Understanding Bitcoin as a Speculative Asset

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Abstract

The recent price history of Bitcoin can be characterized as a speculative bubble. I find that there is substantial evidence against the hypothesis that the large price movements experienced by Bitcoin were due to changing expectations about fundamentals. I also use a novel dataset to show that news coverage of Bitcoin induced individuals who had not previously traded Bitcoin to invest for the first time. Finally, I document the existence of short-sale constraints in the market for Bitcoin, show instances of speculators anticipating attention-driven inflows of new investors, and present a model which shows that short-sales constraints and speculative anticipation of investor inflow jointly generate a price bubble.

Introduction

Bitcoin is an anonymous, decentralized, digital currency designed in late 2009 by a researcher under the pseudonym of Satoshi Nakamoto. Nakamoto's algorithms allow users to own and transfer Bitcoins just as they would a physical asset—the Bitcoin protocol prevents double-spending and maintains a permanent record of ownership. Bitcoins can be used to purchase goods and services, and traded for dollars on web-based exchanges. As an asset, Bitcoin is economically interesting because of its explosive price growth: as Figure 1 shows, from the start of 2011 to the end of 2013, the price of a single Bitcoin increased by over 400,000 percent, from less than $0.30 cents to over $1,100 , before decreasing to less than $250 at the time of this writing.

At its peak, the total value of all Bitcoins in circulation was almost $14 billion; the current value is less than $3 billion. The total volume of Bitcoin traded on exchanges followed a similar pattern (Figure 2), starting from an average of less than $3,000 per day in 2011, spiking to a high of over $100 million per day in late 2013 and plummeting down to less than $10 million per day by July 2014. In this paper, I show that the rapid increase and equally-rapid collapse in Bitcoin's price, valuation, and trade volume can be explained by regarding Bitcoin as a speculative asset. I argue that the Bitcoin price bubble was inflated by investors who were more focused on reselling their holdings to a "greater fool" than on the fundamental value of Bitcoin as a potential currency.

All previous economic analyses of Bitcoin have tried to understand it from the perspective of monetary economics, and concluded that it behaves more like a speculative asset than a bona fide currency. However, they stop short of examining this speculative behavior in depth. I reinforce previous findings by showing that Bitcoin trading activity is not correlated with the trading activity of other assets exposed to the same fundamentals, which suggests that trade in Bitcoin is driven by speculative considerations instead of changes in fundamental valuation. I then show the existence of two market characteristics, which I argue combine to generate speculative trading: attention-driven investor inflow, and short-sales constraints.

Attention-driven inflow describes the simple fact that in 2011 many individuals who would eventually invest in Bitcoin did not know of its existence. Before they could decide to buy Bitcoin they had to learn about it, most likely through some form of news media. I use a novel dataset to show that, holding changes in market fundamentals constant, users were more likely to buy Bitcoin for the first time on days in which it attracted large amounts of news media attention. The other important feature I document, the existence of short-sales constraints, describes restrictions which make it more difficult for traders to short an asset than to buy it—for example, in the U.S. many retail brokerage platforms don't offer shorting as an option. I show evidence of short-sales constraints in the Bitcoin market by finding that it has been extremely expensive for traders who are bearish about the future of Bitcoin to bet against it. This results in pessimists leaving the market, inflating valuations. When combined with attention-driven inflow short-sales constraints can generate a speculative price bubble, in which speculators try to buy up Bitcoin in advance of news coverage but overshoot, leading to inflated prices followed by a correction. I argue that this dynamic can explain the recent price history of Bitcoin, and is generally applicable to assets which experience large increases in public interest over time.

The rest of the paper is organized as follows: Section I provides a background description of the technical features, trading ecosystem, and recent history of Bitcoin. Section II reviews related literature. Section III establishes that trading activity in Bitcoin is uncorrelated with trading activity in other assets that should be exposed to the same fundamentals. Section IV shows that investors who had previously not bought Bitcoin were more likely to do so on days in which Bitcoin received news coverage. Section V investigates the existence of short-sales constraints in the Bitcoin ecosystem, and shows that exchange risk imposes large costs on would-be short sellers. Section VI motivates and constructs a simple model in which short-sales constraints and speculation over attention-driven investor inflow result in a price bubble, and Section VII concludes.

I Background

The technology of Bitcoin

This section provides the bare minimum of technical detail about Bitcoin required to understand the rest of the paper; Nakamoto (2009), the original paper describing the Bitcoin protocol, is the best reference for readers seeking greater depth. The simplest way to think of Bitcoin is as a commodity that happens to be virtual: individuals can hold Bitcoin, and instantaneously transfer arbitrarily-sized amounts of their holdings to each other,[1] with the Bitcoin protocol guaranteeing that coins are never double-spent or duplicated. Transac-

1. This is not strictly true: the smallest possible increment is 1×10^{-8} BTC, also known as a Satoshi. However, this increment is incredibly small: it would have been worth less than 0.002 cents, even at Bitcoin's peak price. Moreover, the protocol could theoretically be amended to allow for even smaller increments in the future.

tions are permanent and irreversible. Extending the commodity analogy are Bitcoin "miners," who receive newly-created Bitcoins in exchange for verifying transactions and solving processor-intensive computational problems.

In order to start using Bitcoin directly, a user must download the Bitcoin client, which is free and open-source, and set up a cryptographic "wallet" which holds the total amount of Bitcoin owned by the user. In practice this is often very inconvenient, as the user risks losing all of her Bitcoins if she experiences computer problems which corrupt the wallet. Consequently, many users opt to pay a small fee to web-based wallet services, akin to banks, who maintain wallets on their behalf. Some of these wallet services also process and exchange Bitcoins for retailers, handling the business of converting Bitcoins to dollars themselves so that business can accept Bitcoins as payment without being exposed to fluctuations in price.

Individuals who wish to trade Bitcoins for dollars must do so on third-party online exchanges. These websites maintain centralized order books and account ledgers, and match buyers and sellers of Bitcoin much as the New York Stock Exchange and Chicago Board of Trade do for equities and commodities. In order to buy Bitcoin a user must wire dollars to the exchange, complete a trade on the exchange platform, and then request that the exchange transfer the Bitcoins to his wallet; in order to sell Bitcoins the user must send them to the exchange's wallet, complete a trade, and request that the exchange wire her dollars. In the context of trade conducted on exchanges, Bitcoin is often abbreviated BTC.

Because there is no centralized Bitcoin authority there has been a proliferation of exchanges competing with each other for business. In the early years of Bitcoin the trading ecosystem was dominated by a single exchange, Mt. Gox, which represented about 90 percent of BTC/USD trade volume between mid-2011 and mid-2013. However, starting in mid-2013 other exchanges started to take Mt. Gox's market-share, due in part to allegations that Mt. Gox had lost Bitcoins and was on the verge of insolvency; in February of 2014 Mt. Gox declared bankruptcy, suggesting that the rumors were true. Because Bitcoin exchanges operate without legal regulation, users who had funds stored in Mt. Gox lost them without recourse. Since the collapse of Mt. Gox, there has been no single dominant exchange. The trading data I use for my analysis is manually aggregated on the trade-by-trade level from the public trade logs of the four largest Bitcoin exchanges: Mt. Gox, Bitfinex, BTCe, and Bitstamp. This represents an improvement over most previous analyses, which only used trade data from Mt. Gox, because it helps control for idiosyncratic events that may have affected Mt. Gox's relationship to other exchanges but not the broader Bitcoin ecosystem.

Trading activity

Though Satoshi Nakamoto's paper describing the Bitcoin protocol was published in late 2009, and his reference implementation of the Bitcoin client was released shortly afterwards, Bitcoin saw very little economic activity until 2011. As late as July 2011, when the Mt. Gox online exchange started service, the total value of Bitcoins exchanged across the network was less than \$6,000 per day,[2] and the market price was less than \$0.10 per coin. Activity started to pick up with the launch of Silk Road, an anonymous online marketplace that let users exchange Bitcoin for illicit items such as drugs and weapons, in early 2011.

Interest in Bitcoin and Silk Road exploded in mid-2011 following a handful of articles in the popular media describing Silk Road as "the underground website where you can buy almost anything," and Bitcoin as the "wampum" of the Internet. (Chen 2011) This increase in media attention to, and public interest in, Bitcoin corresponded to a similarly-large increase in both price and trading activity. However, as the media moved on to other news stories, interest in Bitcoin gradually trailed off—and with it went price and trading volume (see Figures 3 - 6). This represented the first of many attention-fueled spikes in Bitcoin price and trading activity.

Following the price increase and collapse of mid-2011, trading activity in Bitcoin settled into periods of relative calm, punctuated by occasional short-lived price spikes, each of which were usually accompanied by increases in the amount attention paid to Bitcoin. However, all activity was relatively minor: the Bitcoin price would not pass its 2011 high until mid-2013. The increase in public interest of 2011 had mostly been fueled by new media outlets such as blogs and web-forums; in 2013, traditional print and broadcast media venues such as the *New York Times* and the *Wall Street Journal* started to cover Bitcoin as well, as Figure 7 shows. The price of Bitcoin, which began 2011 at less than \$15 per coin increased to over \$1200 a coin at its all-time high in mid-November 2013 (Figure 8). This was followed by a steady but drawn-out decline—as of this writing, the price of a Bitcoin is around \$250 per coin. In this paper I focus my analysis on the period between early 2011, when Bitcoin started to attract public attention, and late 2013, when the price of Bitcoin peaked.

2. The Bitcoin protocol publicly records every single transaction; this figure is approximately equivalent to money supply $\times$ daily money velocity in conventional monetary economics

II Related Research

Due to Bitcoin's novelty and the relative technical sophistication required to understand the protocol, it has been the subject of only two major economic analyses, both still in the working-paper stage: Böhme et al. (2014) and Yermack (2014). Böhme et al. provide a general introduction to the Bitcoin protocol, focusing on its potential as a replacement for existing monetary and payment systems. The authors calculate the costs of using Bitcoin for e-commerce, and find that buying goods online with Bitcoin is not necessarily cheaper than buying goods with credit cards after accounting for the rebates, rewards programs, and fraud protection, provided by the latter. They similarly find that Bitcoin's fees for international money transfers are not significantly lower than those of competing services such as Paypal or Western Union. The authors also identify several unique risks borne by users of Bitcoin, including the market risk that a user's holdings rapidly lose value due to Bitcoin's extreme price volatility, the legal risk that governments decide to outlaw the use of Bitcoin, the technical risk that a user's Bitcoin wallet is hacked, and the counter-party risk that the exchange or wallet service holding a user's Bitcoins becomes insolvent. They conclude that while the technology behind Bitcoin has promise, it does not currently offer an especially compelling advantage over other means of payment.

Yermack (2014) studies Bitcoin from the perspective of monetary economics, and comes to a similar conclusion. He finds that Bitcoin's extremely high volatility, lack of regulation, and technological barriers to entry, all prevent it from being useful as a unit of exchange or a store of value. He calculates that the BTC/USD exchange rate is over 40 times more volatile than the EUR/USD exchange rate and even more volatile when compared to the U.S. CPI. This means that consumers holding Bitcoin face significantly more uncertainty about the future value of their currency than they would holding dollars or Euros. Yermack also observes that the Bitcoin ecosystem lacks many of the institutional features businesses have come to expect from a currency, such as banks with deposit insurance, regulatory oversight, and a well-developed derivatives market. Moreover, he notes that the BTC/USD exchange rate is often not even stable between exchanges at any given time, with price dispersions of up to 10 percent between exchanges. This suggests that high transaction costs and/or withdrawal delays prevent would-be arbitrageurs from entering the market. These costs make it harder for businesses to manage the risk of transacting in Bitcoin, discouraging Bitcoin-denominated commerce. Yermack concludes that Bitcoin is more of a speculative asset than a currency, and quotes the CEO of Coinbase, the largest Bitcoin wallet service in the world, as estimating that in 2014 about 80 percent of Bitcoin trade volume was speculative, down from 95 percent a year earlier.

The economic evidence that Bitcoin's financial characteristics make it unattractive as a store of value and medium of exchange is bolstered by observational findings from researchers outside of economics which suggest that a large majority of Bitcoin traders do not buy Bitcoin with the intent to use it as currency. Glaser et al. (2014) study the relationship between the amount of Bitcoin traded on exchanges and the amount of Bitcoin transacted across the entire network. The former measure captures exclusively financial activity, while the latter captures all transactions denominated in Bitcoin. They conclude that most individuals trading in Bitcoin do not do so in order to purchase goods and services, and are instead mostly interested in financial speculation. Similar dynamics seem to apply to individuals who choose to acquire Bitcoin through mining instead of purchase: Meiklejohn et al. (2013) find that over 60 percent of Bitcoins mined have never been spent. Taken together, the accumulated evidence from past research thus establishes that only a minority of the agents involved in the Bitcoin market intend on using it as currency. Other researchers have found that there is a connection between public interest in Bitcoin and Bitcoin trading activity. Kristoufek (2013) and Garcia et al. (2014) both use vector autoregressions to show a connection between Google searches, Twitter mentions, and Wikipedia pageviews for Bitcoin and BTC price. However, both papers stop at presenting reduced-form VAR regression results: neither paper provides an economic explanation for their results, and neither paper is able to determine whether high prices lead to increased interest in Bitcoin or vice-versa.

There is has been much more economic research concerning short-sales constraints. A large body of theoretical research, beginning with Miller (1977), shows that in the presence of short-sales constraints, disagreements between investors about the expected payoff of an asset can lead to inflated prices. The simplest case involves two classes of investors, optimists and pessimists, who disagree about the terminal value of a risky asset. With a short-sales constraint in place, pessimists are unable to bet against the asset when they market price dips below their expected value, and are forced to exit the market. This results in an equilibrium price which over-represents the opinions of the optimists. Harrison and Kreps (1978) show that in infinite time the price bubble persists and includes an additional component: speculators become willing to buy the risky asset at a price above their fundamental valuation because they plan on reselling it to another agent, with whom they agree to disagree, in the future. Scheinkman and Xiong (2003) extend the formulation to continuous time, and show that disagreement can be generated from each class of agent overestimating the informational value of a signal which the other class disregards.

Hong et al. (2006) show a possible connection between disagreement, short-sales constraints and the dot-com bubble. They model an asset with lockups preventing insiders from selling their holdings until a certain date, analogous to the lockups restricting sales by pre-IPO investors in many Internet stocks. Speculators disagree about the effect the lockup expiration will have: optimists think that insiders will agree with them, and value the asset highly, while pessimists think the insiders will want to sell. In the presence of a short-sales constraint the pessimists will be pushed out of the market, and the optimistic opinion will dominate. When the lockup expires, and the actual volume of insider selling is greater than the optimists expected, the price will decrease. The authors observe that empirical evidence from the dot-com bubble is consistent with this theory: prices, turnover, and volatility of dot-com stocks all tended to drop after lockup expiration.

There is a wealth of other empirical evidence in the literature establishing a connection between short-sales constraints and speculative activity. Haruvy and Noussair (2006) show that in experimental settings imposing short-sales constraints increases price bubbles, while relaxing them decreases prices. Lamont and Thaler (2003) study equity carve-outs during the dot-com bubble and identify six provable violations of the law of one price. They find that in each case the stocks in question had unusually high costs of shorting, imposing limits to arbitrage. Similarly, Xiong and Yu (2011) find instances in which the price of put warrants traded on Chinese exchanges far exceeded their Black-Scholes values, and argue that this is related to short-sales constraints imposed on Chinese investors. They show a positive relationship between warrant turnover rates and warrant prices, which is predicted by the speculative bubble theory—because trade volume and the size of the bubble are both increasing in the amount of disagreement between pessimists and optimists—but not conventional asset-pricing theories.

There is also also a relatively large body of literature investigating attention-driven trading behavior. Standard asset-pricing theory holds that agents who have not previously traded an asset should only enter the market, and begin trading that asset, if their expectations about the expected payoff change. That is, it is usually assumed that agents form price expectations about all assets under consideration in each period, and choose to refrain from trading in an asset if and only if their expected profit is negative. The literature on attention-driven trading points out that this assumption often fails, especially for retail investors. As Odean (1999) observes, while retail investors can theoretically choose to buy any of the thousands of assets tradeable through their brokerage, they only have the time to form price expectations about a handful. In the presence of short-sales constraints, this search problem becomes asymmetric: while retail investors can buy any available asset, they can usually only sell assets which they already own. Odean suggests that retail investors solve this time-constrained search problem by focusing their buying activity on assets which have already attracted their attention, and therefore require less time to investigate.

Subsequent research has provided some empirical backing for this theory: Tetlock (2011) shows that retail investors are more likely than institutional investors to trade on "stale" news stories, where stale stories are defined as stories which are very similar to past stories, whose informational content should already be integrated into the stock price. Tetlock finds that retail investors overreact to stale news, resulting in abnormal returns which are reversed in the weeks following the stale news event. This suggests that an increase in the amount of attention paid to an asset can increase the price of that asset, even in the absence of any changes in the asset's underlying fundamentals. Similarly, Seasholes and Wu (2007) find that stocks in the Shanghai price exchange which hit daily upper price limits attract increased buying activity from retail investors, especially investors who had not previously been involved with the stock in question. Seashole and Wu argue that because stocks which hit their upper price limits experience large amounts of media attention, hitting an upper price limit serves as a useful proxy for retail investor attention to a stock. Barber and Odean (2007) also use market variables to proxy for attention: they show that retail investors are net buyers (and therefore institutional investors are net sellers) of stocks which experience unusually high volume and price changes.

III Fundamental value

As discussed previously, a large body of research has established that most agents who buy Bitcoin do so because they wish to profit from future appreciation in price, not because they wish to use it as currency in exchange for goods or services. These anticipated price increases can themselves be decomposed into two main components: increases due to future growth in demand for Bitcoin from consumers who wish to use it as a currency and increases due to future growth in demand from other investors. I denote investors who anticipate price increases of the former sort "fundamental," because they are ultimately concerned with the factors which affect Bitcoin's strength as a potential currency, and investors who anticipate price increases of the latter sort "speculative," because they are more concerned with factors which affect the price estimates of other investors. Speculative bubbles often feature large

	BTC	GBP	EUR	JPY	CHF	AUD	CAD	GLD
BTC	1.00							
GBP	-0.03	1.00						
EUR	-0.02	0.63	1.00					
JPY	-0.06	0.23	0.12	1.00				
CHF	-0.04	0.65	0.93	0.28	1.00			
AUD	0.00	0.53	0.50	0.24	0.46	1.00		
CAD	-0.02	0.47	0.47	0.12	0.45	0.63	1.00	
GLD	0.07	0.31	0.41	0.16	0.39	0.42	0.34	1.00

Table 1: Correlations between changes in the USD exchange rates of Bitcoin, major reserve currencies, and gold. Gold and the major reserve currencies all share exposure to the dollar factor, but Bitcoin does not.

numbers of these investors, each planning to resell their holdings to a "greater fool."

If speculative investors dominated the Bitcoin landscape we would expect to see idiosyncratic trading behavior driven by speculative dynamics unique to Bitcoin. By contrast, if most Bitcoin trade was carried out by fundamental investors then we would expect to see a correlation between trading activity in Bitcoin and trading activity in assets exposed to the same fundamental factors—for example, other currencies, or stocks of companies which stand to lose market-share if Bitcoin succeeds. In this section, I show that no such correlation exists. This finding supports the hypothesis that most Bitcoin trading is driven by speculative considerations.

Because Bitcoin aspires to be a major currency, one way to evaluate its asset value is through comparison with major conventional currencies. The dollar price of a Bitcoin can be thought of as a BTC/USD exchange rate; if Bitcoin is priced according to currency-market fundamentals, this exchange rate should show some relationship other dollar exchange rates. This is because all exchange rates are two-sided: the BTC/USD exchange rate is dependent on both the strength of Bitcoin and the strength of the dollar. A change in investor expectations about the future strength of the dollar—due, for example, to changes in U.S. monetary policy—should be reflected in the exchange rate between the dollar and all other currencies. As Table 1 shows, a positive correlation does appear between the dollar exchange rates of major conventional currencies, as well as the dollar price of gold, but does not extend to Bitcoin.

As an additional test, I compute the first principal component of changes in the exchange rates between the dollar and the six major currencies (see Table 4 for loadings). As Figures 15-16 show, while changes in the price of gold do correlate strongly with this component, changes in the BTC/USD exchange rate do not. These results suggest that agents involved in trading Bitcoin for dollars do not strongly consider changes in fundamentals affecting the prospects of the dollar when setting price expectations. This implies that exchange-rate expectations of Bitcoin are not driven by the same fundamental factors as the exchange-rate expectations of other currencies, or even the price expectations of assets such as gold, which behave like currencies .

In addition to analyzing Bitcoin as a currency, exposed to the same fundamentals as other currencies, we can also see it as a nascent payment system which investors are hoping will expand over time. Under this framework, the Bitcoin price should reflect investor expectations that large amounts of commerce currently transacted in dollars will eventually transition to being transacted in Bitcoin. In this case Bitcoin, which includes instantaneous transmission of value as part of its protocol, should take market-share from companies which currently specialize in expediting online transfers of dollars. To test this theory, I calculate correlations between weekly log returns and weekly changes in log volume of Bitcoin and the stocks of the three largest money-transfer companies in the United States: Euronet, MoneyGram, and Western Union. These stocks should be exposed to many of the same fundamental factors as Bitcoin, and were identified by research analysts at Bank of America Merrill Lynch as the best comparable equities when calculating a price target for Bitcoin. (Woo et al. 2014)

A strong positive correlation between returns would suggest that prices of Bitcoin and money-transfer company equities were reacting to the same market fundamentals, e.g., news that might affect the number of people seeking money-transfer services in the future; a strong negative correlation would imply that investors in money-transfer company stocks were pricing in the threat of Bitcoin as a potential competitor. In either case, there should be a strong positive correlation in weekly differences in trading volume, as investors in both Bitcoin and the stocks should be reacting to many of the same events. For example, performing a similar exercise on Netflix and Blockbuster—which represent a similar instance of an upstart technology taking market-share from an incumbent—shows a significantly positive correlation between both the returns and trading volume of their stocks.

However, as Tables 2-3 show, while the returns and trading volume of the money-transfer equities are correlated with each other, they are uncorrelated with Bitcoin. As an additional test, I calculate the first principal component of changes in returns and trading volume for the money-transfer stocks. As Table 5 shows, the loadings on these principal components all have the same sign, suggesting that the money-transfer stocks move in concert in reaction to certain factors affecting the underlying market. The first principal components explain more than half of the variance in both returns and changes in trade volume. As Tables 6-7 shows, these principal components are highly significantly correlated with returns and trade volume changes in the stocks of Mastercard, Visa, and Ebay, which are partially exposed to many of the same payment-processing fundamentals (Ebay because of its ownership of Paypal). However, there is no relationship between these principal components and returns or trade volume changes in Bitcoin.

There is a broad consensus among Bitcoin proponents, the investment community, and interested academics that in order to generate increased demand Bitcoin needs to start establish itself as either a genuinely independent currency or a major money-transfer platform. However, as shown in this section, there is no statistically significant relationship between Bitcoin trading activity and trading activity in major currencies or money-transfer company equities. This suggests that most agents involved in the Bitcoin market during its price bubble were probably not "fundamental" investors, as they were not reacting to changes in factors that would affect future fundamental demand.

	BTC	WU	EEFT	MGI
BTC	1.00			
WU	-0.09	1.00		
EEFT	0.01	0.30	1.00	
MGI	-0.00	0.27	0.23	1.00

Table 2: Correlations between (log) weekly returns on Bitcoin, Western Union (WU), Euronet (EEFT), and MoneyGram (MGI)

	BTC	WU	EEFT	MGI
BTC	1.00			
WU	0.01	1.00		
EEFT	0.04	0.32	1.00	
MGI	0.06	0.28	0.39	1.00

Table 3: Correlations between difference in (log) weekly trading volume for Bitcoin, Western Union (WU), Euronet (EEFT), and MoneyGram (MGI)

IV Attention-Driving Buying

Another way to build support for the hypothesis that the Bitcoin price bubble was due to speculative trading is to show the existence of trade patterns which rational speculators could try to anticipate and profit off of. In this section, I use a novel dataset to show that investors who had not previously purchased Bitcoins were more likely to do so for the first time on days in which Bitcoin was the subject of news coverage, even after controlling for changes in expectations about Bitcoin's fundamental value. This finding runs counter to conventional asset-pricing theory, which assumes that previously-uninvolved investors would only choose to enter the market if their expectations about Bitcoin's future payoff changed.

My results can be best understood through the framework of attention-driven buying described by Barber and Odean (2007). Many retail investors did not have the time to independently learn about Bitcoin, and so were left out of the market until informed of its existence by media reportage. Once Bitcoin had attracted retail investors' attention, they started to form price expectations, and some chose to buy in. Speculators anticipated this process and bought Bitcoin before it was well-known, essentially profiting off being aware of Bitcoin before the general public.

Data

The data I use to calculate investor inflow into Bitcoin comes from the leaked transaction log of the Mt. Gox Bitcoin exchange. This log was taken from Mt. Gox in March, 2014 by an anonymous hacker group seeking revenge against Mt. Gox after it declared insolvency in February, 2014. The logs record each trade made on Mt. Gox from its founding in April, 2011 to November, 2013, and associate a user ID with the buyer and seller in each transaction. This dataset has not been previously analyzed in the academic literature, so to ensure accuracy I have verified the leaked logs by cross-checking them with the public trade logs used in previous research, which record individual trades but do not associate trades with user IDs. On an anecdotal level, several individuals have publicly stated that their full trade history is perfectly matched with that of a user ID in the leaked data, while to my knowledge no individuals have said that their trades do not appear in the data. This suggests that the data is genuine, and suitable for use in my analysis.

Unfortunately, though the leaked data runs to November, 2013, I must restrict my analysis to the period between April, 2011 to mid-April, 2013. This is because there were reports that traders at the Mt. Gox exchange were facing withdrawal delays, and rumors that the exchange was facing insolvency, for many months before the actual collapse of the exchange in February 2014. This caused a price dispersion between Mt. Gox and other exchanges—the price of Bitcoin on Mt. Gox was artificially inflated because Mt. Gox seemed to honor Bitcoin withdrawal requests more readily than dollar withdrawal requests—and led to a decrease in the percentage of total exchange-traded Bitcoin volume transacted on Mt. Gox. In order to prevent this change in Mt. Gox's position within the broader Bitcoin ecosystem from biasing my results, I restrict my data to the period before the noticeable changes started to occur. Figures 17-18 show the problem, and establish April 15 2014 as a reasonable cutoff date.

Because the leaked data matches each trade with a buyer and seller user ID, I am able to find the date at which each user ID first appeared, which is the date on which that user first traded on Mt. Gox. I eliminate users whose first trade was a sell order, as these are likely to be miners, inter-exchange arbitrageurs, or retailers accepting Bitcoin, all of whom were probably involved in the Bitcoin market before their first trade. Because Mt. Gox accounted for well over 75 percent of Bitcoin exchange volume during the period (see Figure 17), and was widely touted as the most user-friendly Bitcoin exchange, it is very likely that for the remaining users the first trade on Mt. Gox represents the first interaction with the Bitcoin market. By summing the number of users whose first trade occurred on each date, I can therefore arrive at an estimate of the number of investors buying Bitcoin for the first time on that date. I can also measure the number of traders who decided to exit the Bitcoin market by calculating the number of users who sold all of the Bitcoin in their account on each day. This value turns out to be very low: though the number of traders involved in Mt. Gox more than doubled between 2011 and 2013, fewer than 5 percent of users ever completely liquidated their Bitcoin holdings and left the market completely. This suggests that while there was a large amount of investor inflow into Bitcoin during my period of study there was not much outflow.

As Figures 19-20 show, the distribution of the number of new traders joining Mt. Gox per day is heavily right-tailed, with a relatively low average of around 50 new traders per day, and occasional spikes of very high activity. Also of note is the number of dollars spent by new traders on their first day of trading: as Figure 21 shows, this measure follows a similar pattern. Interestingly it appears that traders who joined the market in 2013 spent more on their first day than traders who joined the market in 2011: about $1120 per trader in 2013 vs. about $440 per trader in 2011. This suggests that the demographic profile of the type of investor interested in Bitcoin might have shifted over time towards more risk-loving, or less capital-constrained, agents. Unfortunately, I have no additional sources of information about the characteristics of the Bitcoin investor base, so I am unable to more directly test this hypothesis, but if true it would provide even more of an incentive for speculators to try and anticipate future investor inflow.

I use two measures of the attention paid to Bitcoin on each day: the number of news articles published referencing Bitcoin on that day as well, and the number of Google searches for "Bitcoin" and related terms on that day. To measure news coverage, I scraped the Lexis-Nexis, ProQuest, and Thomson Reuters databases and extracted all news articles referencing Bitcoin in their text. Between them, these databases cover articles from the *New York Times*, the *Washington Post*, the *Financial Times*, Reuters, and the *Wall Street Journal* (see Table 8 for the number of articles from each source). In order to eliminate articles which merely mentioned Bitcoin in passing, I restricted my analysis to articles which mentioned "Bitcoin" or "Bitcoins" at least twice in the body of the text. Unlike commonly-traded equities, for which news coverage can often be divorced from financial coverage, I can be confident that any news coverage of Bitcoin as a subject will be related to its behavior as an asset: while it is possible that a news story mentioning a publicly traded company such as "Toyota" may be concerned with that company's products and not its equity value, with Bitcoin the product is identical to the asset. This makes news coverage a uniquely good measure of the attention paid to Bitcoin as an asset.

In order to measure Google searches for "Bitcoin", I use the Google Trends platform, which publishes data showing the frequency of searches for a given term over a specified period. Because Google Trends only provides data at a weekly resolution for time spans longer than three months, and normalizes search frequencies to a scale of 0 to 100 for the given time period, I use a chaining method adapted from Kristoufek (2013) to reconstruct a normalized daily series from successive overlapping three month intervals. The resulting index is roughly linear in the number of searches, but unfortunately Google provides no way to estimate the actual number of searches corresponding to each index value. Figure 22 shows the evolution of this search index over the period under consideration.

Analysis

In order to test the hypothesis that investors who have not previously traded Bitcoin are more likely to buy it on days in which Bitcoin attracts large amounts of attention, I regress daily new investor activity—as measured by the number of new investors entering the market on any given day, and the number of dollars spent by new investors on that day—on the daily attention paid to Bitcoin, as measured by searches and news articles . As Tables 9 - 10 show, attention significantly affects new investor activity across all specifications. Though a Dickey-Fuller test rejects the null hypothesis of a unit root for all the series under consideration (see Table 11), I perform an additional robustness check by taking first-differences of regressors and dependent variables; as Tables 12 - 13 show, the relationship between attention and new investor activity is still significant, showing that the results are not merely due to spurious regression.

In order to ensure that my results are well-identified, I control for observable market variables which could affect the decision calculus of an agent deciding whether or not to enter the Bitcoin market. It is conceivable that an event which causes agents to update their estimation of Bitcoin's future fundamental value—for example, the adoption of Bitcoin by a major retailer—could also lead to increased news coverage. However, this case, we would expect to see increased volume, volatility, and returns, as the rest of the market priced in the good news. Including these variables in the regression controls for this type of bias.

Previous analyses of the relationship between attention and retail investor purchases, such as Barber and Odean (2007) and Seasholes and Wu (2007), use abnormally-high trading volume and price changes as a proxy for the amount of attention retail investors pay to an asset. However, it seems likely that assets experience an abnormally-large amount of trading volume and price movement on days in which information relevant to the fundamental value of the stock is released. In this case, retail investors might rationally decide to purchase a stock because their expectations of future returns have increased. By focusing on news articles, Google searches, and trade activity by first-time traders—which would not have been specifically observable by contemporaneous market participants—I can cleanly identify the effect of attention on investor inflow.

These regressions show that even after controlling for changes in expectations about the "fundamental" price of Bitcoin, the mere existence of news articles covering Bitcoin caused a meaningful increase in the number of investors buying in for the first time. Each additional news article corresponded to more than a standard-deviation increase in the amount of money spent by first-time traders on buying Bitcoin, and slightly less than $\frac{3}{4}$ of a standard-deviation increase in the number of new traders entering the Bitcoin market. Interestingly, when both Google searches for "Bitcoin" and the number of articles mentioning "Bitcoin" are included in the regression specification, the coefficient on the number of articles becomes much less significant, suggesting that Google searches are absorbing the effect of published articles on new-user inflow. This makes intuitive sense: it seems likely that agents who were made aware of Bitcoin's existence through reading news articles would follow-up with further online research before making the decision to buy, and much of this research activity would probably be funneled through Google searches. The results are therefore broadly consistent with the hypothesis that over time investors who had not previously known about Bitcoin learned about it through the news media, and decided to buy.

V Short-sale Constraints

Short-sale constraints—aspects of an asset market which make it more difficult for investors to go short an asset than go long—are a key component of many models of speculative assets, because they introduce a natural asymmetry between buying and selling activity. In the presence of a short-sale constraint pessimists, who believe that an asset is overvalued, have no way to bet against it, and so must exit (or never participate in) the market. The equilibrium price thus reflects the views of the optimists, often resulting in a price bubble.

There has not been much research into the issue of short-selling in the Bitcoin market: Böhme et al. (2014) note that markets which permit derivatives trading and short-selling are rare in the Bitcoin ecosystem, but do not delve into the issue further, whereas Yermack (2013) asserts that short-selling and derivatives trading is not possible with Bitcoin. However, there are services which claim to provide short-selling and derivatives-trading services for Bitcoin investors, suggesting that there might be more to the story. After investigation I conclude that Yermack and Böhme et al. are broadly correct: while one major exchange does facilitate short-sales of Bitcoin, lack of liquidity and exchange risk result in extremely high costs, which introduce a meaningful asymmetry between going long and short on Bitcoin.

There is only one major exchange platform which lets Bitcoin traders go short: Bitfinex, a trading platform headquartered in Hong Kong, which has offered a platform for borrowing/lending both BTC and USD since mid-2013. Since then, the total value of outstanding loans on Bitfinex has averaged over $4 million. There are other platforms which claim to provide short-selling services, but upon investigation all turned out to have negligible volume and liquidity. Bitfinex, which also hosts one of the largest conventional Bitcoin exchanges in the world, lets traders lend Bitcoins in their trading account to those who wish to short the asset in exchange for a daily interest rate (Figure 9), which has averaged an value-weighted average annualized rate of 14 percent since June of 2013.[3] By comparison, D'Avolio (2002) re-

3. I am grateful for Bjorn de Wolf of Bitfinex for providing me with historical data concerning Bitcoin

ports that the borrowing cost of shorting the average U.S. equity is about 0.6 percent per year; even the most expensive 9 percent of stocks, which D'Avolio designates as "special" stocks, with a uniquely high cost of shorting, have an average annualized interest rate of 4.69 percent. The provably overpriced equities identified by Lamont and Thaler (2006) experienced maximum monthly borrowing costs of 10-50 percent (annualized); the maximum monthly borrowing cost for shorting Bitcoin on Bitfinex was 42 percent (annualized), and annualized rates were higher than 10 percent for about half of 2013. Bitcoin thus falls squarely within the range of assets for which price discovery is meaningfully hampered by high costs of shorting.

In addition to paying high borrowing costs, traders who wish to short Bitcoin on Bitfinex must shoulder substantial exchange risk—I show that this implicit exchange risk actually outweighs the already-high explicit price of shorting. Short-sellers are not allowed to withdraw their dollars from Bitfinex until after their short-sale contract closes out, so they are forced to assume the risk that exchange will fail, and take their earnings with it, in the interim. There is a long history of Bitcoin exchanges failing without warning, especially during market downturns—Moore and Christin (2012) find that 46 percent of all Bitcoin exchanges have collapsed—so there is no guarantee that pessimistic traders would be able to collect their gains in the event of a collapse in the price of Bitcoin. The counterparty risk is heightened by the lack of legal recourse: there have been no audits of Bitfinex, or any other Bitcoin exchange, by certified accountants, and there is no legal precedent of traders being able to recover lost assets after an exchange failure. Because Bitfinex also lets traders lend dollars to each other, for use in margin trading, I am actually able to estimate the value holders of dollars place on this exchange risk. I find that it shows evidence of a pronounced disagreement between those who own Bitcoin and those who do not.

Though Bitfinex did not formally guarantee short contracts in the case of counterparty default until March 2014, it maintained aggressive position-closing and margin-calling algorithms, as well as an optional insurance facility, which anecdotally succeeded in minimizing the risk of counterparty default for traders in short contracts. This can be shown quantitatively in the lack of a price response to the announcement that Bitfinex would guarantee all loans of both BTC and USD on March 15, 2015. As Figures 10-11 show, the market interest rates charged by lenders of BTC and USD did not change after the March 15 announcement, which was not anticipated or discussed beforehand; statistical tests also fail to reject the null hypothesis that the mean interest rate was the same before and after the announcement.

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borrowing and short-selling on Bitfinex

This suggests that an agent lending dollars to Bitcoin traders engaged in margin trading only needs to consider the exchange risk that Bitfinex might collapse leaving the agent unable to recover her money. Given that the risk-free rate for dollars has been essentially zero in the period under consideration, the entire interest rate the agent earns for lending money on Bitfinex can be attributed to the risk premium she receives for taking on exchange risk. This risk premium is enormous: the value-weighted annualized interest rate charged by lenders of dollars since June 2013 is about 66 percent, significantly higher than the rates charged for even the most distressed debt. This suggests that the average investor holding dollars—who is probably more optimistic about Bitcoin's prospects than the average individual looking to short— sees exchange risk from the collapse of the Bitfinex platform as a massive deterrent to trading, outweighing the actual published costs of going short.

Agents who hold Bitcoins and wish to lend them to short-sellers in exchange for an interest rate face the exact same situation: they receive payment in exchange for assuming the risk of an exchange collapse. It could be argued that given Bitcoin's extreme volatility, and Bitfinex's lack of an option for lenders to recall their assets before the end of the contract, lenders also forfeit a valuable option to sell their Bitcoins if the price moves against them, but comparing the average interest rate on two-day loans with the average interest rate charged on thirty-day loans shows no significant difference,[4] suggesting that traders lending out Bitcoin do not place any value on this option. Therefore, I can estimate the difference in the perception of exchange risk between those who hold Bitcoin and the general public by examining the difference between the annualized interest charged for borrowing BTC and the annualized interest charged for borrowing USD.

As Figure 13 shows, this difference is notable, averaging about 90 percentage points on a volume-weighted basis since June of 2013. This shows that there is a substantial disagreement among investors, not merely about the expected future price of Bitcoin, but also about the security of the very exchanges on which Bitcoin is traded, and that this heterogeneity in beliefs creates a situation in which the expected cost of shorting Bitcoin is too high for pessimists to bear. Perhaps for these reasons, shorting volume on Bitfinex is relatively small: since shorting was offered as a feature in April of 2013, the average number of days to cover—a measure defined as the short interest in an asset divided by its average daily volume—has been less than 0.2 (see Figure 14 for evolution over time), a very low value by the standards of equity markets. For comparison, the average S&P 500 component had a days to cover of

4. Two-day loans make up about 27 percent of the amount of BTC borrowed, and thirty-day loans make up about 55 percent

3.61 around the time of his writing, and even the safest equities usually hover around 1.

In conclusion, though there is clearly demand for a platform that would allow pessimists to enter the market and bet against the price of Bitcoin, the Bitcoin community's love of anonymity and distrust of financial regulation have historically created prohibitively high costs. In the absence of regulation sufficient volatility, compared with the fact that exchange platforms for a risky asset are usually structurally long that asset, can endogenously lead to short-sales constraint. Without the meaningful ability to sell short, pessimists who believe that Bitcoin is overvalued are forced to exit the market, harming price discovery, and possibly leading to a price bubble.

VI Speculative Anticipation and Price Bubbles

In general, the attention-driven buying observed in section IV should lead to a gradual increase in the price of Bitcoin: as the number of agents interested in Bitcoin increases, per-capita supply will decrease,[5] so equilibrium price should be pushed up. There is empirical evidence for this in the findings of Kristoufek (2013) and Garcia et al. (2014), who estimate a vector autoregression on Bitcoin data, and find that positive changes in attention paid to Bitcoin—as measured by Google searches, Tweets, and Wikipedia page views—lead to positive price changes. In this case, there should be an opportunity for speculators to buy Bitcoin ahead of attention shocks, with the intention of selling to new traders once they enter the market. In this section, I present an example in which such speculative behavior seems apparent, and construct a simple model which shows that in the presence of short-sales constraints, and speculators who disagree with each other about the precise size of an anticipated attention shock, pessimistic speculators will be forced out of the market for a risky asset, leading to a price bubble.

The model presented here builds heavily off of the model suggested by Miller (1977), and refined by Harrison and Kreps (1978) and Scheinkman and Xiong (2003) which shows that, in the presence of a short-sales constraint, investor disagreement about the future value of a risky asset can lead to inflated asset prices. As Hong, Scheinkman, and Xiong (2006) note, in such models the price bubble caused by short-sale constraints has two components:

5. While the supply of Bitcoin is technically also increasing over time it does so at a deterministic and publicly-known rate, so any increases in float should already be priced in. Moreover, by the time under consideration, the rate of Bitcoin supply growth was negligible in comparison to the size of investor inflow: the number of investors involved in Bitcoin increased by 275 percent between 2012 and 2013, while the total number of Bitcoins in circulation only increased by about 10 percent.

what they call the "optimism effect," which results from pessimists being forced to exit the market because they cannot bet against the asset, and the "resale effect," which results from speculators paying higher than their fundamental valuation of a risky asset because they anticipate being able to resell it at a profit to another agent later on.

The key insight of model I develop is that in the presence of attention-driven inflow the two effects are closely related. Speculators agree that some number of investors will be induced to join the market in the next period, giving value to the resale option, but disagree about the precise size of the inflow. In the presence of this disagreement, the short-sale constraint pushes pessimistic speculators out of the market, creating an optimism effect. The benefit of this modeling approach is that it generates both a price bubble and an ensuing pop: when the anticipated inflow happens, and is smaller than the optimistic speculators expected, the equilibrium price will decrease.

An illustrative example: *The Good Wife*

Unfortunately, due to endogeneity concerns, it is very difficult to directly test the hypothesis that price bubbles in Bitcoins are caused by optimistic speculators overestimating the number of new traders becoming aware of the asset. However, there is a fascinating example which seems to provide an illustration of the principles behind the model at work.

On January 15, 2012, the T.V. series *The Good Wife* aired an episode titled "Bitcoin for Dummies." The plot of this episode centered on Bitcoin, and featured a cameo by Jim Cramer, of *Mad Money* fame, (fictionally) endorsing it as an investment. At the time that the show aired, the Bitcoin ecosystem was extremely small, averaging around 1,100 traders and $630,000 per day. By contrast, *The Good Wife* had over 9 million viewers, most of whom were probably unaware of Bitcoin's existence: the *New York Times* review of the episode described the focus of the plot as "obscure digital currency called Bitcoin that many of the show's viewers probably assumed was fictional." (Hale 2012) If, as hypothesized, retail investors were not participating in the Bitcoin market because they had previously not paid attention to it, we would expect to see an increase in investor inflow after the episode brought attention to Bitcoin. Indeed, Google searches and Wikipedia pageviews for "Bitcoin" more than tripled immediately following the episode's airing, while the number new of traders joining Mt. Gox doubled. However, the benefits of increased attention were short-lived—investor inflow rates reverted to their normal levels within a few days.

This episode is especially interesting because would-be speculators were able to precisely anticipate the date of the attention shock. *The Good Wife*, like many T.V. shows, releases casting calls for extras in each episode, with the episode title and plot summary attached to the call. In the case of "Bitcoin for Dummies," the first online reference to the episode comes from the discussion site BitcoinTalk on November 29, 2011.[6] Over the next six weeks, the users of BitcoinTalk discussed the benefits the episode might bring to Bitcoin. As Figure 23 shows, the price of Bitcoin steadily increased during this period, peaking just before the episode's air date, and descending immediately afterwards. Perhaps most interestingly, the three accounts which bought the most Bitcoin during the month before the episode aired—together accounting for a net stake of about $214,000, approximately equivalent to a day's total trade volume—sold nearly all of their holdings in the three days afterwards. Though it is impossible to prove, it seems very likely that these users, and other optimistic speculators, bid up the price of Bitcoin ahead of the episode's air date, only to be disappointed and have the price decrease afterwards.

The model

Consider a simple three period model, with one risky asset which pays a dividend $\tilde{d}$ in period 3. There is a representative investor who only cares about consumption in period 3, and believes that $\tilde{d} \sim N(\mu_I, \sigma_I^2)$. He has CARA utility with risk-aversion parameter γ_I, and so maximizes $\mathrm{E}[W] - \frac{\gamma_I}{2}\mathrm{Var}[W]$, where W is period 3 wealth. The limited risk capacity of this investor gives the stock a downward-sloping demand curve. In period 1 the per-capita supply of the asset is Q, but in period 2 the per-capita supply decreases to $Q - \tilde{t}$ for $\tilde{t} > 0$, representing an increase in the number of investors interested in the asset. The price in period 1 is

$$p_1 = \mu_I - Q\gamma_I\sigma_I^2 \tag{1}$$

and the price in period 2 is

$$p_2 = \mu_I - (Q - \tilde{t})\gamma_I\sigma_I^2 \tag{2}$$

so the equilibrium price of the asset increases between periods 1 and 2:

$$p_2 - p_1 = \tilde{t}\gamma_I\sigma_I^2 > 0 \tag{3}$$

Now, add a speculator, also with CARA utility and risk-aversion parameter γ_S, who enters the market in period 1, liquidates her holdings in period 2, and believes that $\tilde{t} \sim N(\mu_S, \sigma_S^2)$.

6. `https://bitcointalk.org/index.php?topic=53235.0`

If the speculator purchases x_S of the asset in period 1, her expected profit from anticipating the decrease in per-capita supply is

$$p_2 x_S - p_1 x_S = \left(\mu_I - (Q - \tilde{t})\gamma_I \sigma_I^2 - p_1\right) x_S \tag{4}$$

so she will maximize

$$(\mu_I - (Q - \mu_S)\gamma_I \sigma_I^2 - p_1)x_S - \frac{\gamma_S}{2}\sigma_S^2 \left(\gamma_I \sigma_I^2\right)^2 x_S^2 \tag{5}$$

which obtains at

$$x_S = \frac{\mu_I - (Q - \mu_S)\gamma_I \sigma_I^2 - p_1}{\gamma_S \sigma_S^2 \left(\gamma_I \sigma_I^2\right)^2} \tag{6}$$

so we have the market-clearing condition

$$Q = \frac{\mu_I - p_1}{\gamma_I \sigma_I^2} + \frac{\mu_I - (Q - \mu_S)\gamma_I \sigma_I^2 - p_1}{\gamma_S \sigma_S^2 \left(\gamma_I \sigma_I^2\right)^2} \tag{7}$$

which solves to

$$p_1 = \frac{\mu_I - \gamma_I Q \sigma_I^2 + \gamma_I^2(-Q)\sigma_I^4 \gamma_S \sigma_S^2 + \gamma_I \mu_I \sigma_I^2 \gamma_S \sigma_S^2 + \gamma_I \sigma_I^2 \mu_S}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{8}$$

$$= \frac{\mu_I + \gamma_I \mu_I \sigma_I^2 \gamma_S \sigma_S^2 - \gamma_I \sigma_I^2 (Q - \mu_S) - Q\gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{9}$$

which implies that the price change from period 1 to period 2 is

$$p_2 - p_1 = \frac{\gamma_I \sigma_I^2 (Q - \mu_S) + Q\gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2 - (Q - \tilde{t})\gamma_I \sigma_I^2 - (Q - \tilde{t})\gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{10}$$

$$= \frac{\gamma_I \sigma_I^2 (\tilde{t} - \mu_S) + \tilde{t}\gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{11}$$

so that in the case in which the speculator's beliefs are unbiased, $\mu_S = \tilde{t}$, prices increase by $\frac{\tilde{t}\gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1+\gamma_I \sigma_I^2 \gamma_S \sigma_S^2}$ from period 1 to period 2, because the risk-aversion of the speculator prevents her from fully pricing in the forecasted increase in demand. A comparison to (3) shows that the addition of the unbiased speculator attenuates the price difference between periods 1 and 2:

$$\frac{\tilde{t}\gamma_I^2\sigma_I^4\gamma_S\sigma_S^2}{1+\gamma_I\sigma_I^2\gamma_S\sigma_S^2} < \frac{\tilde{t}\gamma_I^2\sigma_I^4\gamma_S\sigma_S^2}{\gamma_I\sigma_I^2\gamma_S\sigma_S^2} = \tilde{t}\gamma_I\sigma_I^2 \tag{12}$$

Next, assume that instead of a single representative speculator there are two types of speculator: optimists, who believe that $\tilde{t} \sim N(\mu_S^H, \sigma_S^2)$, and pessimists, who believe that $\tilde{t} \sim N(\mu_S^L, \sigma_S^2)$, with $\mu_S^H > \tilde{t} > \mu_S^L$ and $\frac{1}{2}(\mu_S^H + \mu_S^L) = \tilde{t}$, so that there is no net optimism or pessimism. In this case, as long as both types of speculators participate in the market, p_1 must satisfy the market-clearing condition

$$Q = \frac{\mu_I - p_1}{\gamma_I\sigma_I^2} + \frac{\mu_I - (Q-\mu_S^H)\gamma_I\sigma_I^2 - p_1}{\gamma_S\sigma_S^2\left(\gamma_I\sigma_I^2\right)^2} + \frac{\mu_I - (Q-\mu_S^L)\gamma_I\sigma_I^2 - p_1}{\gamma_S\sigma_S^2\left(\gamma_I\sigma_I^2\right)^2} \tag{13}$$

so that

$$p_1 = \frac{2\mu_I + \gamma_I\sigma_I^2\mu_S^H + \gamma_I\sigma_I^2\mu_S^L - 2Q\gamma_I\sigma_I^2 - Q\gamma_I^2\sigma_I^4\gamma_S\sigma_S^2 + \gamma_I\mu_I\sigma_I^2\gamma_S\sigma_S^2}{2+\gamma_I\sigma_I^2\gamma_S\sigma_S^2} \tag{14}$$

The pessimistic investor will want to sell the asset short at all values of p_1 greater than her expectation of the price in period 2, that is whenever

$$p_1 > \mu_I - (Q-\mu_S^L)\gamma_I\sigma_I^2 \tag{15}$$

Substituting in (14) and simplifying shows that the pessimistic investor will want to sell short whenever

$$0 > \gamma_I\sigma_I^2\left(2+\gamma_I\sigma_I^2\gamma_S\sigma_S^2\right)\left(-\mu_S^H + \mu_S^L\left(1+\gamma_I\sigma_I^2\gamma_S\sigma_S^2\right)\right) \tag{16}$$

Therefore a short-sale constraint binds the pessimistic investor, and forces her to exit the market, if and only if

$$\left(\frac{1}{1+\gamma_I\sigma_I^2\gamma_S\sigma_S^2}\right)\mu_S^H > \mu_S^L \tag{17}$$

This shows that in the presence of a short-sale constraint the pessimistic trader will exit the market whenever the difference in opinion between her and the optimist is greater than $\frac{\gamma_I\sigma_I^2\gamma_S\sigma_S^2}{1+\gamma_I\sigma_I^2\gamma_S\sigma_S^2}$. In the case that she does exit the market, the problem reverts to the initial setup with only one speculator, the optimist, so applying (9) and (11)

$$p_1 = \frac{\mu_I + \gamma_I \mu_I \sigma_I^2 \gamma_S \sigma_S^2 - \gamma_I \sigma_I^2 (Q - \mu_S^H) - Q \gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{18}$$

$$p_2 - p_1 = \frac{\gamma_I \sigma_I^2 (\tilde{t} - \mu_S^H) + \tilde{t} \gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \tag{19}$$

Because $\mu_S^H > \tilde{t}$ by hypothesis, the price change from p_2 to p_1 is negative whenever

$$-\gamma_I \sigma_I^2 (\tilde{t} - \mu_S) > \tilde{t} \gamma_I^2 \sigma_I^4 \gamma_S \sigma_S^2 \tag{20}$$

This holds whenever

$$0 > \gamma_I \sigma_I^2 \left(-\mu_S^H + \gamma_I \sigma_I^2 t \gamma_S \sigma_S^2 + t \right) \tag{21}$$

which implies

$$\left(\frac{1}{1 + \gamma_I \sigma_I^2 \gamma_S \sigma_S^2} \right) \mu_S^H > \tilde{t} \tag{22}$$

Because $\tilde{t} > \mu_S^L$ by hypothesis, this a sufficient condition for (17) to hold, and push the pessimistic speculator out of the market as well. Therefore, whenever condition (22) holds, we will observe the pessimists sitting out of the market in period 2, which leads to a price bubble that pops in period 3 when the number of new investors that enter the market is smaller than expected.

One testable implication of this model is that size of the price bubble should be increasing in the volume of Bitcoin traded. Trade occurs when speculators resell their holdings to new investors entering the market; the volume of trade is therefore proportional to the size of the inflow. As (14) shows, when both types of speculators are in the market p_1 is increasing in $\mu_S^H + \mu_S^L$, which is directly proportional to the size of the expected investor inflow. In cases where the short-sales constraint binds, and the optimistic speculator is the only type left in the market, p_1 is increasing in μ_S^H, which should also be proportional to the size of the expected inflow. A similar relationship between volume traded and the size of the price bubble is generated by Scheinkman and Xiong (2003)—in their model, which does not directly treat new-investor inflow, trade volume and the value of the resale option are linked because both are increasing in the depth of disagreement between two classes of investors.

I test this hypothesized relationship by regressing the number of Bitcoins traded per day on the volume-weighted average price of Bitcoin on that day. The number of Bitcoins traded per day corresponds to daily turnover rate, the measure suggested by Scheinkman and Xiong (2003) as well as Xiong (2011) for measuring the relationship between volume and price.[7] As Table 14 shows, I find a statistically-significant positive relationship between price and volume of Bitcoins traded. The result is also economically significant: a one standard-deviation increase in price corresponds to approximately $\frac{1}{3}$ of a standard-deviation increase in volume. I also regress the number of new users joining Mt. Gox on each day on the average price for that day; the slope is similarly positive and significant, and a one standard-deviation increase in price corresponds to slightly more than $\frac{1}{2}$ a standard-deviation increase in the number of new traders. These findings confirm a key prediction of models in which speculative behavior arises from short-sale constraints, adding support to the hypothesis that Bitcoin trading activity was driven by speculation.

VII Conclusion

This paper argues that massive price movements experienced by Bitcoin between 2011 and 2013 were the result of speculative activity. Trade variations in Bitcoin cannot be explained by changes in expectations regarding Bitcoin's fundamental strength as a currency or money-transfer platform. Furthermore, I show that gradual attention-driven investor inflow into the Bitcoin platform, and the lack of a corresponding outflow, created an opportunity for speculators to profit by anticipating the demand of future first-time buyers. In the presence of short-sales constraints, which I extensively document, speculators were likely to overestimate the size of the future influx, creating a price bubble. Close analysis of trade activity surrounding a single major anticipated attention shock, and regression results establishing general relationship between Bitcoin price and trade volume, provide empirical support for this hypothesis.

My results show that the study of speculative assets should expand its consideration of dynamics affecting the size and composition of an asset's investor base over time. The observation that speculative bubbles are often inflated by individuals who buy "hot" assets after hearing about them through the news media seems intuitively obvious, but is not extensively modeled in the theoretical literature. It would be especially interesting to endogenize attention-getting news coverage: it seems likely that news media only decide to start covering assets such as Bitcoin after they have passed a certain threshold level of popularity and

7. I do not directly calculate turnover, because it is difficult to calculate the percentage of outstanding Bitcoins which are available for trade on exchanges

importance, and that news coverage is often induced by large changes in price. This could lead to a feedback cycle in which news coverage induces new-investor inflow, which inflates a price bubble, which leads to future news coverage. However, showing this relationship empirically will require clean identification of a relationship between price increases and news coverage—in the case of Bitcoin, changes in both news coverage and price are often the result of new information which changes investor expectations of price fundamentals.

The findings of this paper also have implications for policymakers trying to prevent future speculative bubbles. Sudden increases in the amount of attention paid to an asset can serve as an indicator of speculative activity, and data from Google Trends and computer-aggregated news coverage can be used to quantify the size of these increases. Regulators could monitor indices of attention levels, and allocate more time to investigating assets experiencing large movements. I also show that regulators concerned about speculative activity in an asset should support the development of a low-cost short-sales market for that asset. Reducing short-sales constraints would allow for better price discovery by allowing pessimists to bet against the bubble. Importantly, in the case of risky assets with large differences of opinion, viable short-sales markets might not arise without regulatory intervention to mitigate exchange risk.

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Figures and Tables

GBP	EUR	JPY	CHF	AUD	CAD
0.35	0.47	0.28	0.52	0.49	0.27

Table 4: Loadings for the first principal component of exchange USD rate changes. All the loadings are positive, showing that the exchange rates all respond to the "dollar factor" in the same direction. This principal component explains about 50 percent of the variation in the data.

Variable	WU	EEFT	MGI
Return	0.75	0.33	0.57
Volume Change	0.44	0.48	0.76

Table 5: Loadings for the first principal component of money-transfer stock returns and volume changes. All loadings are positive, showing that the equities move together. The first principal component explains about 53 percent of the variance in the data for returns and 57 percent of the variance in the data for volume changes.

	1st principal component of money-transfer stock returns			
	(1)	(2)	(3)	(4)
Ebay Return	0.52***			
	(0.14)			
MasterCard Return		0.79***		
		(0.22)		
VISA Return			0.61**	
			(0.30)	
Bitcoin Return				−0.02
				(0.03)
Constant	−0.003	−0.01	−0.004	0.001
	(0.01)	(0.005)	(0.01)	(0.01)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression of the first-principal component of weekly log returns of money-transfer equities (WU, EEFT, MGI) on weekly log returns of Bitcoin and the stocks of MasterCard, VISA, and Ebay. The returns of other equities are related to the returns of money-transfer equities, but the returns on Bitcoin are not. Newey-West heteroskedasticity and autocorrelation robust standard errors are in parenthesis.

	1st principal component of money-transfer equity trade volume changes			
	(1)	(2)	(3)	(4)
Δ Ebay Volume	0.58***			
	(0.19)			
Δ MasterCard Volume		0.82***		
		(0.18)		
Δ VISA Volume			0.77***	
			(0.18)	
Δ Bitcoin Volume				0.11
				(0.17)
Constant	0.01	0.01	0.01	−0.002
	(0.04)	(0.04)	(0.03)	(0.05)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression of the first-principal component of changes in weekly log volume of money-transfer equities (WU, EEFT, MGI) on changes in the weekly log volume of Bitcoin and the stocks of MasterCard, VISA, and Ebay. Volume changes of other equities are related to the volume changes for-transfer equities, but volume changes of Bitcoin are not. Newey-West HAC standard errors are in parentheses.

Source	Number of Articles
Reuters	6
New York Times	4
Washington Post	11
Financial Times	13
Wall Street Journal	8

Table 8: Number of articles from each source mentioning ”Bitcoin” or ”Bitcoins” at least twice published before 4/15/2013

	Dollars Spent by New Traders		
	(1)	(2)	(3)
Articles #	$120,221.40^{***}$		$23,588.80^{*}$
	(17,201.03)		(12,757.53)
Search Index		$6,123.26^{***}$	$5,669.40^{***}$
		(406.94)	(324.92)
Daily Volatility	$26,168.93^{***}$	$6,229.98^{***}$	$5,944.01^{**}$
	(7,455.24)	(2,173.35)	(2,430.22)
Log Return	$155,276.90^{*}$	$207,131.30^{**}$	$202,492.80^{**}$
	(85,567.47)	(97,079.38)	(99,490.16)
Δ_t Trading Volume	−1,896.68	4,534.89	4,706.78
	(1,952.44)	(3,268.78)	(3,796.37)
Δ_t Transaction Volume	4,223.39	1,292.36	2,483.62
	(4,639.22)	(2,726.64)	(3,000.49)
Time Trend	100.13^{**}	27.27^{**}	24.46^{*}
	(42.69)	(13.55)	(13.30)
Constant	$-1,556,930.00^{**}$	$-436,745.30^{**}$	$-392,544.60^{*}$
	(668,632.40)	(210,122.80)	(205,689.50)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Regression of the dollars spent by first-time traders on each given day on measures of attention. Newey-West HAC standard errors are in parentheses.

	Number of new traders		
	(1)	(2)	(3)
Articles #	50.97^{***}		-14.84
	(10.84)		(17.99)
Search Index		3.58^{***}	3.86^{***}
		(0.58)	(0.87)
Daily Volatility	18.90^{***}	4.94	5.12
	(5.77)	(3.34)	(3.61)
Log Return	18.92	48.16	51.08
	(72.44)	(62.79)	(68.15)
Δ_t Trading Volume	-2.27	2.33	2.22
	(1.89)	(1.72)	(1.67)
Δ_t Transaction Volume	3.31	2.88	2.13
	(3.26)	(2.13)	(1.78)
Time Trend	0.06^{*}	0.003	0.004
	(0.03)	(0.02)	(0.02)
Constant	-830.88^{*}	-10.05	-37.86
	(456.67)	(358.68)	(339.42)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10: Regression of the number of first-time traders on each given day on measures of attention. Newey-West HAC standard errors are in parentheses.

Variable	τ
Number of New Traders	-3.99
USD Volume by New Traders	-7.85
Number of Articles Mentioning Bitcoin	-10.06
Search Index	-5.73

Table 11: Augmented Dickey-Fuller test statistics for tests of the null hypothesis that variables follow a unit-root process against the alternative hypothesis of stationarity. The critical value for 1% significance is -2.58 (p is decreasing in τ)

	Δ_t Dollars Spent by New Traders		
	(1)	(2)	(3)
Δ_t # of Articles	$95,868.36^{***}$		$91,669.68^{***}$
	(36,638.56)		(30,852.63)
Δ_t Search Index		$4,476.05^{***}$	$3,275.29^{*}$
		(1,550.45)	(1,879.53)
Daily Volatility	−1,843.35	270.31	−2,701.15
	(3,205.65)	(2,087.00)	(3,293.90)
Log Return	255,800.30	309,851.10	256,436.80
	(207,867.30)	(212,898.50)	(208,631.00)
Δ_t Trading Volume	16,217.97	$12,711.00^{*}$	14,650.07
	(11,404.64)	(6,581.74)	(11,139.57)
Δ_t Transaction Volume	2,778.93	−4,151.70	1,063.41
	(8,214.27)	(10,365.66)	(7,988.92)
Time Trend	−4.41	−0.76	−8.41
	(14.70)	(6.90)	(12.36)
Constant	65,275.73	16,669.69	130,373.80
	(230,112.10)	(107,082.60)	(193,587.00)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Regression of the first-difference of the dollars spent by first-time traders on each given day on first-differences of measures of attention, included as a robustness check against spurious regression. Newey-West HAC standard errors are in parentheses.

	Δ_t # of New Traders		
	(1)	(2)	(3)
Δ_t # of Articles	23.75***		21.58***
	(8.20)		(4.91)
Δ_t Search Index		1.98***	1.70***
		(0.50)	(0.21)
Daily Volatility	1.82	2.07	1.37
	(1.71)	(1.64)	(1.06)
Log Return	43.62*	56.52	43.95
	(24.81)	(57.57)	(37.66)
Δ_t Trading Volume	7.72***	6.45**	6.91***
	(2.09)	(2.87)	(2.34)
Δ_t Transaction Volume	2.65	0.54	1.76
	(3.07)	(3.56)	(3.02)
Time Trend	0.01	0.01	0.003
	(0.01)	(0.004)	(0.003)
Constant	−79.93	−72.96	−46.20
	(93.76)	(63.03)	(49.36)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 13: Regression of the first-difference of number of first-time traders on each given day on first-differences of measures of attention, included as a robustness check against spurious regression. Newey-West HAC standard errors are in parentheses.

	Dependent variable:	
	# of BTC Traded	# of New Traders
	(1)	(2)
Bitcoin Price	672.53^{***}	1.90^{***}
	(128.51)	(0.19)
Constant	$44,519.39^{***}$	27.12^{***}
	(4,447.11)	(5.97)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 14: Regression showing a significant relationship between Bitcon price and measures of both trade volume and the change in per-capita asset supply. I remove one extremely high-leverage point related to volume spikes around technical issues experienced by Mt. Gox on April 12, 2013; the slope coefficients in both regression are both positive and significant at the 1 percent level when this point is included in the regression. Newey-West HAC standard errors are in parentheses.

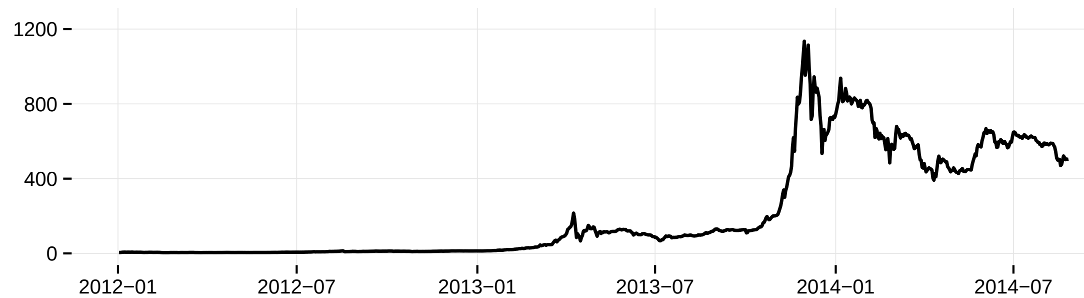

Figure 1: Bitcoin price ($) over time

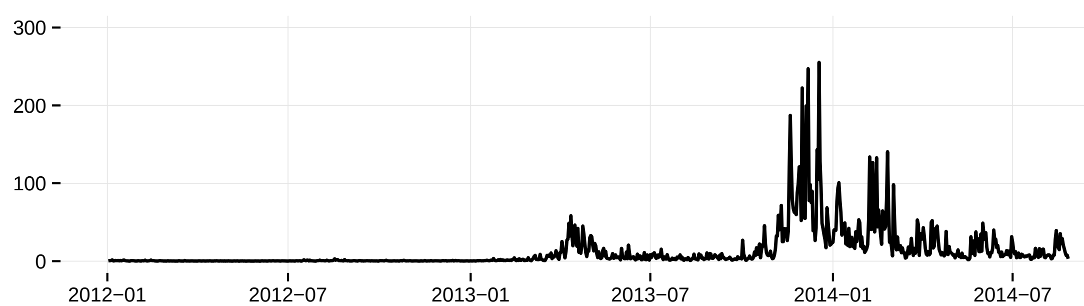

Figure 2: Bitcoin volume traded ($M) over time

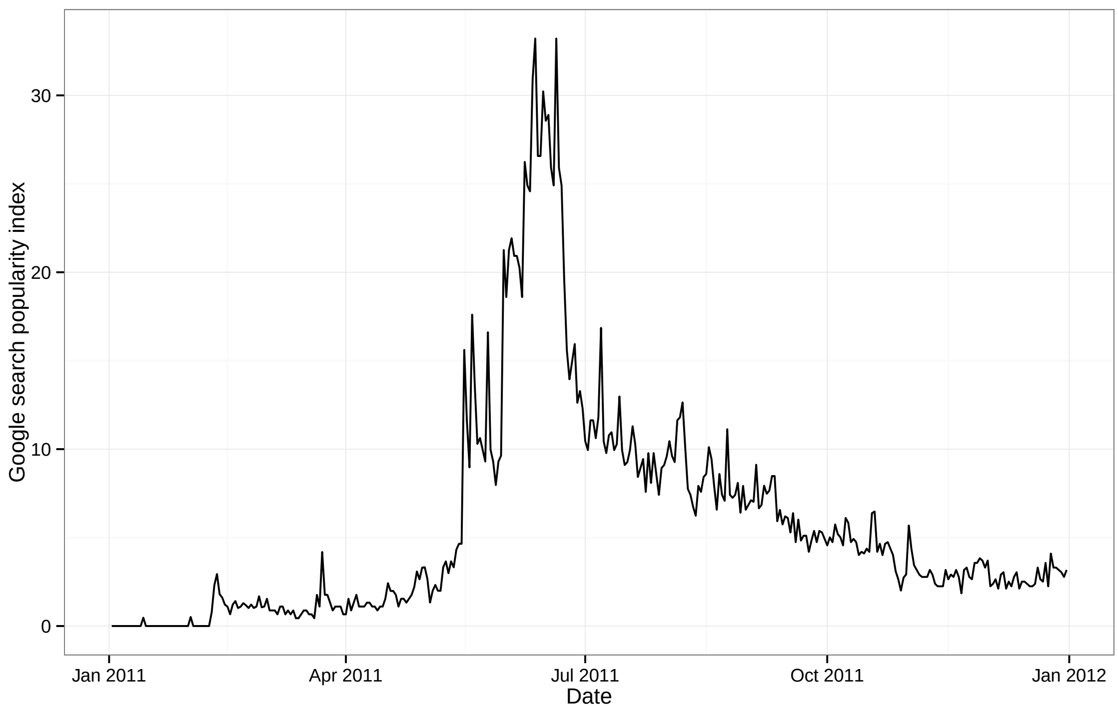

Figure 3: Google searches for 'Bitcoin' in 2011

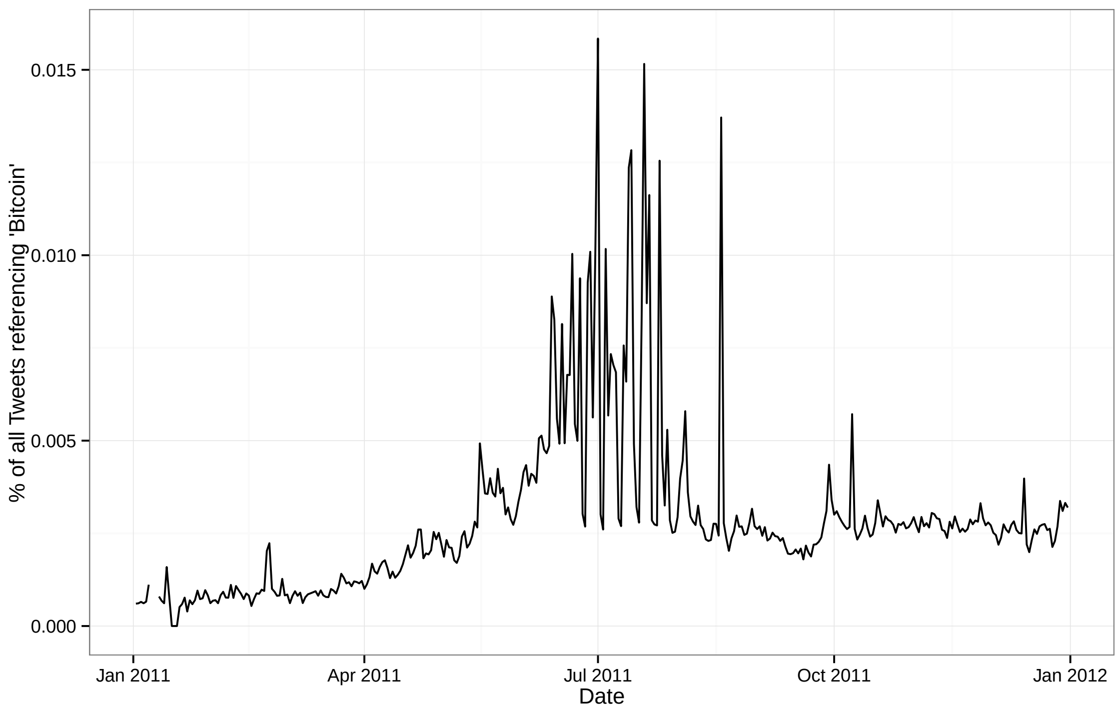

Figure 4: Tweets mentioning 'Bitcoin' in 2011 (% of all tweets)

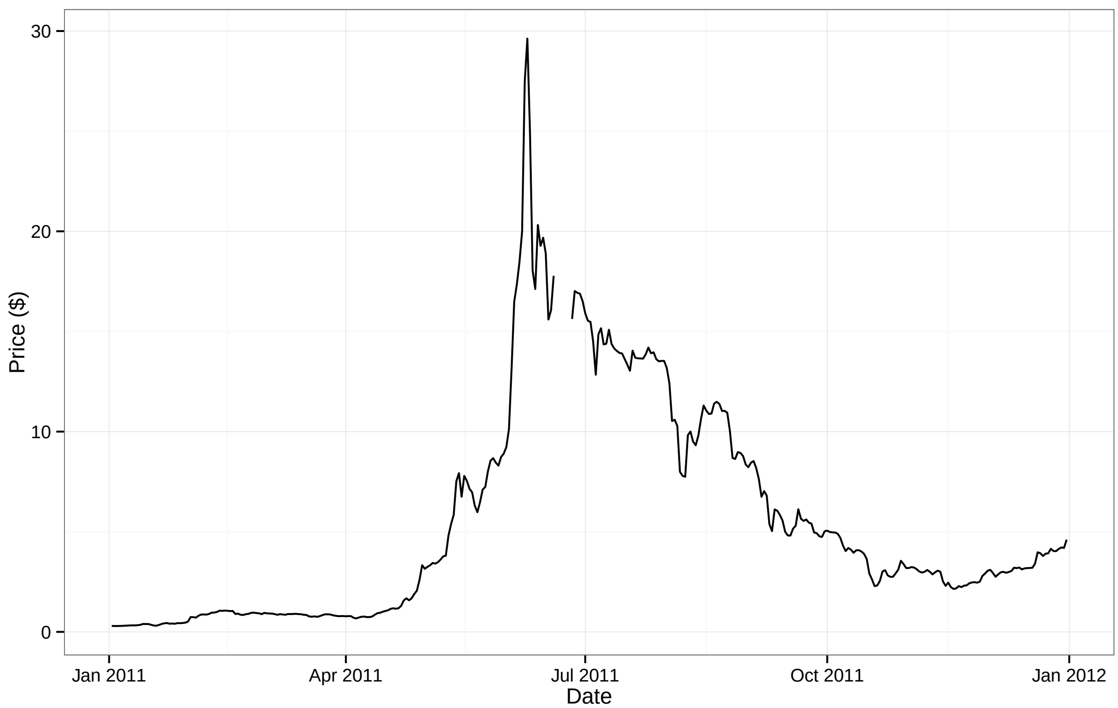

Figure 5: Bitcoin price in 2011

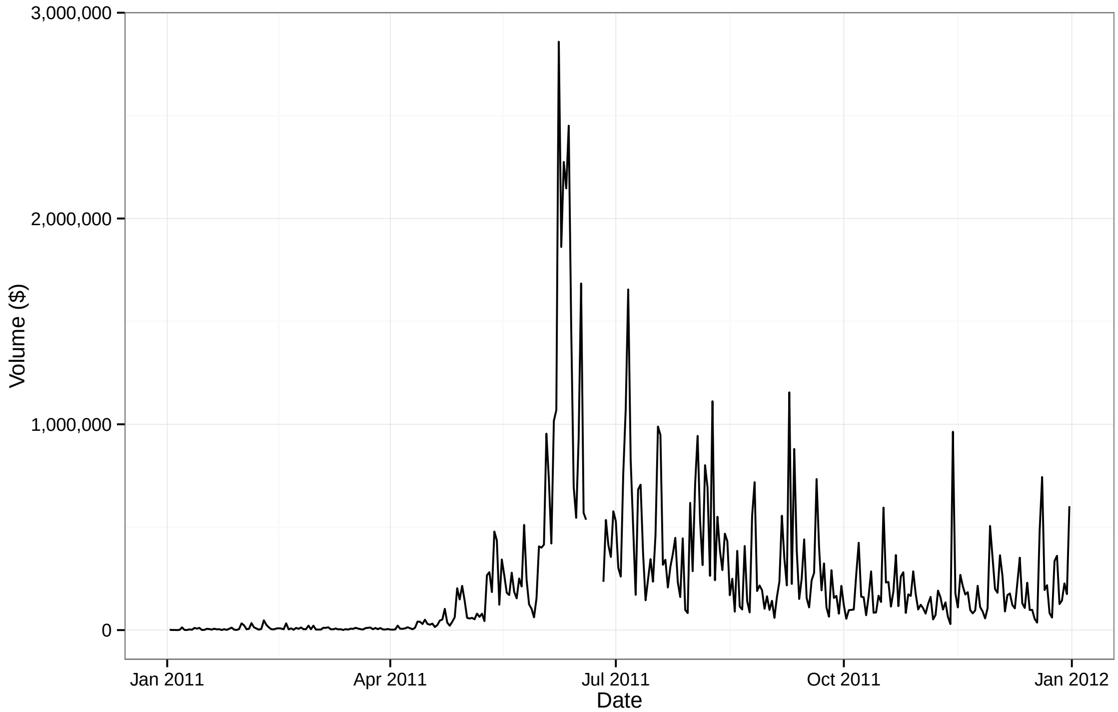

Figure 6: Bitcoin volume in 2011

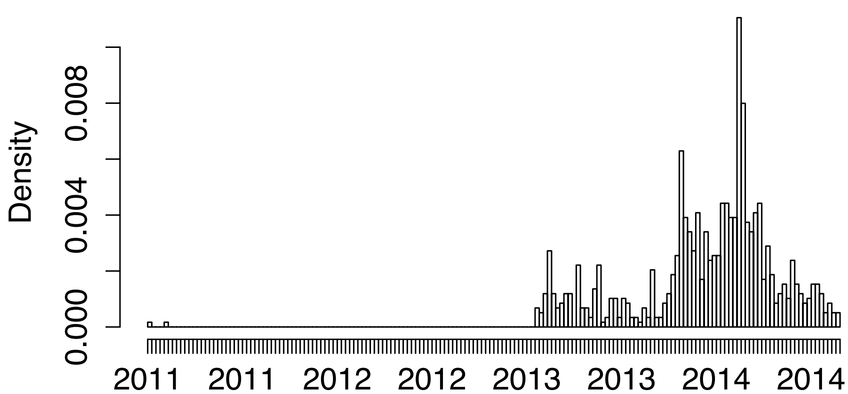

Figure 7: Histogram of news articles in print-media sources (New York Times, Financial Times, Wall Street Journal, Reuters, and Washington Post) mentioning Bitcoin at least 5 times by week

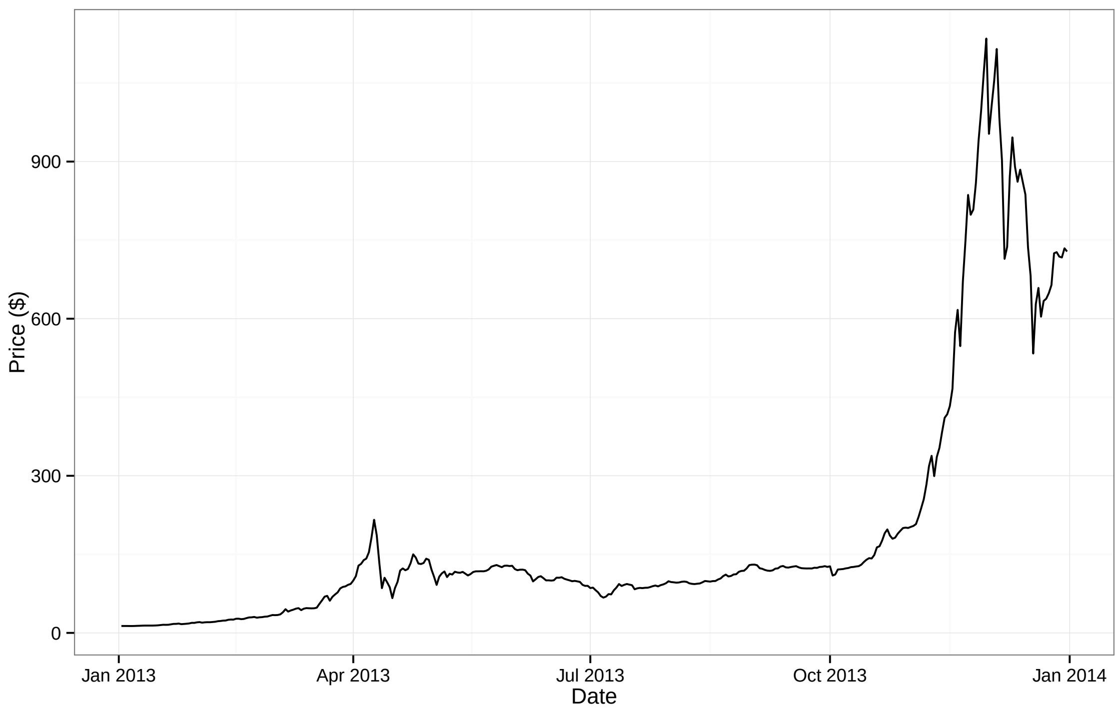

Figure 8: Bitcoin Price ($) in 2013

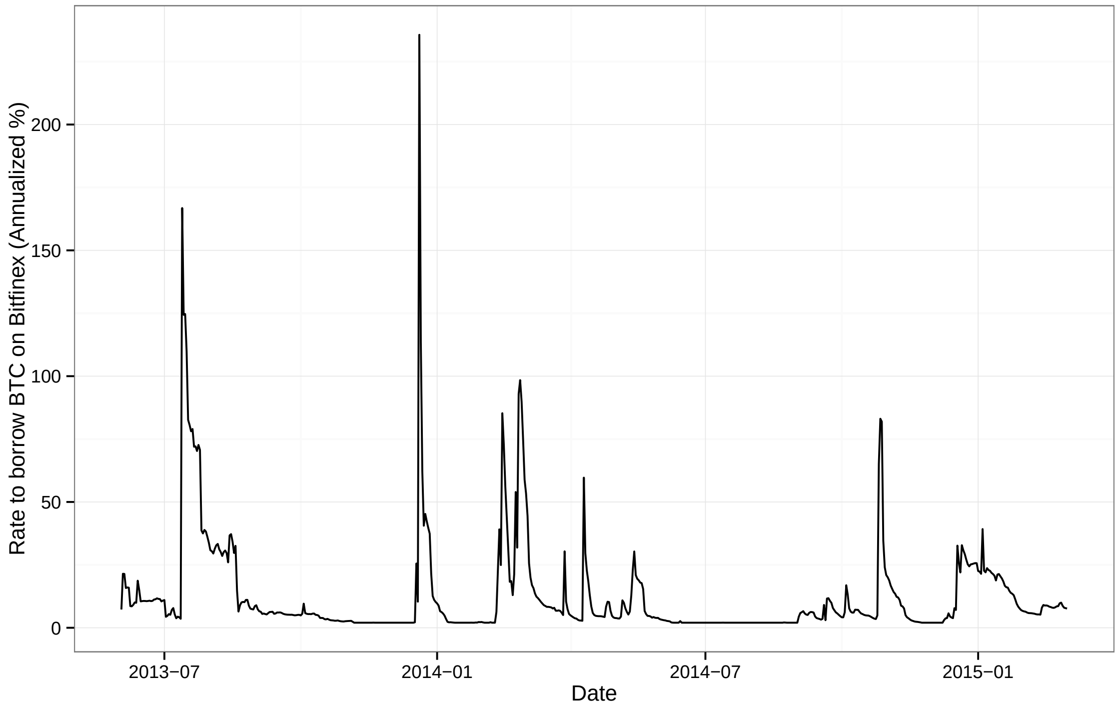

Figure 9: Annualized interest rate paid by traders shorting Bitcoin on Bitfinex

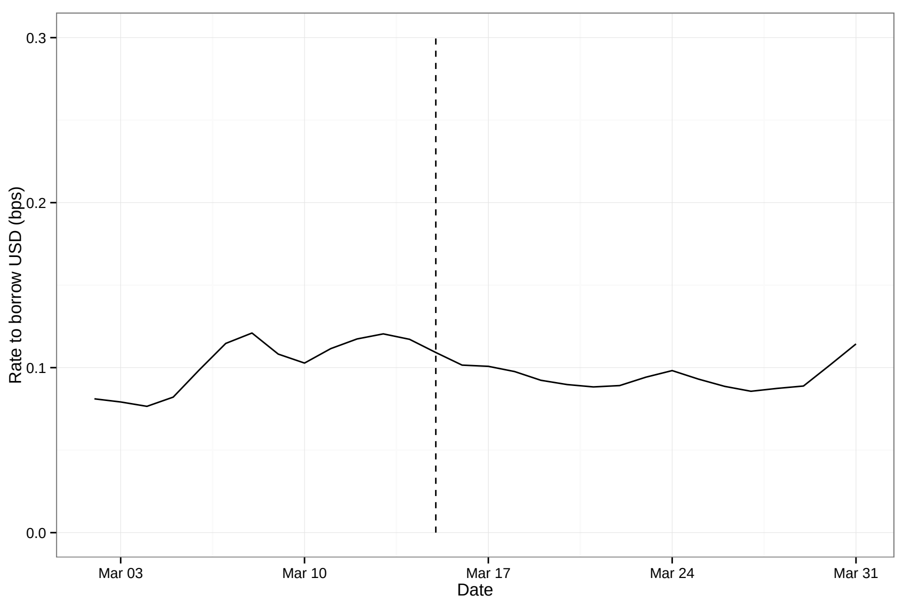

Figure 10: Interest rate on USD lent on Bitfinex for margin trading. Dotted line shows date of announcement of exchange guarantee.

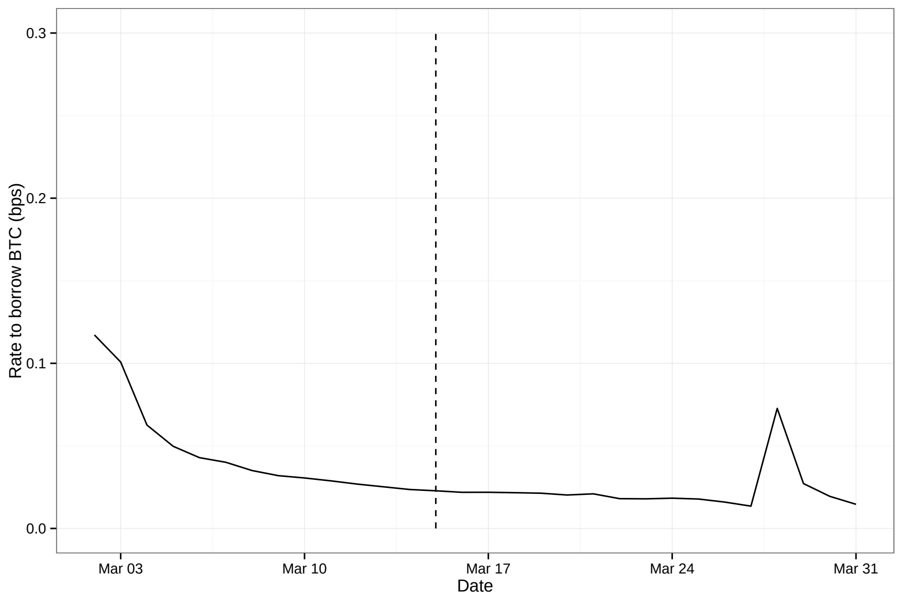

Figure 11: Interest rate on BTC lent on Bitfinex for short-selling. Dotted line shows date of announcement of exchange guarantee.

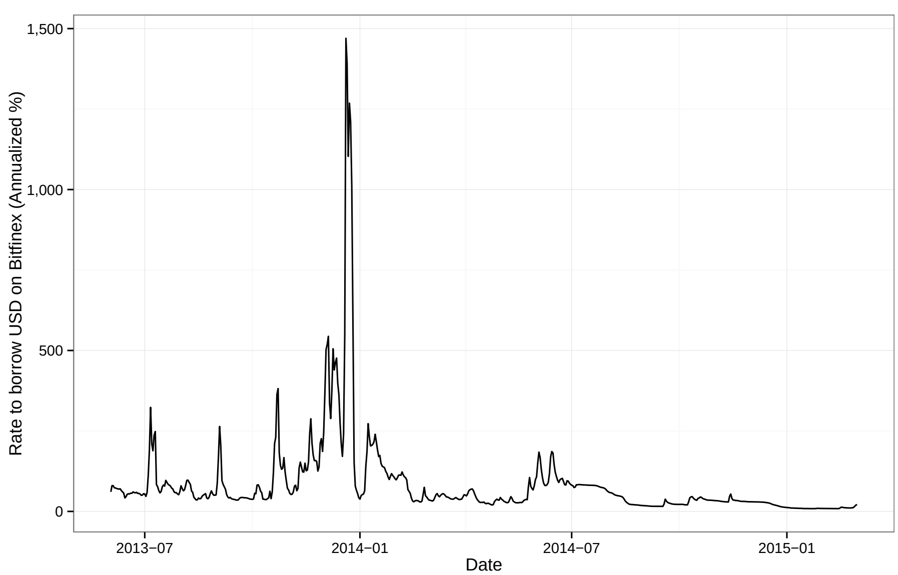

Figure 12: Annualized interest rate paid to agents who lend USD to margin traders on Bitfinex

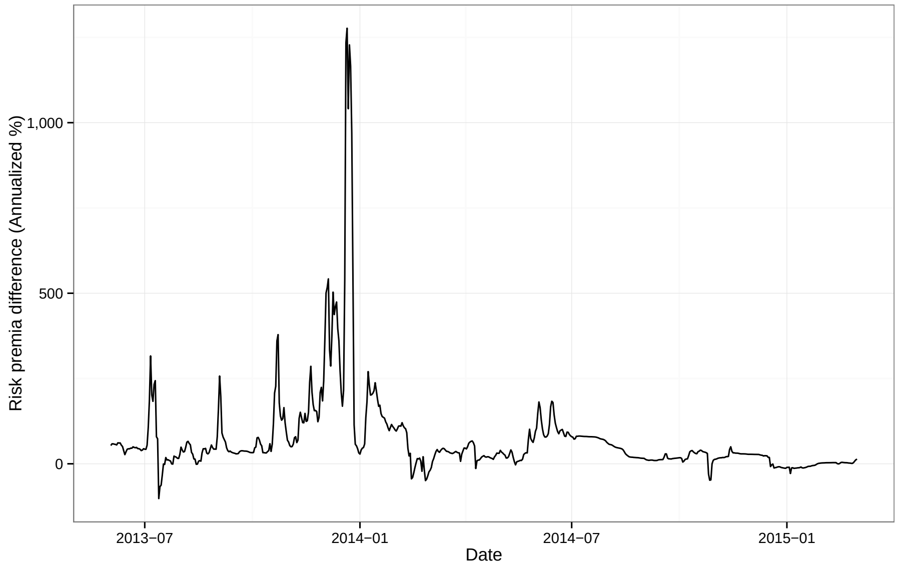

Figure 13: Difference in risk premia paid to USD lenders and Bitcoin lenders for Bitfinex exchange risk

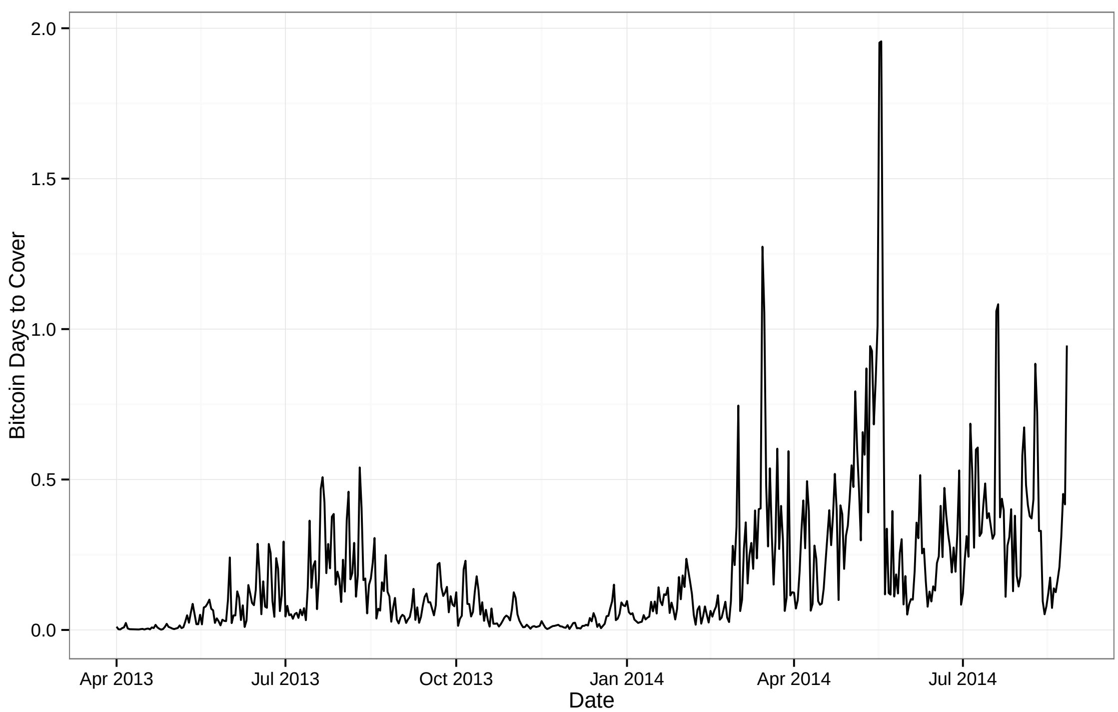

Figure 14: Bitcoin days to cover (based on Bitfinex shorts)

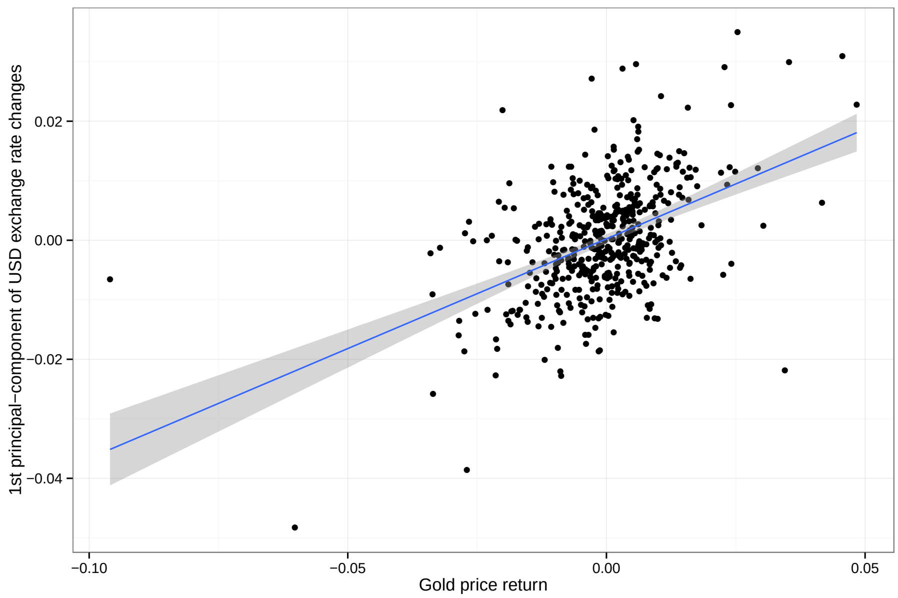

Figure 15: Plot of the first principal component of major-currency USD exchange rates against changes in the dollar price of gold. The slope of the regression line is highly significantly different from zero ($t = 11.5$)

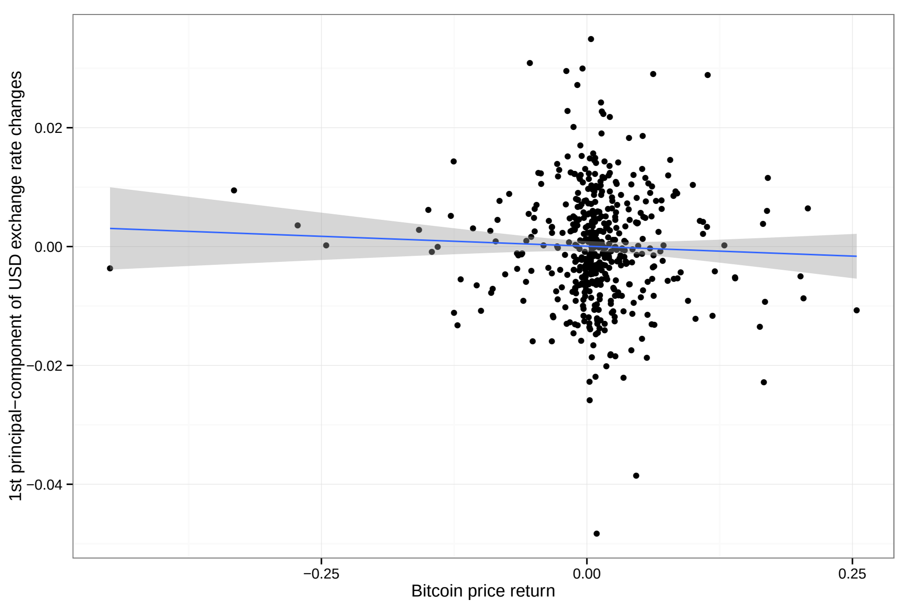

Figure 16: Plot of the first principal component of major-currency USD exchange rates against changes in the dollar price of Bitcoin. The slope of the regression line is not significantly different from zero ($t = -0.9$)

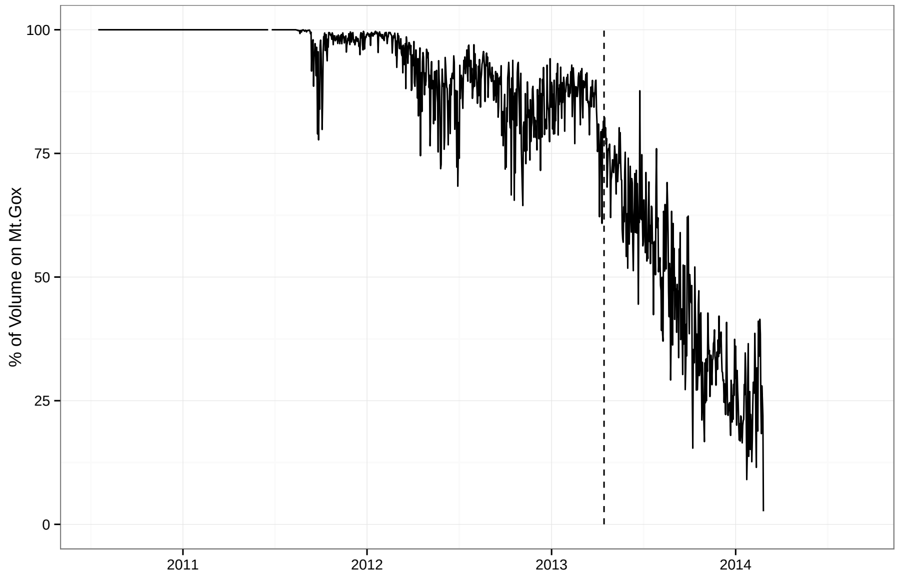

Figure 17: Percent of all Bitcoin exchange volume accounted for by Mt. Gox. Dotted line marks April 15, 2013

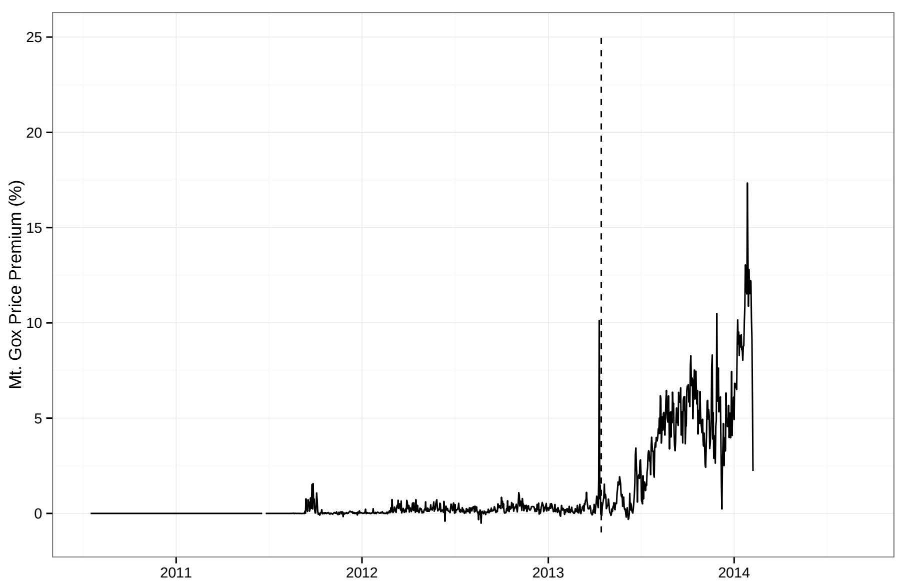

Figure 18: Price premium charged for Bitcoins on Mt. Gox vs. other exchanges. Dotted line marks April 15, 2013

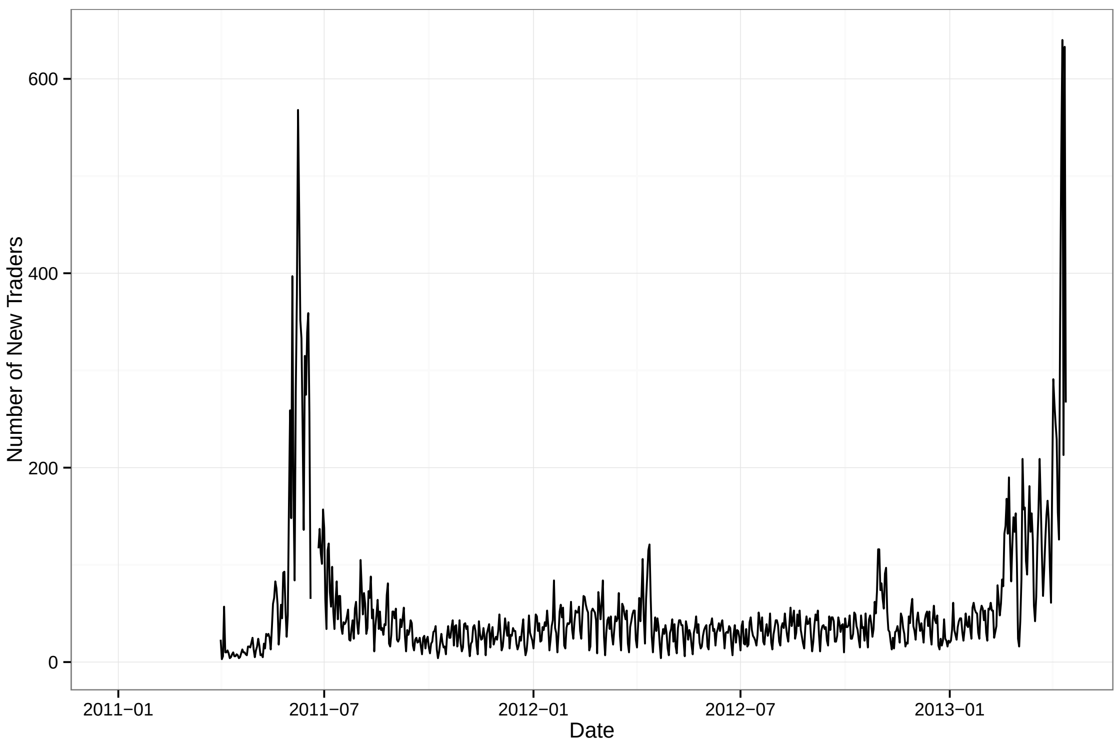

Figure 19: Number of new traders joining Mt. Gox per day

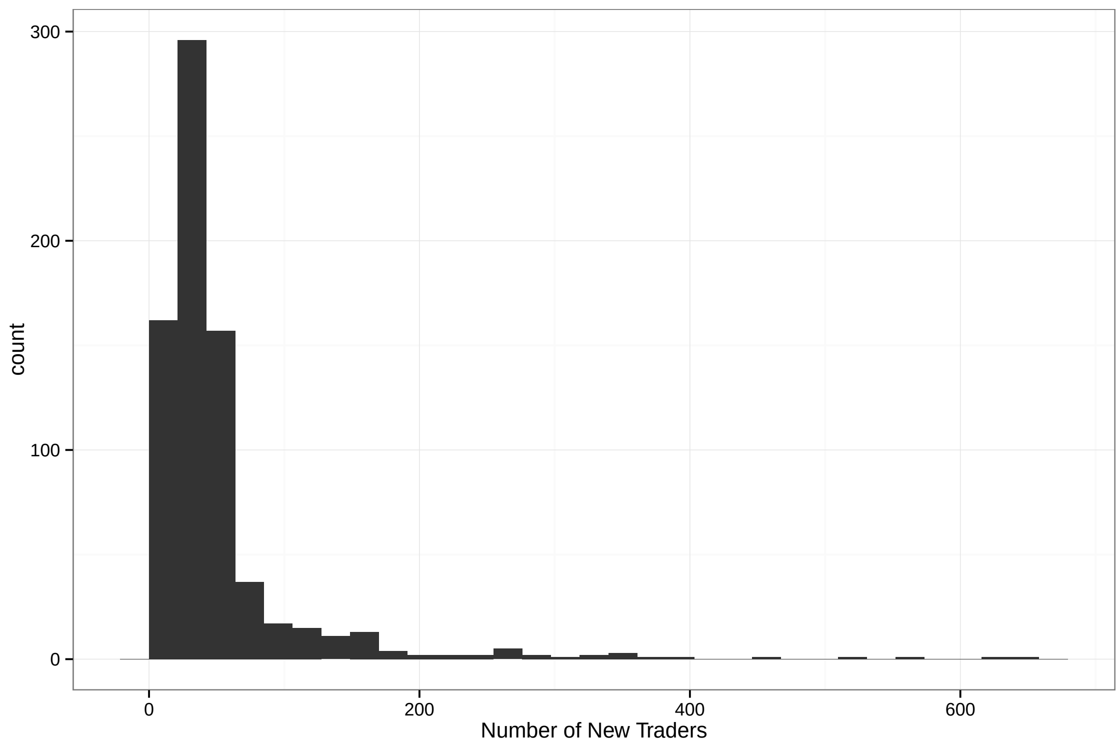

Figure 20: Distribution of number of new traders joining Mt. Gox per day

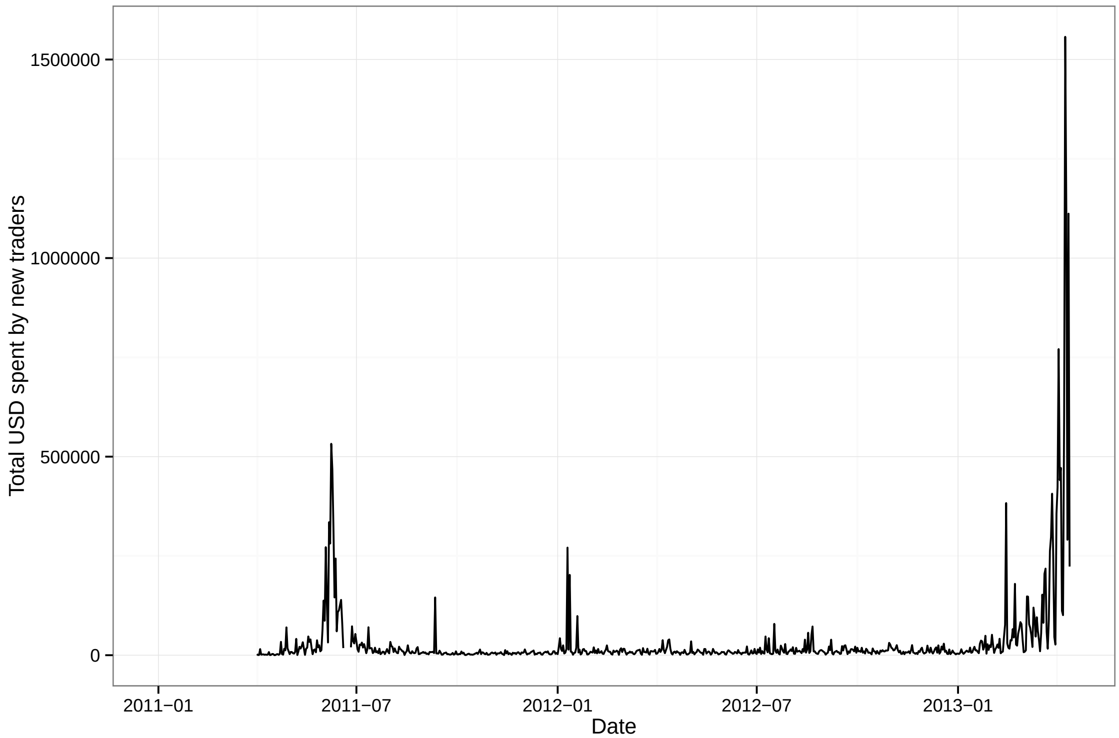

Figure 21: Growth in the dollars spend by first-time buyers joining Mt. Gox per day

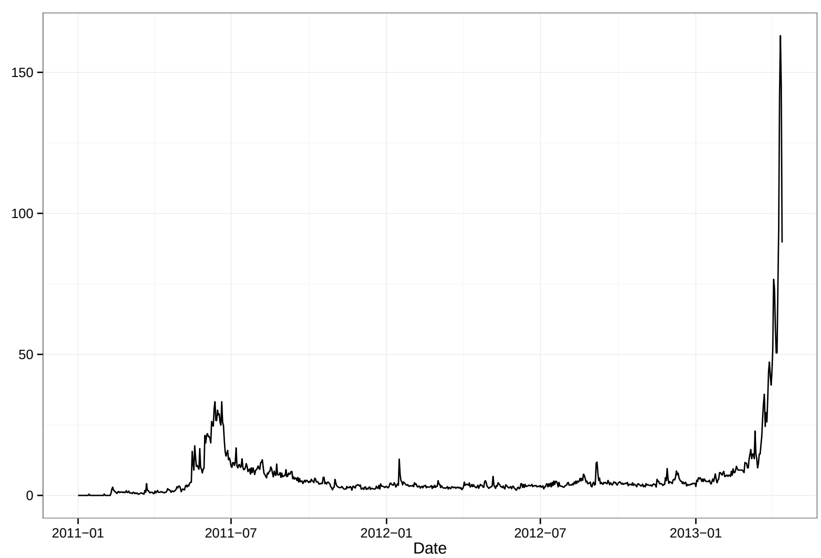

Figure 22: Google search index for searches for “Bitcoin” over time. The index value is roughly linear in the number of searches.

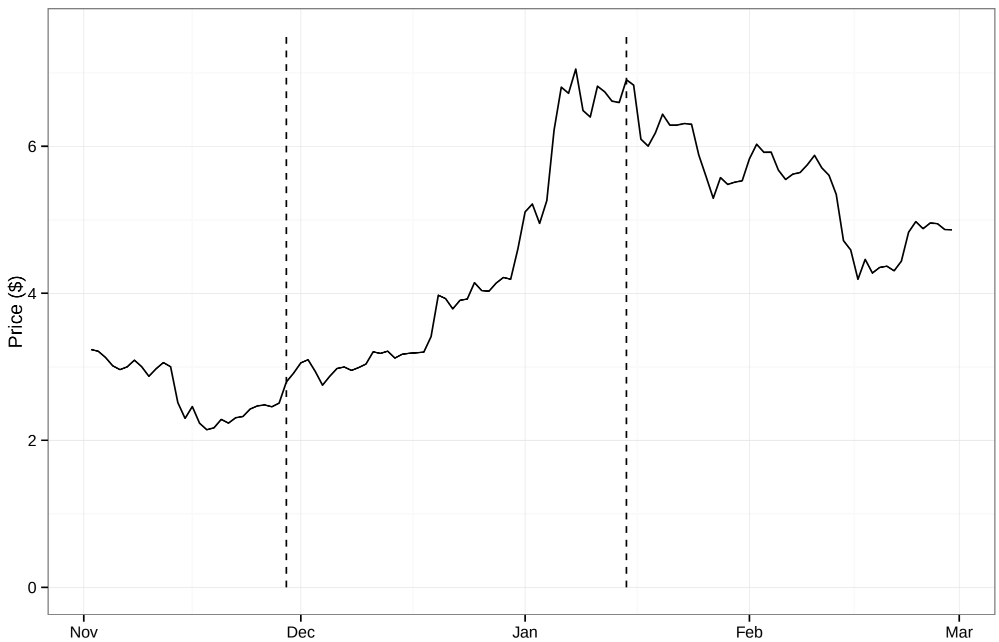

Figure 23: Bitcoin price from late 2011 to early 2012. The first dashed line marks when information about the *The Good Wife* episode "Bitcoin for Dummies" was posted to BitcoinTalk; the second marks its air date