Competition in the Crypto-Currency Market

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July 1, 2014

Abstract

We analyze how network effects affect competition in the nascent crypto-currency market. We do so by examining the changes over time in exchange rate data among crypto-currencies. Specifically, we look at two aspects: (1) competition among different currencies, and (2) competition among exchanges where those currencies are traded. Our data suggest that the winner-take-all effect is dominant early in the market. During this period, when Bitcoin becomes more valuable against the USD, it also becomes more valuable against other crypto-currencies. This trend is reversed in the later period. The data in the latter period are consistent with the use of crypto-currencies as financial assets (popularized by Bitcoin), and not consistent with "winner-take-all" dynamics. For exchanges, we find little if any evidence of arbitrage opportunities. With no arbitrage opportunities, it is possible for multiple exchanges to coexist in equilibrium despite two-sided network effects.

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1 Introduction

Even though it was introduced in 2009, the digital currency Bitcoin caught the interest of the mainstream media only in 2012. Due to its supposed anonymity, Bitcoin and other digital currencies are often compared to cash. However, unlike cash, these currencies are purely digital and used primarily online. Digital currencies have the potential to compete against other online payment methods such as credit/debit cards and PayPal. It is possible that Bitcoin and other digital currencies may have a large long-term effect on both currency and payments systems, but these currencies are currently in their infancy. There are many unanswered questions about their viability, as well as the potential of digital currencies to be a disruptive technology.

Current developments within the Bitcoin ecosystem, as well as competition with other digital currencies may have an important impact on the future success of this technology. We focus on decentralized digital currencies that use cryptography, called *crypto-currencies*. In this paper, we analyze how network effects affect competition in the nascent crypto-currency market. We do so by examining the changes over time in exchange rate data among crypto-currencies. Specifically, we look at two aspects: (1) competition among different currencies (Bitcoin, Litecoin etc), and (2) competition among exchanges where those currencies are traded. Because the supply of crypto-currencies is either fixed or deterministically changing, changes in prices are a good indication of changes in demand.

Both in the context of currency competition, and competition between exchanges, network effects play an important role. Positive network effects are present when the value of a product or service increases with the number of users. A currency is more useful as more people adopt it. An exchange is more liquid when there are more buyers and sellers. From the 'network effects' literature (cf. Katz and Shapiro 1985), in such environments we might expect a "winner-take-all" dynamics and convergence to one dominant player. The more popular the currency the easier it attracts new users. Similarly, the larger exchange will be more attractive to new buyers and sellers. Therefore, the larger competitor will grow even larger, eventually dominating the whole market. However, we do not see a clear winner-take-all dynamics currently in the crypto-currency market.

It is less surprising for the exchanges. The nature of network effects is different for currency competition than for competition between the exchanges. In the exchanges, sellers benefit from a larger number of buyers, and buyers benefit from a larger number of sellers (so called *positive cross-side effects*). However, sellers would prefer a lower number of other sellers, as they compete for buyers. Similarly, buyers would prefer lower number of other buyers competing against them (so called *negative same-side effects*). There are no such negative effects for currency adoption—it is always positive when more users adopt it. In the case of exchanges, the negative same-side effects may counter the "winner-take-all" dynamics (cf. Ellison and Fudenberg 2003, Halaburda and Piskorski 2011). Therefore, in an equilibrium multiple exchanges may coexist as long as they do not provide arbitrage opportunities (i.e., neither buyers nor sellers would gain by trading at a different exchange).

The market for exchanges is a very vibrant one. The exchanges considered to be the "major players" changed significantly over time. New ones appeared, and existing one were pushed out of the market. The Mt.Gox failure in February 2014 showed that even a large exchange may suddenly exit the market. But do we expect the market to eventually settle on one dominant exchange or multiple coexisting exchanges?

With the data we analyze, we find that there is little, if any, arbitrage opportunities. We test for two types of arbitrage. First, we test for triangular arbitrage within one exchange. For example, whether exchanging USD to Bitcoin, then Bitcoin to Litecoin, and finally Litecoin to USD is profitable. We find no evidence of such arbitrage opportunities. The second type of arbitrage we examine is arbitrage across exchanges. We find that there may have been some arbitrage opportunities early in the market, but these have dissipated with time. Moreover, those arbitrage opportunities may have been outweighed by the cost of moving funds between the exchanges. Without arbitrage opportunities, it is possible for multiple exchanges to coexist in equilibrium.

In competition between crypto-currencies, we see that some of the analyzed currencies lose value and do not recover, while others keep their value for a long time. Thus, consistent with the winner-take-all dynamics there are "winners" and "losers", and a successful currency grows more successful. But the winner-take-all dynamics is not the only force in this market, and we do not see the market tipping to one dominant currency.

Our data suggest that the winner-take-all effect is dominant early in the market. During this period, when Bitcoin becomes more (less) valuable against the USD, it also becomes more (less) valuable against other crypto-currencies. Bitcoin is the most poplar crypto-currency at the beginning of this period and further improves its position during this period, both against the USD and against other crypto-currencies.

But in the latter period, this pattern reverses. When Bitcoin strengthens (weakens) against the USD, it weakens (strengthens) against other top crypto-currencies. At the end of this period, Bitcoin is stronger against the USD and weaker against other top crypto-currencies than it was at the beginning of the period. Thus, we no longer see winner-take-all dynamics.

It has been pointed out that Bitcoin and other crypto-currencies may be purchased as financial assets rather than for usage as currency. Both effects probably matter in the crypto-currency market. The lack of winner-take-all dynamics in the later period points more towards the financial asset function. As Bitcoin's price and volatility increases, we see a substitution effect increasing the demand for other crypto-currencies. If only network effects were present, driving adoption of currency, we would see clear winner-take-all dynamics.

2 Brief Background on Crypto-Currencies

Bitcoin and the other digital currencies considered here are decentralized systems, i.e., have no central authority. They use cryptography to control transactions, increase the supply, and to prevent fraud. Hence, they often are referred to as *crypto-currencies*. Once confirmed, all transactions are stored digitally and recorded in a 'blockchain,' which can be thought of as an accounting system. Payments are validated by network nodes. Sometimes, as in case of Bitcoin, powerful, expensive computers are needed for the process.

Bitcoin's algorithm provides an effective safeguard against 'counterfeiting' of the currency. However, the eco-system is vulnerable to theft. Users keep keys to their Bitcoins and make transactions with the help of wallets. Exchanges facilitate trade between Bitcoins and fiat currencies, and also allow for storing Bitcoins. Bitcoins can be stolen through wallets or exchanges. Up until this point, exchanges have been targeted more frequently than wallets. Many wallets are located on users' computers, while exchanges by their nature are on-line. This makes exchanges an easier target. It was revealed in February 2014 that $350 million worth of Bitcoins were stolen from Mt.Gox, which led to the shut-down of the exchange.[1]

The supply of most crypto-currencies increases at a pre-determined rate, and cannot be changed by any central authority. In the case of Bitcoin, there are about 11–12 million Bitcoins currently in circulation, with the ultimate number reaching 21 million.

[1] Wired.com, "Bitcoin Exchange Mt.Gox Goes Offline Amid Allegations of $350 Million Hack," by Robert MacMillan on February 24, 2014 (http://www.wired.com/wiredenterprise/2014/02/Bitcoins-mt-gox-implodes/)

Bitcoin was initially popular in part because its (perceived) anonymity enabled trade in illegal goods. On October 2, 2013 the US government shut down the largest website involved in that activity. (In the process, the FBI received about 1.5% of all Bitcoins in circulation at the time). Despite the government action, Bitcoin prices continued to climb. This is in part due to the fact that the currency has a strong deflationary aspect to it, due to limited supply. There are also massive fluctuations in value, in part due to speculation, security problems, and general uncertainty as to how the industry will develop.

In our analysis, we use data from Bitcoin exchanges. Those exchanges operate as matching platforms. That is, users do not trade with the exchange. Rather, they announce limit orders to buy and sell, and the exchange matches buyers and sellers when conditions of both the buyer and the seller are met.

3 Related Literature

Bitcoin only very recently became subject of research in economics. The topic has been of interest for longer in computer science. A small number of theoretical papers written by computer scientists address incentives. Eyal and Sirer (2013) show that mining is not incentive-compatible and that the so called "selfish mining" can lead to higher revenue for miners who collude against others. The threshold for selfish mining to be profitable is lower than for double-spending attacks. Babaioff et. al (2012) argue the current Bitcoin protocols do not provide an incentive for nodes to broadcast transactions. This is problematic, since the system is based on the assumption that there is such an incentive. Additional work in the computer science field include Christin (2013), who examines the anonymous online marketplace in crypto-currencies. Böhme (2013) examines what can be learned from Bitcoin regarding Internet protocol adoption.

There is some work on Bitcoin in legal journals as well, but there is very little in the economics literature. One of the few exceptions is the European Central Bank's (2012) report on virtual currencies. Using two examples, Bitcoin and Linden Dollars, the report focuses on the impact of digital currencies on the use of fiat money. Gans and Halaburda (2013) analyze the economics of private digital currencies, but they explicitly focus on currencies issued by platforms like Facebook or Amazon (that retain full control), and not decentralized currencies like Bitcoin. Dwyer (2014) provides institutional details about digital currency developments. Yermack (2013) analyzes changes in Bitcoin price against fiat currencies and concludes that its volatility undermines its usefulness as currency. Moore and Christin (2013) empirically examine Bitcoin exchange risk. Using Bitcoin traffic at Wikipedia, Glaser et. al (2014) examine whether user interest in crypto-currencies is due to interest in a new investment asset or in the currencies themselves. Their results suggest that most of the interest is due to the asset aspect.

4 Data

Our analysis focuses primarily on the top currencies that have been traded for a relatively long period of time (since May 2, 2013). For consistency, we compare data for trades between currencies on the same exchange. We take advantage of the fact that some of the exchanges trade not only in Bitcoin and Litecoin but other crypto-currencies as well. We focus the analysis on the BTC-e exchange,[2] a leading exchange that has traded several currency pairs for a relatively long time. Seven crypto-currencies have been traded on BTC-e since May 2, 2013. They are Bitcoin (BTC), Litecoin (LTC), Peercoin (PPC), Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC), and Terracoin (TRC).[3] We analyze how their relative prices changed over time between May 2013 and February 2014.

We also use price data from other exchanges as well. We employ Cryptsy because like BTC-e it has traded the main crypto-currencies against Bitcoin for a relatively long period of time (although for less time than BTC-e.) But Cryptsy did not trade in USD. We also employ trade data from Bitstamp and Bitfinex, as they were the largest exchanges trading Bitcoin against USD and against Litecoin.

The source for our pricing data is http://www.cryptocoincharts.info/. This site is publicly available. Price and volume data are aggregated from all trades at every exchange. We use the 'closing rate,' which (from our discussions with the site manager) is the rate at midnight GMT. Similarly, daily volume is from 0:00 to 24:00 GMT. Some days have no data for a particular trading pair or an exchange. In such cases, it means that either the API of the exchange or something at cryptocoincharts.info was not working properly.

[2]BTC-e, an exchange based in Bulgaria, allows for trades in several crypto-currencies and two fiat currencies (USD and Russian ruble). It started trading on August 7, 2011.

[3]Novacoin and Feathercoin were created by "forking" Peercoin. While the top three crypto-currencies (BTC, LTC and PPC) have been stable in terms of their market capitalization ranking, the other coins are more volatile. As of January 13, 2014, NMC was fifth, FTC twelfth, NVC fourteenth and TRC twenty-second.

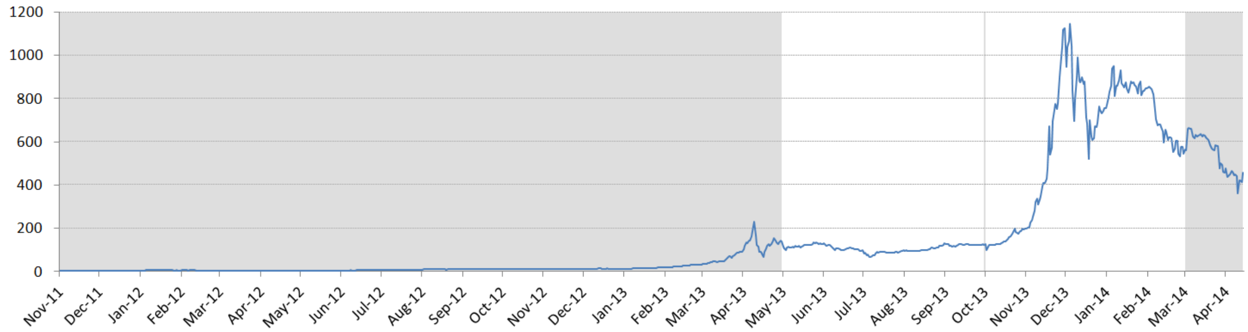

Figure 1: Bitcoin prices (in USD) over time. Shading highlights the first period (May–Sep 2013) and the second period (Oct 2013–Feb 2014) of our analysis. (Source: http://www.coindesk.com/price)

Casual observation of Bitcoin prices (in USD) within our data time frame, from May 2, 2013 to February 28, 2014, shows a clear difference between the price trend up to September 2013, and then from October on (see Figure 1). During the May–September period the USD/BTC exchange rate traded within a relatively narrow range (from $65/BTC to $130/BTC), while in the period from October to February, the volatility was much greater and the value of Bitcoin relative to the USD ranged from $101/BTC to $1076/BTC. This price trend change may be related to the October 2nd shutdown of Silk Road, a website trading in illegal substances. Additionally in October, Chinese Internet giant Baidu started accepting Bitcoin, which increased Bitcoin's popularity in China. Further, in mid-November 2013, U.S. Congressional hearings cast crypto currencies in a relatively favorable light. For all of these reasons, this seems like a natural break in the data.[4] Therefore, we examine those two periods separately. In subsequent analysis, we call the period from May 2 to September 30, 2013 the *first period*, and the period from October, 2013 to February 28, 2014 the *second period*. Table 1 summarizes the differences between the two periods.

5 Competition between the Currencies

In this section, we analyze the competition between crypto-currencies using price data. Media coverage has mostly focused on Bitcoin. Thus, it may come as a surprise that there are

[4]It is not important that the break point occurs exactly in the middle of our data. Our results are robust to shifting the break point. We start with May 2, 2013 because we could not obtain data on all crypto-currencies used in the analysis before this date.

	First Period	Second Period
dates	May 2 – Sep 30, 2013	Oct 1, 2013 – Feb 28, 2014
major events/ media coverage	none	Silk Road raid Baidu accepts Bitcoin US Congress hearings
BTC/USD price range	\$ 65–130/BTC	\$ 101–1076/BTC

Table 1: First and second period in our data

around 200 crypto-currencies.[5]

The other crypto-currencies in our analysis are very similar to Bitcoin and have been created by "forking" the main Bitcoin protocol. Hence, they are called *altcoins*. But they are not exactly the same. For example, Litecoin will generate 4 times as many coins (84 million), and the transactions are added to the blockchain 4 times faster than Bitcoin (2.5 minutes against Bitcoin's 10 minutes).[6] Peercoin relies on proof-of-stake in addition to proof-of-work to record transactions in the blockchain (i.e., mining), thus mitigating the need for powerful, expensive computers that became necessary for mining in Bitcoin. Peercoin also does not have a limit on the total number of coins generated (although the number of coins generated at any time is known in advance).

Market capitalization values for different "coins" are quite skewed. According to http://coinmarketcap.com/, total market capitalization in digital currencies was approximately \$8.1 Billion on February 26, 2014.[7] Bitcoin accounts for approximately 90% of total digital currency market capitalization. The second largest market capitalization is Litecoin with approximately 5% of total digital currency market capitalization. Peercoin, the digital coin with the third largest market capitalization value accounts for 1% of total market capi-

[5]See http://coinmarketcap.com/

[6]There are, of course, other differences between the Bitcoin and Litecoin, like a different hashing algorithms.

[7]This calculation excludes Ripple, which had a market capitalization of approximately \$1.4 billion. Ripple currency, XRP, only exists (and trades) within the Ripple system and Ripple was designed as a currency exchange and payment system, rather than an alternative digital currency.

talization. These currencies were among the early entrants into the crypto-currency market. Bitcoin—the oldest one—was established in 2009, Li tecoin in 2011, and Peercoin in 2012. Interest has grown recently, and many new crypto-currencies entered the market in 2013 and 2014.

Many of the altcoins—especially early ones, like Litecoin and Peercoin—were developed to fix what their developers perceived as shortcomings of Bitcoin. Some of the changes may attract only a narrow group of users (e.g., Namecoin aims at more anonymity than Bitcoin), while some may have wider appeal as alternatives to Bitcoin.[8] However, it has been postulated that the recent surge in entry into the digital coin market is due to the fact that on the one hand the entry is relatively costless, and on the other hand the founders of coins have made significant profits (even the coin with the 34th largest market capitalization had a value of more than one million dollars in February 2014).

Those two explanations for introduction of new crypto-currencies illustrate a disagreement about what is driving the demand for crypto-currencies — whether people buy them due to their potential as currency, or they buy them for speculative purpose, i.e., as a financial asset.[9]

We argue that both forces are present in the market, with different effects:

(1) *Reinforcement effect* is the result of the one-sided network effects present in the currency adoption process: As Bitcoin becomes more popular, more people would believe that it will win the "winner-take-all" race against other crypto-currencies. With this expectations, the demand will further increase.

(2) *Substitution effect* is the result of speculative dynamics, i.e., treating crypto-currencies as financial assets: As Bitcoin becomes more popular and more expensive, people fear it may be overvalued (or too volatile) and look for alternative crypto-currency investment.

We analyze relative prices of seven crypto-currencies traded at BTC-e: Bitcoin (BTC), Litecoin (LTC), Peercoin (PPC), Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC),

[8]It has been recently reported in the press that merchants increasingly accept Litecoin as a less-costly alternative to Bitcoin. (http://www.businessweek.com/news/2014-04-24/Bitcoin-runner-up-Litecoin-emerges-as-low-price-challenger-tech)

[9]See Yermack (2013) and Glaser et al (2014)

Currency	May 2, 2013 beginning of data	September 30, 2013	February 28, 2014 end of data
USD/BTC	106.8	123.0	537.5
LTC/BTC	31.3	56.6	40.9
PPC/BTC	378.8	471.7	166.1
NMC/BTC	97.8	246.3	166.7
NVC/BTC	31.9	33.5	74.5
FTC/BTC	197.2	1111.1	2500.0
TRC/BTC	198.4	769.2	2777.8

Table 2: Exchange rates of selected currencies against BTC on BTC-e exchange.

and Terracoin (TRC). Since the supply of all those currencies is either fixed or deterministically changing (i.e., not adjusted in response to prices), changes in prices are a good measure of changes in demand.[10]

Table 2 shows exchange rates of currencies used in the analysis against BTC. The table reports the first and last day of our data (May 2, 2013 and February 28, 2014) as well as the threshold date between the first and second periods (September 30, 2013). Figure 2 graphically represents the changes in the exchange rates over those three dates.

We see two effects in Figure 2. First, some coins take off, while others do not. We can distinguish two groups: LTC, PPC and NMC retained their value against BTC over time (we call them 'successful'), while FTC and TRC declined significantly in value in both periods.[11]

Second, the value of the coins that take off increases only in the second period. In the first period, as Bitcoin becomes more valuable (against the USD), its value also increases against the other crypto-currencies. In the second period Bitcoin's value in USD increases further, but also the successful coins' (LTC, PPC and NMC) values increase against Bitcoin. That means that in the second period, their values against the USD increase faster than Bitcoin's.

Of course, three data points are not enough to draw conclusions. Hence, we also examine correlations in the daily exchange rates of the successful crypto-currencies and the USD

[10] At the same time, in this case, trade volumes may be misleading as an indicator of demand. If everybody wants to buy Bitcoin, e.g. believing it will become widely adopted as currency, the volume would be low or null, since nobody wanted to sell, but the price would be high.

[11] NVC loses quite a bit of value as well, but its decline takes place in the second period.

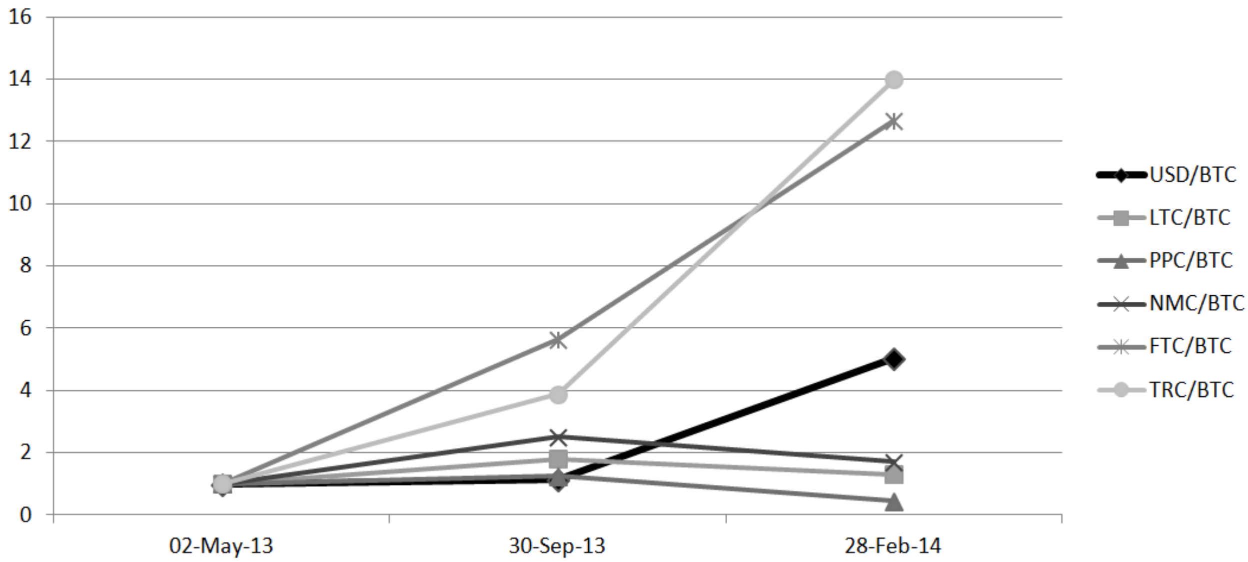

Figure 2: Changes in exchange rates of various currencies against BTC over the threshold dates in our data. Rate on May 2, 2013 is normalized to 1.

	USD/BTC	LTC/BTC	PPC/BTC	NMC/BTC
USD/BTC	1.00			
LTC/BTC	0.78	1.00		
PPC/BTC	0.09	0.31	1.00	
NMC/BTC	0.28	0.72	0.45	1.00

(a) in first period (152 observations)

	USD/BTC	LTC/BTC	PPC/BTC	NMC/BTC
USD/BTC	1.00			
LTC/BTC	-0.78	1.00		
PPC/BTC	-0.77	0.93	1.00	
NMC/BTC	-0.61	0.91	0.92	1.00

(b) in second period (150 observations)

Table 3: Correlations in daily closing prices at BTC

against Bitcoin. The results are shown in Tables 3a and 3b.[12] We use r(USD/BTC) to denote the exchange rate between USD/BTC, and similarly for other exchange rates. The positive correlations in Table 3a show that during the first period, when Bitcoin increased in value against the USD, it also increased in value against other crypto-currencies. However, the correlations in the first period are mostly weak. That is, the demand for one crypto-currency was weakly affected by prices of other currencies.

In the second period, the correlations reflect the patterns observed in Table 2. In particular, we find that there is a strong negative correlation between the exchange rate

[12]Note that we do not include the failing currencies from Table 2 in subsequent tables.

	LTC/BTC	PPC/BTC	NMC/BTC
LTC/BTC	1.00		
PPC/BTC	0.15	1.00	
NMC/BTC	0.19	0.32	1.00

(a) in first period (117 observations)

	LTC/BTC	PPC/BTC	NMC/BTC
LTC/BTC	1.00		
PPC/BTC	0.93	1.00	
NMC/BTC	0.91	0.91	1.00

(b) in second period (149 observations)

Table 4: Correlations in daily closing prices at Cryptsy

r(USD/BTC) and the rates for three other major currencies (r(LTC/BTC), r(PPC/BTC), and r(NMC/BTC)). This means that when Bitcoin was appreciating against the USD, it was depreciating against Litecoin and the other major crypto-currencies. The other three digital currencies' prices move in lock-step and the correlation among them is much higher than in the first period.[13]

To check that this is not an artifact of one exchange, we examine the same correlation at a smaller exchange, Cryptsy. We employ Cryptsy, because like BTC-e, it has traded in the main crypto-currencies versus BTC for a relatively long period of time. Unlike BTC-e, however, Cryptsy did not trade in USD. The correlation between crypto-currencies' prices at Cryptsy are reported in Tables 4a and 4b, and show a similar pattern as those in Tables 3a and 3b.

One interpretation of these observations is that in the first period the reinforcement effect is dominant. The demand for the most popular crypto-currency, Bitcoin, grows even stronger, and the demand for all other currencies grows weaker. For the other relatively successful currencies, demand is not strongly correlated. During that period Bitcoin received moderate coverage in mainstream media, but other currencies received none. It seems reasonable to expect that at that time crypto-currencies were acquired by enthusiasts, possibly more likely believing in their potential as currencies. It is possible that Bitcoin, as being the only one popularized by media, also could attract some demand from people previously

[13] In the second period, Bitcoin's price (in USD) rose dramatically, peaking at more than 1000 USD per Bitcoin in mid-December 2013. Afterwards, Bitcoin's price steadily declined - and it was worth 537.5 USD at the end of the period. When we break the second period into two subperiods, we find that the negative correlation we found between r(USD/BTC) and (say) r(LTC/BTC) obtains both during the rise and the fall of Bitcoin against the USD.

were not aware of crypto-currencies.

In the second period the network effects drive the division between the "winners" and "losers" in the crypto-currency market. But the observations within the successful currencies is no longer consistent with the reinforcement effect. The substitution effect dominates. In that second period the interest in some other crypto-currencies grows. Media coverage of Bitcoin increases significantly during that time, and some media also cover alternative crypto-currencies. As the value of Bitcoin increases in terms of USD during the second period, the value of the successful altcoins also increased against USD and at a faster rate (their value rose against Bitcoin). This substitution effect may be a result of the arrival of new people to the market, who acquire and trade the crypto-currencies more as financial assets than for their currency potential. We argue that it would be unlikely to sustain prices of crypto-currencies as financial assets if no one believes in their potential as currency.[14] This is why very few crypto-currencies are actively traded for a long period of time. Thus, we interpret our results as indicating that for each of the four successful crypto-currencies there is a group of traders who believe in its future as a currency. However, once the speculation is a significant force, we no longer can deduce the relative strength of these beliefs from the relative prices.

To assess the validity of our interpretation that there is more popular interest in altcoins in the second period, we employed Google Trends. Google Trends reports on relative search volume (for searches using the Google search engine) for individual terms over time, by month. It also illustrates the relative search volumes of multiple terms. We checked for the terms 'Bitcoin' and 'Litecoin'. The results are presented in Figure 3. Google Trends does not report the absolute value of the number of searches, but the highest value in the chart is normalized to 100. Because of this normalization, a positive number of searches may show up as 0 in Google Trends, if it is a sufficiently small fraction of the highest number. July 2012 is the first month that the search volume for 'Litecoin' shows a positive number in Google Trends.

There are always fewer searches for Litecoin than for Bitcoin, but the changes over time are quite similar for the two currencies. The correlation in the number of searches between the two crypto-currencies is 0.95. The data show that searches for both Bitcoin and Litecoin first peaked in April 2013, when the price of Bitcoin reached \$214/BTC. By May 2, 2013 (when our analysis begins), the price of Bitcoin had fallen to \$106.8/BTC. The Bitcoin price

[14] Although there exist models in finance literature showing that it could be possible.

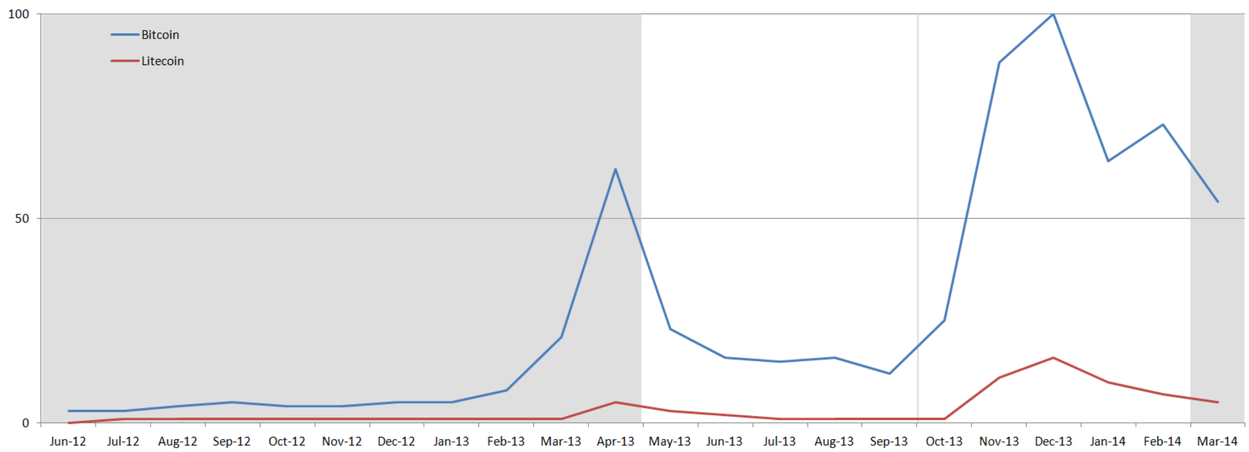

Figure 3: Google Trends results showing relative search volumes per month for terms 'Bitcoin' and 'Litecoin'. (Accessed April 2014)

stays in a relatively narrow range from that point until the end of September. Similarly, the number of searches for both coins in Google Trends also stays in a very narrow range for the same period. Beginning in October 2013, the number of searches increases and reaches a second peak in December 2013. At this peak the number for Litecoin is 16 while for Bitcoin is 100. Bitcoin's first peak was 62, while Litecoin's was 5. Thus, the second Bitcoin peak was 61% higher than the first peak, while for Litecoin, the second peak was 220% higher than the first peak. Hence, there is relatively more interest in Litecoin during the second period than in the first one.

A similar pattern is present for Peercoin. Peercoin searches are a fraction of Litecoin searches, and an even smaller fraction of Bitcoin searches. Hence, the data are not easily visible if put on the same graph with the other two. When we look at the search intensity of Peercoin by itself over time, it also peaks in December 2013. Google Trends reports positive value for Peercoin searches only from October 2013 on, which also speaks to the increased interest in alternative crypto-currencies in the second period of our data.

Granger causality analysis

We have observed some interesting patterns in the above analysis. A natural question to ask is whether movements in the USD/BTC exchange rate 'predict' future changes in other digital currencies. Since the analysis above suggests that the first period is different from the second, we also analyze them separately here.

Given the limitations of our data, we are restricted to testing for predictability or causality in the narrow, technical sense formalized by Granger (1969) and Sims (1980). In this interpretation, a variable x causes y if lagged values of x are significant in explaining y in a regression in which lagged values of y are also explanatory variables. It is, of course, possible that causality can exist in both directions. This test can be performed using vector auto-regressions (VARs). We are not estimating a structural model when performing these tests; nevertheless, we believe that this type of analysis is useful in assessing whether there are differences in changes in currency movements over time. We conduct the analysis for r(LTC/BTC) and r(USD/BTC)

Not surprisingly, both of these series are non-stationary in both periods. Further, they are not co-integrated. This means that we need to conduct Granger causality tests using differenced data, that is, using the daily change in exchange rates.[15]

In order to conduct the analysis, we first define the following lagged variables:

r(LTC/BTC)(-1) = the lagged value of r(LTC/BTC),

r(USD/BTC)(-1) = the lagged value of r(USD/BTC).

Then the differences in the two exchange rates are defined as follows:

Δr(LTC/BTC) = r(LTC/BTC) - r(LTC/BTC)(-1),

Δr(USD/BTC) = r(USD/BTC) - r(USD/BTC)(-1) .

We first run a regression of Δr(LTC/BTC) on its own lagged value and on the lagged value of Δr(USD/BTC). We then run a regression of Δr(USD/BTC) on its own lagged value and on the lagged value of Δr(LTC/BTC). We run each of these regressions for both the first period and second period. The results are reported in Table 5 below.[16] We find that for the first period, neither of the lagged series are significant in explaining daily movements of either of the two exchange rates.

In the second period, we obtain different results. In the case when Δr(LTC/BTC) is the dependent variable, we find that the lagged value of Δr(USD/BTC) is significant in

[15] The differenced data series are stationary. Of course, R-squared values are much smaller with differenced data, but the key question is whether there is feedback.

[16] In all tables involving regressions, t-statistics are in parentheses.

	Dependent Variables			
	ΔLTC/BTC		ΔUSD/BTC	
	First Period	Second period	First Period	Second period
Independent Variables				
Constant	0.17 (1.25)	-0.060 (-0.13)	0.024 (0.08))	3.41 (0.78)
ΔLTC/BTC(-1)	0.0059 (0.07)	-0.12 (-0.14)	0.13 (0.66)	**1.88 (2.35)**
ΔUSD/BTC(-1)	-0.015 (-0.41)	**-0.018 (-1.98)**	0.022 (0.27)	-0.023 (-0.27)
# of Observations	152	148	152	148
Adjusted R-squared	-0.01	0.01	-0.01	0.03

Table 5: Granger regressions (t-values in parentheses; statistically significant results highlighted)

explaining changes in the exchange rate between Litecoin and Bitcoin. Similarly, in the case when Δr(USD/BTC) is the dependent variable, we find that the lag of Δr(LTC/BTC) is significant in explaining changes in the exchange rate between USD and Bitcoin.

We can summarize our results as follows. In the first period, neither lagged value of the difference in the exchange rates predicts the difference in the exchange rates. In the second period, the cross-lagged value of the difference predicts the difference in the exchange rates. This indicates that unlike period one, in period two, there is two-way feedback between the difference of the exchange rates. Again, these results suggest that the first and second periods are quite different in terms of currency movements.

It is consistent with our interpretation of the driving forces in the market—that in the first period the overlap of users trading in multiple crypto-currencies was quite small. In the second period, we see more direct competition between Bitcoin and Litecoin. Hence, the results from both the correlation data and the Granger causality tests suggest that there is more interaction between the currency exchange rates in the second period.[17]

[17] When we perform the Granger analysis using PPC instead of LTC, we find no feedback in the first period and feedback from PPC/BTC to USD/BTC (but not vice versa) in the second period. Finally, when we perform the Granger analysis using NMC instead of LTC, we find no feedback at all in either period.

6 Currency Exchanges

The availability of reliable currency exchanges is critical for competition among digital currencies. The currency exchange market has been evolving rapidly over time, and it is clear that we are far from an equilibrium in that market.

Mt. Gox was the dominant exchange until mid-2013. In May 2013, FBI shut down a Wells Fargo account belonging to a Mt. Gox subsidiary, seizing $2.9 million. This weakened the exchange, as it became difficult for US customers to access it (they needed to first transfer funds to a non-US account). By November 2013, Mt Gox was still an important player, but no longer a dominant exchange. The largest Bitcoin exchange at that time was BTC China, with 35% of the trades. BTC China trades only Bitcoin against Chinese Yuan (CNY).[18] Mt.Gox was second, with 27%. The third and fourth were Bitstamp, with 24%, and BTC-e, with 14% of the trades. The latter three exchanges traded Bitcoin against USD.

The landscape in the exchange markets continued to change rapidly. As of February 2014, Mt. Gox ceased operations altogether, in large part due to a security breach—and a huge loss of Bitcoins. During this period, a large percentage of trade occurred at two exchanges in China: BTC China and OKCoin. These exchanges, where the only fiat currency allowed in trades is the Chinese Yuan (CNY), totaled more than 75% of the volume on many days. The relative ranking of exchanges by volume also changed significantly. In the Chinese market, once dominant BTC China lost a lot of volume after the December 5 announcement by the Bank of China banning financial institutions from processing transactions in Bitcoin.[19] In contrast, the initially small exchange OKCoin gained a lot of volume.

In the case of trades involving BTC and USD, by mid-February 2014 there were three major exchanges: BTC-e, Bitstamp, and Bitfinex. BTC-e was the first of the three to trade BTC/USD, and had about 25% of the volume for this currency pair. Bitstamp, which only trades BTC/USD, had about 50% of the volume in this currency pair, while Bitfinex, a later entrant, had 25% of this market. Many other exchanges were active in this currency pair (USD/BTC), but the volume traded was extremely small.

In the case of LTC/BTC and LTC/USD trades, BTC-e was the dominant exchange with about 90% and 97% respectively of the volume of trade in these two currency pairs. In the

[18]See "US has Already Ceded Dominance in Bitcoin Trading," by Jon Matonis, coindesk.com, November 16, 2013, available at http://www.coindesk.com/us-already-ceded-dominance-Bitcoin-trading/

[19]http://www..businessweek.com/articles/2014-03-20/btc-chinas-bobby-lee-Bitcoin-isnt-really-banned-in-china-and-its-quickly-gaining-ground

Exchange	Trading pairs	Volume (in BTC) Mid February	Percent
OKCoin	2 (BTC/CNY, LTC/CNY)	156,380	74.0
BTC-e	19	14,284	6.8
Bitstamp	1 (BTC/USD)	13,263	6.3
Bitfinex	3 (USD/BTC, LTC/BTC & USD/LTC	12,325	5.8
BTCChina	1 (BTC/CNY)	7,565	3.6
Bter	84	2,222	1.1
Cryptsy	148	1,256	0.6
Other Exchanges		4,007	1.9
Total		211,301	100

Table 6: Major crypto-currency exchanges by currencies exchanged and volume (volume data for a 24 hour period)

case of LTC/BTC, five other exchanges had non-trivial trade (i.e., more than 1%) in this currency pair. In the case of LTC/USD, only one other exchange had more than 1%. For PPC/BTC, the picture is similar to LTC/BTC: BTC-e dominated with about 90% of the market. Three other exchanges had more than 1%. In the case of NMC/BTC, BTC-e had more than 95% of the volume.

Several new exchanges have entered the market. The website http://www.cryptocoincharts.info/v2/markets/info gives daily information on digital currency exchanges and transaction volume. Table 6 offers a snapshot for mid-February 2014.

Given the multiplicity of the exchanges, the question arises whether the prices at the exchanges differ, whether they allow for arbitrage opportunities. Shall we expect that in the long run there will still be multiple exchanges, or will all the trade converge to one exchange?

The argument in favor of convergence to a single exchange follows from the presence of two-sided network effects. A seller prefers to sell his Bitcoin (or other crypto-currency) in an exchange that has more buyers, as it increases the probability that the trade occurs faster and at a better price. Similarly, buyers prefer to buy Bitcoins where there are many sellers. Thus, larger exchanges create thicker, more liquid markets. We would expect that larger exchanges (with most buyers and sellers) attract many new buyers and sellers and thus larger to grow faster than smaller exchanges.

At the same time, due to two-sidedness of the market, there is negative same-side effect which may prevent tipping. While a seller prefers an exchange with more buyers, he also prefers to avoid the exchange with a larger number of sellers, as other sellers compete for the same buyers. Existing results in the literature[20] suggest that if there is no arbitrage opportunity between the exchanges it is possible for multiple exchanges to coexist in the long run, despite network effects.

In the following subsections, we investigate (i) triangular arbitrage opportunities within the BTC-e exchange and (ii) arbitrage opportunities across exchanges.

6.1 Test for Triangular Arbitrage within BTC-e Exchange

BTC-e trades multiple currencies. Based on the pairs traded at BTC-e we can check for triangular arbitrage: whether exchanging USD to BTC, then BTC for currency X, and finally X for USD is profitable. We check this for X being LTC, PPC and NMC. We do not find any arbitrage opportunities among any of these currencies at the BTC-e exchange.

BTC-e allows for trades of USD/BTC, USD/LTC and LTC/BTC. No triangular arbitrage among these currencies implies that $r(\text{LTC/BTC}) = \frac{r(\text{USD/BTC})}{r(\text{USD/LTC})}$. The correlation between these two series, $r(\text{LTC/BTC})$ and $\frac{r(\text{USD/BTC})}{r(\text{USD/LTC})}$, is 0.9995 in the first period and 0.9999 in the second period. We follow the same procedure for Peercoin, and then for Namecoin. For those two, we only examine the second period, as there was no USD/PPC or USD/NMC trade in the first period in our data. The correlation between the series $r(\text{PPC/BTC})$ and $\frac{r(\text{USD/BTC})}{r(\text{USD/PPC})}$ is 0.999. And correlation between $r(\text{NMC/BTC})$ and $\frac{r(\text{USD/BTC})}{r(\text{USD/NMC})}$ is 0.9998. The high correlations suggest that prices of those currencies are moving in lock-step.[21]

In order to formally test for arbitrage opportunities, we used daily data to run the following regressions (below) using the BTC-e exchange data. No triangular arbitrage means that $\beta_0 = 0$ and $\beta_1 = 1$. The regression results are reported in Table 7.[22]

[20] E.g., Ellison and Fudenberg 2003

[21] BTC-e does not have trade between the following currency pairs: PPC/LTC, PPC/NMC and NMC/LTC.

[22] In all tables involving regressions, t-statistics are in parentheses. Adding controls for various events (e.g., regulatory) that took place during the period for which we have data has no effect on any of the regression results on arbitrage.

Using BTC-e exchange	Dependent Variable			
	LTC/BTC		PPC/BTC	NMC/BTC
	First Period	Second period	Second Period	Second period
Independent Variables				
Constant	0.010 (0.10)	0.030 (0.50)	0.73 (0.86)	1.24 (2.69)
(USD/BTC | USD/LTC)	0.999 (390.61)	0.999 (950.97)		
(USD/BTC | USD/PPC)			0.996 (191.94)	
(USD/BTC | USD/NMC)				0.994 (619.22)
# of Observations	152	150	91	144
Adjusted R-squared	0.9990	0.9998	0.9976	0.9996

Table 7: Test for triangular arbitrage within BTC-e exchange (t-statistics in parenthesis)

$$r(\text{LTC/BTC}) = \beta_0 + \beta_1 \cdot \frac{r(\text{USD/BTC})}{r(\text{USD/LTC})}, \qquad \text{for first and second periods}$$

$$r(\text{PPC/BTC}) = \beta_0 + \beta_1 \cdot \frac{r(\text{USD/BTC})}{r(\text{USD/PPC})}, \qquad \text{for second period only}$$

$$r(\text{NMC/BTC}) = \beta_0 + \beta_1 \cdot \frac{r(\text{USD/BTC})}{r(\text{USD/NMC})}, \qquad \text{for second period only}$$

The estimated slope coefficients are 0.999 in both periods for Litecoin. Further, a 95% confidence interval for the slope includes 1.00. Finally, the estimated intercept coefficients are insignificant. A formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ for the first period yields an f-statistic $F(2, 150) = 0.98$, (p-value$= 0.38$). A formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ for the second period yields an f-statistic $F(2, 148) = 0.42$, (p-value$=$ 0.66). This strongly suggests that there is no triangular arbitrage among LTC, BTC and USD, which are the major ones traded at BTC-e.

In the case of Peercoin, the regression results are quite similar. A 95% confidence interval for the slope includes 1.00 and the estimated intercept coefficient is insignificant. A formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$, yields an f-statistic $F(2, 89) = 0.49$, (p-value$= 0.62$). This, again, is consistent with no triangular arbitrage opportunities among PPC, BTC and USD.

In the case of Namecoin, the estimated slope coefficient is 0.994. But a 95% confidence interval does not include 1.00. Additionally, the estimated intercept coefficient is significantly different from zero in this case. Further, a formal test of the hypothesis that $\beta_0 = 0$ and

$\beta_1 = 1$, yields an f-statistic $F(2, 142) = 7.19$, (p-value$= 0.001$). Hence, without transaction fees, there may have been some small arbitrage opportunities among NMC, BTC and USD. Once the 0.2-0.5% transaction fees at BTC-e are taken into account, however, it is likely that there were not any arbitrage opportunities among these three currencies.

It is intuitive that there would be little arbitrage opportunities involving Litecoin and Peercoin, since these are the second- and third-largest crypto-currencies in terms of market capitalization. Namecoin on the other hand, is a less important currency. Taken together, the data suggest no (or very little) triangular arbitrage among currencies traded at BTC-e.

6.2 Tests for Arbitrage across Exchanges

In this section, we investigate whether there is an arbitrage opportunity from trading the same pair of currencies on different exchanges. We focus on trades involving BTC/USD, LTC/USD, LTC/BTC, and the Chinese Yuan (CNY) versus BTC.

We compare the exchange rate between USD and BTC on BTC-e and Bitstamp, the largest exchange trading BTC/USD. In the case of our first period (May–September 2013), the correlation in prices for this currency pair across the two exchanges is 0.994.[23] In the second period (October 2013–February 2014), the correlation in USD/BTC prices is 0.998 across the two exchanges.

To check whether there is arbitrage opportunity between exchange for LTC/BTC trade, we compared BTC-e and Bitfinex, as Bitfinex is the largest exchange facilitating LTC/BTC trades. However, Bitfinex only began trading in this currency pair during the second period, so we have only 97 observations. The correlation for this currency pair across those two exchanges is 0.994.

The high correlations suggest that price movements are very similar for the relevant currencies across the exchanges. To further check whether the arbitrage opportunities were present, we run the following regressions using exchange rates from the different exchanges:

$$\begin{aligned} &r(\text{USD/BTC, at BTC-e}) = \beta_0 + \beta_1 \cdot r(\text{USD/BTC, at Bitstamp}), && \text{for first and second periods;} \\ &r(\text{LTC/BTC, at BTC-e}) = \beta_0 + \beta_1 \cdot r(\text{LTC/BTC, at Bitfinex}), && \text{for second period only.} \end{aligned}$$

The results are reported in Table 8. The slope coefficients are 0.958 and 0.974 for the two periods of USD/BTC trade across BTC-e and Bitstamp. But a 95% confidence interval

[23] Only 104 observations are available here.

USD/BTC	Dependent Variable		
	USD/BTC (BTC-e)		LTC/BTC (BTC-e)
	First Period	Second period	Second Period
Independent Variables			
Constant	2.33 (2.22)	3.25 (0.83)	0.07 (0.29)
USD/BTC (Bitstamp)	0.958 (97.44)	0.973 (199.37)	
LTC/BTC (Bitfinex)			0.984 (88.83)
# of Observations	104	148	97
Adjusted R-squared	0.989	0.995	0.988

Table 8: Test of arbitrage across exchanges.

does not include 1.00. A formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ during the first period yields an f-statistic $F(2, 102) = 94.61$, (p-value= 0.000). The same test during the second period yields an f-statistic $F(2, 146) = 34.92$, (p-value= 0.000). These results suggest that there might be small (gross) arbitrage opportunities across these two exchanges.

When we compare the slope coefficients and f-statistics across the two periods, it appears that any arbitrage opportunities that existed were reduced during the second period: the f-statistic is smaller in the second period, and the estimated slope coefficient rises from 0.958 to 0.974.

All the exchanges in the analysis charge transaction fees in the range of 0.2-0.5%. In addition they charge various withdrawal fees on fiat currencies, often also on withdrawal of Bitcoins (e.g., BTC-e). Some of them, e.g. Bitstamp, also charge deposit fees when fiat funds are transferred to the exchange account. But they do not charge deposit fees on Bitcoins or Litecoins. Given the transaction fees involved, it is unlikely that there were significant (net) arbitrage opportunities across the exchanges for trade in USD/BTC.

In the case of LTC/BTC trade (data for the second time period only), the estimated slope coefficient is 0.984 and a 95% confidence interval includes 1.00. The estimated intercept coefficient is not significantly different from zero. A formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ yields an f-statistic $F(2, 95) = 7.59$, (p-value= 0.001). These results suggest small (gross) arbitrage opportunities. With transaction, withdrawal, and deposit fees involved in trading at the two exchanges, it is unlikely that there were net arbitrage opportunities.

The two major exchanges that trade CNY/BTC are OKCoin and BTCChina. In the case of CNY/BTC trade, formal test of the hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ for the second period (since we have BTCChina trade only for that period) yields an f-statistic $F(2, 108) = 2.01$, (p-value= 0.14) This suggests that there are no arbitrage opportunities.

Taken together, the data suggest that any arbitrage opportunities were greater across exchanges than within exchanges. Further to the extent that any arbitrage opportunities existed (after taking the fees into account), these opportunities declined over time. We need to keep in mind, however, that our analysis involved daily trading prices. It is possible that some arbitrage opportunities still exist when comparing individual bid and ask spreads or price differences between exchanges at different times during the day. We leave this more detailed analysis for further research.

7 Conclusions

In this paper, we investigated the nascent market of crypto-currencies in two aspects. First, we examine competition between different currencies, focusing on Bitcoin, Litecoin, Peercoin and Namecoin. Second, we look at competition among the exchanges where those currencies are traded. In both these environments network effects play an important role.

We divide our data into two periods: May–September 2013 and October 2013–February 2014. In the first period Bitcoin's price was relatively stable, while in the second period it was very volatile.

We find that in the first period, Bitcoin's popularity (as measured by exchange rates) increased against the USD and other crypto-currencies. But in the second period, the prices of other crypto-currencies increased even more against the USD than Bitcoin did. In our interpretation of these results, it seems that on the one hand Bitcoin, by its initial popularity "opened up" the market for crypto-currencies in general. At the same time, it enjoys a first-mover advantage in an environment with network effects. In the long term, it is not clear whether this advantage will be sufficient to keep the dominant position. Recently Litecoin, the second strongest digital currency has increased in popularity not only in trading, but also in acceptance. Businessweek.com reported on April 24 that Litecoin is increasingly more often accepted by merchants, as a lower-cost alternative to Bitcoin.[24]

[24] http://www.businessweek.com/news/2014-04-24/Bitcoin-runner-up-Litecoin-emerges-as-low-price-challenger-tech

The analysis of exchanges for crypto-currencies indicated little or no arbitrage opportunities, and any existing arbitrage opportunities decline from the first to the second period. Given the different nature of the network effects—involving negative same-side effects—and no arbitrage opportunities, many exchanges may coexist in the long run, and possibly compete on various fees.

Appendix

A Descriptive Statistics

First period:

Variable	Obs	Mean	Std. Dev.	Min	Max
USD/BTC	152	105.5	15.2	65.5	129.6
LTC/BTC	152	40.7	7.4	28.0	59.7
PPC/BTC	152	677.4	128.8	371.7	943.4
NMC/BTC	152	181.1	36.4	97.7	267.4

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
USD/BTC	150	579.0	281.9	101.1	1076.0
LTC/BTC	150	51.2	23.5	23.8	117.6
PPC/BTC	151	287.2	174.0	106.4	671.1
NMC/BTC	151	239.3	153.7	88.6	787.4

Table 9: Exchange rates of selected currencies against BTC.

First period:

Variable	Obs	Mean	Std. Dev.	Min	Max
LTC/BTC	152	40.7	7.4	28.0	59.7
(USD/BTC | USD/LTC)	152	40.7	7.4	27.6	60.4

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
LTC/BTC	150	51.2	23.5	23.8	117.6
(USD/BTC | USD/LTC)	150	51.2	23.6	23.7	116.6

Table 10: Summary statistics for analysis across currency triplet LTC, BTC, USD at BTC-e.

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
PPC/BTC	91	161.8	24.4	106.4	234.2
(USD/BTC | USD/PPC)	91	161.7	24.5	106.3	232.2

Table 11: Summary statistics for analysis across currency triplet PPC, BTC, USD at BTC-e.

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
NMC/BTC	144	240.0	157.3	88.6	787.4
(USD/BTC | USD/NMC)	144	240.1	158.2	89.1	793.1

Table 12: Summary statistics for analysis across currency triplet NMC, BTC, USD at BTC-e.

First period:

Variable	Obs	Mean	Std. Dev.	Min	Max
USD/BTC (BTC-e)	104	103.8	15.9	65.5	126.4
USD/BTC (Bitstamp)	104	105.9	16.5	66.3	130.7

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
USD/BTC (BTC-e)	148	582.6	282.1	101.1	1076.0
USD/BTC (Bitstamp)	148	595.0	288.9	103.9	1132.0

Table 13: Summary statistics for analysis of USD/BTC rate across BTC-e and Bitstamp.

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
LTC/BTC (BTC-e)	97	20.8	6.6	7.4	40.6
LTC/BTC (Bitfinex)	97	21.1	6.6	7.7	41.3

Table 14: Summary statistics for analysis of USD/BTC rate across BTC-e and Bitfinex.

Second period:

Variable	Obs	Mean	Std. Dev.	Min	Max
CNY/BTC (BTCChina)	110	4150.9	1284.6	1252.9	7005.0
CNY/BTC (OKCoin)	110	4113.5	1270.5	1261.2	6935.0

Table 15: Summary statistics for analysis of CNY/BTC rate across BTCChina an OKCoin.

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