</td>
<td>16.0%</td>
<td>13.9%</td>
</tr>
<tr>
<td>&lt;250K</td>
<td>174</td>
<td>148</td>
<td>121</td>
<td>18016</td>
<td>72.8%</td>
<td>0.7%</td>
<td>10.5%</td>
<td>16.0%</td>
</tr>
<tr>
<td>&lt;500K</td>
<td>256</td>
<td>273</td>
<td>249</td>
<td>2293</td>
<td>76.7%</td>
<td>0.5%</td>
<td>11.1%</td>
<td>11.8%</td>
</tr>
<tr>
<td>&lt;750K</td>
<td>417</td>
<td>356</td>
<td>127</td>
<td>5870</td>
<td>86.5%</td>
<td>0.3%</td>
<td>8.3%</td>
<td>4.9%</td>
</tr>
<tr>
<td>&lt;1M</td>
<td>480</td>
<td>451</td>
<td>357</td>
<td>2162</td>
<td>85.2%</td>
<td>0.8%</td>
<td>6.2%</td>
<td>7.9%</td>
</tr>
<tr>
<td>&gt;1M</td>
<td>1148</td>
<td>349</td>
<td>132</td>
<td>2814</td>
<td>79.5%</td>
<td>0.8%</td>
<td>13.5%</td>
<td>6.3%</td>
</tr>
</tbody>
</table>
## Table 5: Regression Result

|                      | Coefficient | Std   | T-Value | P>|t|  | [0.025 | 0.975 |
|----------------------|-------------|-------|---------|------|--------|--------|
| Intercept            | 12.30       | 0.07  | 177.42  | 0.00 | 12.17  | 12.44  |
| Log(Site Traffic)    | 66780.00    | 3644.20| 18.33   | 0.00 | 59600.00 | 73900.00 |
| Log(Page/User)       | 1.37        | 0.06  | 23.70   | 0.00 | 1.26   | 1.48   |
| Log(Time/s)          | 0.05        | 0.01  | 3.67    | 0.00 | 0.03   | 0.08   |
| N of market pairs    | 0.01        | 0.00  | 37.29   | 0.00 | 0.01   | 0.01   |
| C(Tweet)[T.True]     | 0.31        | 0.04  | 8.67    | 0.00 | 0.24   | 0.38   |
| C(weekday)[T.1]      | 0.00        | 0.06  | 0.00    | 1.00 | -0.12  | 0.12   |
| C(weekday)[T.2]      | 0.03        | 0.06  | 0.46    | 0.65 | -0.10  | 0.15   |
| C(weekday)[T.3]      | 0.01        | 0.06  | 0.10    | 0.92 | -0.12  | 0.13   |
| C(weekday)[T.4]      | 0.00        | 0.06  | 0.04    | 0.97 | -0.12  | 0.13   |
| C(weekday)[T.5]      | -0.22       | 0.06  | -3.48   | 0.00 | -0.35  | -0.10  |
| C(weekday)[T.6]      | -0.20       | 0.06  | -3.21   | 0.00 | -0.33  | -0.08  |
| C(month)[T.2]        | -0.26       | 0.12  | -2.15   | 0.03 | -0.49  | -0.02  |
| C(month)[T.4]        | 1.05        | 0.14  | 7.45    | 0.00 | 0.78   | 1.33   |
| C(month)[T.5]        | 1.08        | 0.07  | 14.70   | 0.00 | 0.94   | 1.23   |
| C(month)[T.6]        | 0.72        | 0.07  | 9.78    | 0.00 | 0.58   | 0.87   |
| C(month)[T.7]        | 0.70        | 0.07  | 9.67    | 0.00 | 0.56   | 0.85   |
| C(month)[T.8]        | 0.74        | 0.07  | 10.19   | 0.00 | 0.60   | 0.88   |
| C(month)[T.9]        | 0.55        | 0.07  | 7.55    | 0.00 | 0.41   | 0.70   |
| C(month)[T.10]       | 0.19        | 0.07  | 2.64    | 0.01 | 0.05   | 0.33   |
| C(month)[T.11]       | 0.22        | 0.07  | 3.05    | 0.00 | 0.08   | 0.37   |
| C(month)[T.12]       | 0.16        | 0.07  | 2.25    | 0.02 | 0.02   | 0.31   |
| R-Squared:           | 0.196       |       |         |      |        |        |
| Observations:        | 48225       |       |         |      |        |        |