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VIRTUAL CURRENCIES: MEDIA OF EXCHANGE OR SPECULATIVE ASSET?

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Virtual currencies: Media of Exchange or Speculative Assets?

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Abstract

This paper uses a theoretical model to analyse the dynamic relationship of virtual currency with fiat currency. The model demonstrates that the price impact of potential users and speculators in virtual currencies adversely affects their property as a medium of exchange and renders a crowding out of existing fiat currencies such as the US dollar unlikely. An empirical analysis of prices and user accounts (wallets) of Bitcoin supports the theoretical result and finds that Bitcoin is mainly used as a speculative investment rather than a medium of exchange. The analysis also shows that Bitcoin returns are uncorrelated with traditional asset classes such as stocks, bonds and commodities both in normal times and in periods of financial turmoil. Finally, we argue that the design and the size of virtual currencies such as Bitcoin do not pose an immediate risk for monetary, financial or economic stability.

Keywords: Bitcoin; virtual currency; digital currency; alternative currency; medium of exchange; asset class; safe haven

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1. Introduction

According to Nakamoto (2008), Bitcoin is a peer-to-peer electronic cash system which allows online payments to be sent directly from one party to another without going through a financial institution. This definition suggests that Bitcoin is mainly used as an alternative currency. However, Bitcoin can also be used as an asset and thus would serve a different purpose. Whilst a currency can be characterized as a medium of exchange, a unit of account and a store of value, an asset does not generally possess the first two features and can be clearly distinguished from a currency. Hence, the objective of this paper is twofold. We analyse the role and usage of virtual currencies both theoretically and empirically. We use a model with two agents, users and speculators, to analyse the question if a virtual currency is predominantly used as an asset or a currency. The empirical analysis focuses on Bitcoin, arguably the most prominent virtual currency.

Potential users of virtual currencies may be attracted by its low transaction costs, its peer-to-peer, global and government-free design and the possibility to purchase special goods (e.g. illegal drugs) for which the seller may prefer virtual currency. However, potential users may be "distracted" if the acceptability of the currency and the confidence in the system are low or if the price of the virtual currency is too volatile. The theoretical and empirical analysis focuses on the usage of virtual currencies, the interactions of users and speculators and the resulting price. A very volatile price of the currency (exchange rate) does not enhance confidence and acceptability but will rather attract speculators and further increase price volatility.

Theoretically and abstracting from the design, if Bitcoin is mainly used as a currency to pay for goods and services, it will compete with fiat currency such as the US dollar, thus influence the value of the fiat currency and ultimately influence monetary policies implemented by a central bank. If, on the other hand, it will mainly be used as an investment, it will compete with a large number of other assets such as government bonds, stocks and commodities and possibly play a minor role. Whether it is a currency or an asset, the potential influence on the economy as a whole, depends on the success of Bitcoin or similar alternatives compared to existing currencies and financial assets.

To answer the question of whether Bitcoin is a currency or an asset, we analyse Bitcoin's financial characteristics comparing them to a large number of different financial assets and investigate the usage of Bitcoins; i.e. are Bitcoins mainly used as an alternative currency to pay for goods and services or are they used as an investment? We find that Bitcoin is mainly used as a speculative investment despite or due to its high volatility and large returns. Interestingly, Bitcoin returns are essentially uncorrelated with all major asset classes in normal and extreme times which offers large diversification benefits. This low correlation also implies low risk from a macro perspective. For example, if Bitcoins showed bubble-like characteristics, a significant fall in the value of Bitcoins could be an isolated event if the correlation remained at zero and thus no other assets would be affected. If, on the other hand, Bitcoin investments were debt-financed, a significant fall in the value could lead to margin calls and then also affect other assets (e.g. see Brunnermeier and Pedersen, 2009 and Kyle and Xiong, 2001).

The paper proceeds as follows: Section 2 contains the theoretical analysis of the dynamic relationship of virtual currencies with fiat currencies. It describes a model of a virtual currency competing with fiat currency and presents the main outcomes of a simulation of the model. Section 3 presents the empirical analysis of the virtual currency Bitcoin. It uses Bitcoin returns and user accounts (wallets) to identify the statistical properties of Bitcoin and the usage of Bitcoins. Finally, Section 4 summarizes the main findings of the paper and provides concluding remarks.

2. Theoretical Analysis

2.1. Background

Historically, there are many examples of dual or multiple currency economies. There have been various commodity currencies as media of exchange including shells, cigarettes, cocoa beans, barley and many others[2]. In the middle ages, gold, silver and copper coins were often circulated simultaneously at predefined exchange rates. In the 1800s, commodity-backed monies as well as government-issued fiat currency were circulated. In the US, multiple currencies as media of exchange were common during the 1930s when privately-issued banknotes were used simultaneously with government-backed fiat and commodity-backed currency. More recently, numerous examples of dual currency economies are observed in developing and emerging economies including Liberia, Cuba and many Latin American states. Switzerland is an example of an advanced industrial country where the foreign currency euro is accepted in most parts despite the global acceptance of the Swiss franc.

[2] An example (Cigarette Money) is analyzed by Burdett, Trejos and Wright (2001).

Previously existing dual currency regimes can be classified into two types: a regime with a commodity-backed currency and a government-issued fiat currency or a regime with two different government-issued fiat currencies. Commodity-backed currencies derive their values from the underlying commodities while government-issued fiat currencies are implicitly backed by the taxation power of the government (see also Selgin, 2015). However, virtual currencies open up a new type of dual currency regime in which two currencies with no intrinsic value, virtual currency and fiat currency, coexist.

When there are multiple currencies in an economy, Gresham's law states that any circulating currency consisting of "good" and "bad" money (both forms required to be accepted at equal value under legal tender law) quickly becomes dominated by the "bad" money (see Bernholz and Gersbach 1992). This is commonly stated as "Bad money drives out good". Here, good money is defined as money that shows little difference between its nominal value and real value.

In contrast, Rolnick and Weber (1986) theoretically investigated the possibility that bad money would drive good money to a premium rather than driving it out of circulation entirely. Although Rolnick and Weber (1986) ignored the influence of legal tender legislation which requires people to accept both good and bad money as if they were of equal value, the experiences of dollarization in countries with weak economies and currencies may be seen as Gresham's Law operating in its reverse form and support the findings of Rolnick and Weber (1986) since the dollar has often not been legal tender in such situations, and in some cases its use has been illegal (see Guidotti and Rodriguez, 1992). Mundell (1998) also explains that in the long-run the reverse of Gresham's Law holds and that strong or "good" currencies, such as the US dollar, drive out bad currencies.

More recent research regarding dual currency regimes has focused on analysing extreme cases, either complete dollarization or an economy with only domestic currency (see Chang and Velasco, 2001, Cooley and Quadrini, 2001, Schmitt-Grohe and Uribe, 2000). The analysis of a fiat currency and a virtual currency in one economy or system can also be regarded as an extreme case as the former is a centralized and government-backed currency and the latter is a decentralized and independent currency.[3] The next section describes and analyses such a system and investigates the potential crowding-out effects of fiat currency by virtual currency.

2.2. A Heterogeneous Agent Model of Fiat and Virtual Currency

The model describes an economy that is populated with two types of agents, currency speculators and currency users.[4] Both types can switch from fiat currency (FC) to the virtual currency (VC) and from the virtual currency to the fiat currency. There is no explicit and direct switching from a speculator to a user or from a user to a speculator but an implicit switching from the fiat currency to the virtual currency and vice versa.

We assume that there are considerably more participants (users and speculators) in FC than in VC and that users affect the demand for a currency and its price. The number of participants in FC is *NFC=100,000* and the number of participants in VC is *NVC=10*. The two numbers are arbitrary and not important for the model outcomes, i.e. different values do not affect the main findings. What matters is the relative small number of participants (users and speculators) in virtual currency compared to fiat currency.

We assume the following switching rules for speculators and users. Speculators switch from FC to VC if there is a positive price trend of VC and speculators switch back to FC if there is a negative price trend due to short-sale constraints in VC. Potential users of VC as a medium of exchange are attracted by a relatively stable price of VC and thus switch from FC to VC if the volatility in the price of VC is relatively low (below a predetermined threshold). They reverse their trade and switch back if the price drops significantly. In other words, speculators and users switch back from VC to FC if the conditions that caused the switch are not met after a certain period of time.

The switching causes the number of participants in FC and VC to change and influence the price of the currencies especially the price of the virtual currency due to its smaller size. We assume that an increased (decreased) number of participants increases (decreased) the demand for the currency and changes its price depending on the supply of the currency. We also assume that any change in the number of participants in one currency equals the change

[3] The European Banking Authority defined virtual currency as "a digital representation of value that is neither issued by a central bank or a public authority, nor necessarily attached to a fiat currency, but is accepted by natural or legal persons as a means of payment and can be transferred, stored or traded electronically.

[4] The modelling is inspired by heterogeneous agents models as outlined in Brock and Hommes (1997), Day and Huang (1990), Farmer and Joshi (2002) and He and Westerhoff (2005).

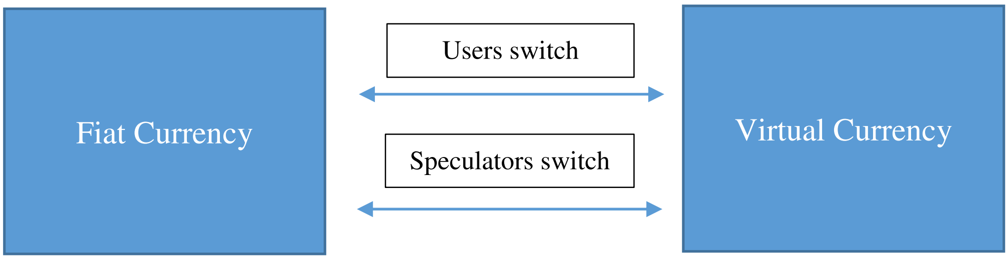
in the number of participants in the other currency. For example, if n participants switch from the FC to the VC, the number of participants decreases in FC by n and increases in VC by n.

The supply of the FC is assumed to increase by one unit in each period and the supply of VC is assumed to increase by one unit in the first period and at a decreasing rate in all future periods. The growth at a decreasing rate is inspired by the predetermined growth path of Bitcoin.

Prices in FC and VC are initially set equal to one.

The core of the model is presented in Exhibit 1 and a formal description of the model is outlined below.

Exhibit 1: Participants (users and speculators) in fiat currency and virtual currency



The supply of FC and VC follows the processes given by

$$S_{FC,t} = S_{FC,t-1} + 1 \quad (1)$$

$$S_{VC,t} = S_{VC,t-1} + (1 - t/T) \quad (2)$$

where T is the future date at which there is no growth of the supply of VC.

Potential users and speculators of VC base their decision to buy or sell units of VC on changes in the price

$$dP_{VC,t} = P_{VC,t-1} - P_{VC,t-lag} \quad (3)$$

The number of speculators present in VC changes according to the indicator variable I as follows

$$I_t = 1(dP_{VC,t} > \text{threshold}) - 1(dP_{VC,t} < \text{-threshold}) \quad (4)$$

$$N_{spec,t} = N_{spec,t-1} + I_t \quad (5)$$

Potential users of VC are assumed to focus on VC's characteristic as a medium of exchange and thus price stability;

$$vol_{dPVC,t} = 1(|dP_{VC,t}| < threshold) - 1(dP_{VC,t} < -threshold) \quad (6)$$

$$N_{user,t} = N_{user,t-1} + vol_{dPVC,t} \quad (7)$$

$$dN_{VC,t} = dN_{spec,t} + dN_{user,t} + \varepsilon_t \quad (8)$$

$$\varepsilon_t \sim N(0, threshold) \quad (9)$$

The price of VC is given by

$$P_{VC,t} = P_{VC,t-1} + b\,(dN_{VC,t} - dS_{VC,t}) \quad (10)$$

and the change in the participants in FC is determined as follows

$$dN_{FC,t} = -dN_{VC,t} \quad (11)$$

Finally, the price of FC is determined by

$$P_{FC,t} = P_{FC,t-1} + c\,(dN_{FC,t} - dS_{FC,t}) \quad (12)$$

The model is mostly deterministic as only the change in the number of virtual currency users (dN_{VC}) contains a random shock.

2.3. Simulation Results

The model is simulated for 100, 250, 500 and 10,000 periods. Figures 1 and 2 present two exemplary simulation outcomes for T=250 and T=500, respectively. The graphical simulation results show four time-series plots: (i) the price of VC, (ii) the relative weight of speculators, (iii) the absolute number of speculators and (iv) the absolute number of users.

Figures 1 and 2 show significant variations of all four series with the price of VC increasing from one to more than 600, the weights of speculators ranging from zero to one and the number of speculators and users constantly changing. The large price variation from a starting value of 1 to a maximum value above 600 is consistent with a speculative asset. Similar price changes have been observed for the most prominent virtual currency, Bitcoin.

Figure 1: Simulation of price of VC, weight of speculators, number of speculators and number of users in VC

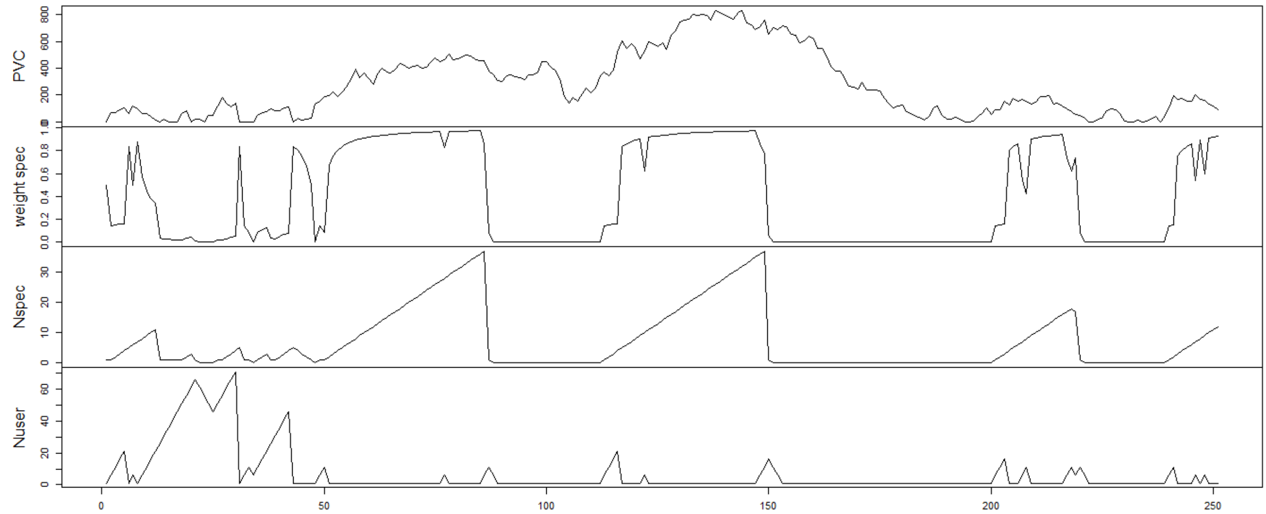
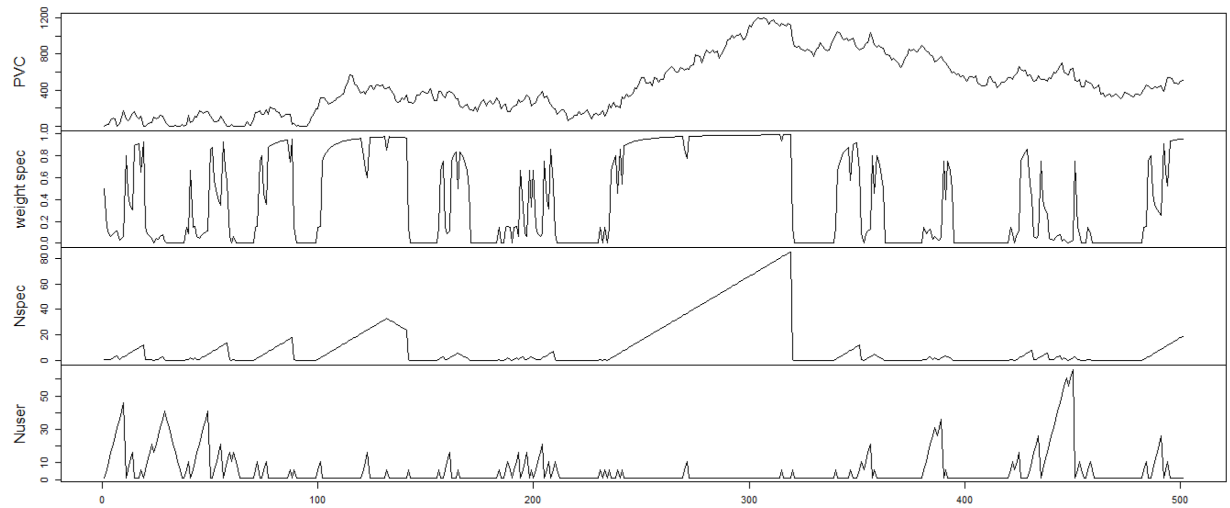


Figure 2: Simulation of price of VC, weight of speculators, number of speculators and number of users in VC



The implications of this simple model setup are as follows: (i) a relatively stable price of VC attracts potential users and tends to increase the price of the VC. If there is a continued increase in the price of VC due to the demand of users, the increased price and volatility will detract further users and in turn attract speculators, (ii) any positive price trend initiated by potential users may be exacerbated by speculators but the exit of potential users due to the increased price and volatility will eventually stop the positive price trend, (iii) an increasing price of VC implies deflation and counterpoises the use of the currency as a medium of exchange. In contrast, a decreasing price of FC (due to the decreased number of participants in FC) implies inflation in FC due to a decreased usage and thus demand of the currency. Note that an increasing number of users of a currency and constant money supply and money velocity implies that the demand for the currency increases and thus the price and the value of the currency increases. An increasing price of a currency should not be confused with inflation where the price of goods and services increases but not the value of the currency.

2.4. Discussion

Kiyotaki and Wright (1993) establish equilibria in a dual currency regime where there is a trade-off between acceptability of a currency and the yield. The authors find equilibria between two currencies with one currency exhibiting a “perfect” acceptability of one and a low yield whilst the other currency exhibits a lower acceptability but a higher yield.

We have implicitly modelled acceptability through price stability and reference to a currency’s ability to function as a medium of exchange and the yield through speculators that are attracted by price trends and expect future price changes in the same direction. The simulated model does not indicate a stable co-existence between fiat currency and virtual currency and thus no equilibrium. The difference is due to agents that influence the price thereby eliminating or greatly reducing price stability and acceptability.

The demand for units of virtual currency could also be rewritten as a function of acceptability and the currency’s yield as in Kiyotaki and Wright (1993). In that case, a higher yield would attract more speculators and a higher acceptability would attract more potential users. The influence on the price of the virtual currency and the conclusions would, however, be very similar, i.e. there would be a positive feedback effect on prices again destroying price stability and thus acceptability. If a higher yield was used to provide incentives to hold the currency and establish it as a medium of exchange, it would also attract speculators that increased the volatility of the currency and thus reduced its usage as a medium of exchange.

Since there is no government that backs the virtual currency, the majority of fiat currency users may not trust the virtual currency as a long-term store of value and as a medium of exchange. In addition, the lack of trust and confidence in the currency may outweigh the low cost associated with transactions using virtual currency. The only way for a virtual currency to gain such trust and confidence is to attract a critical mass of users. If there is a large number of users who are willing to accept a virtual currency as a medium of exchange, potential users could assume that there will be someone who will accept it when they wish to make payments with the virtual currency. Also, a large number of users would increase turnover and liquidity of the virtual currency and thereby decrease price volatility.

The next section presents an empirical analysis of the properties and the usage of the virtual currency Bitcoin.

3. Empirical Analysis

Bitcoin is designed as a decentralized peer-to-peer payment system and thus a medium of exchange. It can be defined as synthetic commodity money (Selgin, 2015) sharing features with both commodity monies such as gold and fiat monies such as the US dollar. Whilst commodity money is naturally scarce and has a use other than being a medium of exchange, fiat money is not naturally scarce but issued by a central bank and its main purpose is that of being a medium of exchange. In addition, both types of money can be used as a store of value.

Bitcoin is a hybrid of commodity money and fiat money. Bitcoin is scarce by design, i.e. its scarcity is determined by an automatic, deterministic rule fulfilled by competitive mining similar but not equal to commodity money (e.g. gold) but its value is better characterised by fiat money as Bitcoin has no "intrinsic" value. Another important similarity of Bitcoin with commodity money and most prominently gold is its non-centrality. The absence of counterparty risk for gold is, however, not matched by Bitcoin's peer-to-peer payment network.

When evaluating the potential future use and acceptance of Bitcoin it is important to analyse the growth path of Bitcoin supply. The supply of Bitcoins is perfectly predictable and will continue to increase in decreasing steps until 2040 and remain at the 2040 level ad infinitum. This has strong implications for the value of Bitcoins and the potential deflationary effects it may entail. Since the demand for Bitcoins, in contrast to its supply, is unpredictable both in the near future and beyond 2040, it is difficult to forecast the future value and usage of Bitcoins. However, if the demand increased steadily, the demand would eventually become larger than the supply leading to rising prices of Bitcoin and thus deflationary effects. These built-in deflationary effects make it more likely that Bitcoins will be used as an investment than as a medium of exchange.[5] If Bitcoins are not viewed as an alternative currency and not used as a medium of exchange, it will not compete with fiat currency and thus has no influence over the effectiveness of monetary policy. If, on the other hand, Bitcoins are seen as a stable money

[5] It would not be rational to use Bitcoin as a medium of exchange in period t if it is commonly known that its value will be higher in period $t+1$.

benchmark and thus as a medium of exchange, it may influence the value of fiat currency and ultimately monetary policy.[6]

Given the potential influence of Bitcoins on fiat money and thus on monetary policy, central banks and regulatory authorities carefully monitor the future developments of Bitcoin and other "virtual currencies".

3.1. Data

Our analysis of the return properties of Bitcoin uses daily data between July 2010 and June 2015. We use the WinkDex data as the daily exchange rate of Bitcoin to US dollar (USD) from the WinkDex website (https://winkdex.com/). According to the website, the WinkDex is calculated by blending the trading prices in US dollars for the top three (by volume) qualified Bitcoin Exchanges.

Table 1
Variables List

This table reports the list of 17 variables, explanation of the variables and the asset classes of the variables used in this analysis.

Variable	Explanation	Asset Class
bitr	WinkDex (Bitcoin exchange rate index)	Digital Currency
sp5r	S&P500 (US equity index)	Equity
sp6r	S&P600 (US equity index)	Equity
gldr	Gold Spot	Precious Metal
silvr	Silver Spot	Precious Metal
eurr	EUR USD (Euro to US Dollar exchange rate)	Currency
audr	AUD USD (Australian Dollar to US Dollar exchange rate)	Currency
jpyr	JPY USD (Japanese Yen to US Dollar exchange rate)	Currency
gbpr	GBP USD (British Pounds to US Dollar exchange rate)	Currency
cnyr	CNY USD (Chinese Yuen to US Dollar exchange rate)	Currency
hufr	HUF USD (Hungarian Forint to US Dollar exchange rate)	Currency
twus	Trade weighted US dollar index	Currency
wtir	WTI 1 month (Crude oil index)	Energy
hhr	HH 1 month (Natural gas index)	Energy
cbr	Bloomberg US Corporate Bond Index	Bond
tbr	Bloomberg US Treasury Bond Index	Bond
hbr	Bloomberg USD High Yield Corporate Bond Index	Bond

[6] If Bitcoin prices were stable and thus quasi-fixed to the US dollar, *Gresham's law* would be applicable. The law predicts changes in the relative values of two alternative monies labeled "good money" and "bad money". Changes in the relative values can lead to a crowding out effect of the "good money" making the "bad money" a medium of exchange and the "good money" a store of value.

All other return data comes from Bloomberg. We base our analysis on excess returns over the 3-month Treasury bill rate, which is also obtained from Bloomberg. Table 1 lists the assets that we analyse against Bitcoin. These assets include US equities, precious metals, commodities, energy, bonds and currencies.

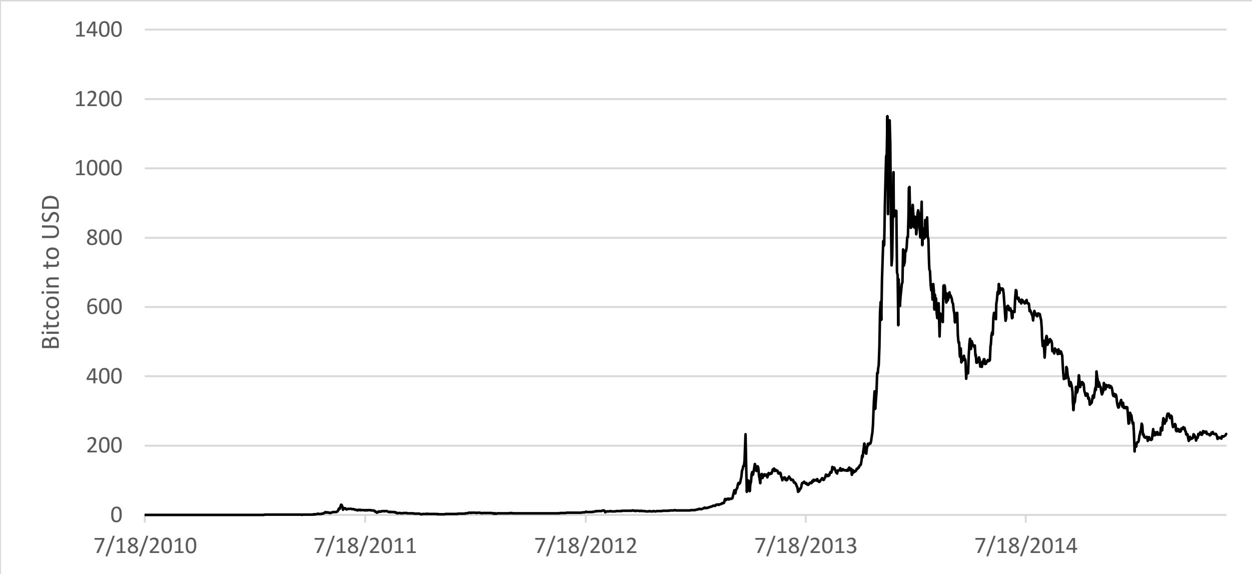
For the analysis of Bitcoin users, we use Bitcoin transaction data from Kondor *et al.* (2014) as available on their website.[7] The data are actual transactions originating from the public Bitcoin ledger. The dataset contains the complete set of individual Bitcoin transactions that have the timestamp, amount transacted, and sending and receiving address IDs (i.e. the Bitcoin wallet addresses). The data also consolidates individual wallets to unique users based on when multiple wallets are used to send Bitcoin.[8] We also remove users that only make two trades within an hour with an ending balance of less than 100 Satoshi[9] as these appear to be 'change addresses' as Meiklejohn *et al.* (2013) identify. The sample period is from the first Bitcoin transaction on 9th January 2009 to 28th December 2013. The shorter period for Bitcoin transactions is because we use data from Kondor *et al.* (2014) which includes timestamps obtained from the blockchain.info website.

3.2. Bitcoin Returns compared with other Assets

In this section we compare the return properties of Bitcoin to other assets. As a first step, Figure 3 shows the Bitcoin price in USD over the sample period. As can be seen, the Bitcoin has experienced a dramatic increase from $5.28 at the beginning of the sample period and ending at $388.55. Bitcoin has been very volatile with several large falls over the sample period. One example is when Bitcoin hit its peak price of $1150.75 on 30/11/13 and fell to $547.53 on 18/12/13. An even larger magnitude fall in Bitcoin happened in April 2013.

[7] http://www.vo.elte.hu/Bitcoin/default.htm
[8] Such consolidation will still overestimate the number of unique users as unrelated wallets may be held by a user.
[9] 1 Satoshi is 100 millionth of a Bitcoin.

Figure 3: Bitcoin Price to USD



3.2.1 *Descriptive Statistics*

Table 2 reports descriptive statistics for the returns of Bitcoin and other asset classes. We find that Bitcoin returns exhibit the highest return and standard deviation (or volatility) compared to the returns of the other 16 assets. As such, the level of historical return and volatility is not comparable to any other asset. The Bitcoin returns also show very high negative skewness and very high kurtosis. Large negative skewness is comparable to the skewness of high yield corporate bonds, gold and silver returns. Such large negative skewness indicates an asymmetric Bitcoin return distribution and that the tails on the left side of the distribution are longer or fatter than the right side. Moreover, Bitcoin returns exhibit extremely high kurtosis compared with other assets. This indicates a greater number of tail events in Bitcoin returns.

Table 2

Descriptive Statistics

This table reports the descriptive statistics (mean, standard deviation, skewness and kurtosis) of the variables. Daily data between July 2010 and June 2015 is used. Bitcoin to USD data is from the WinkDex website. Prices for all other data are from Bloomberg.

	bitr	*sp5r*	*sp6r*	*gldr*	*silvr*	*Eurr*	*audr*	*jpyr*	*gbpr*
Mean	0.65%	0.05%	0.06%	0.00%	-0.01%	-0.01%	-0.01%	0.03%	0.00%
Stdev	7.60%	0.95%	1.27%	1.09%	2.20%	0.60%	0.71%	0.58%	0.47%
Skewness	-1.01	-0.49	-0.24	-0.89	-0.89	-0.32	-0.19	0.38	-0.06
Kurtosis	17.04	8.25	7.64	10.85	12.94	4.79	4.85	8.22	3.63

	cnyr	*hufr*	*twus*	*wtir*	*hhr*	*cbr*	*tbr*	*hbr*
Mean	-0.01%	0.02%	0.01%	-0.03%	-0.04%	0.01%	0.01%	0.03%
Stdev	0.13%	0.93%	0.29%	1.23%	2.27%	0.05%	0.27%	0.18%
Skewness	0.05	0.17	0.29	-0.64	0.00	-0.31	-0.17	-1.92
Kurtosis	13.56	4.36	5.97	9.16	3.87	4.98	3.77	17.58

3.2.2 *Correlations*

We report correlations between Bitcoin returns and other asset returns in Table 3. Consistent with Yermack (2013), it is evident that Bitcoin returns are not correlated with any of the analysed asset returns. Bitcoin displays the largest positive correlation (0.05) with the S&P500 and S&P600 stock indices and high-yield corporate bonds and the lowest negative correlations at (-0.03) with the US Treasury Bond index (*tbr*). No other asset exhibits such weak correlations with other assets across the board. Overall, we conclude that Bitcoin is different from all traditional assets we investigated.

Table 3
Correlation Matrix

This table reports the return correlation between 17 assets used in the analysis, including Bitcoin. Daily data between July 2010 and June 2015 is used. Bitcoin to USD data is from the WinkDex website. Prices for all other data are from Bloomberg.

Correl	*bitr*	*sp5r*	*sp6r*	*gldr*	*silvr*	*eurr*	*audr*	*jpyr*	*gbpr*	*cnyr*	*hufr*	*twus*	*wtir*	*hhr*	*cbr*	*tbr*	*hbr*
bitr	1.00	0.05	0.05	0.04	0.02	0.01	-0.02	0.01	0.01	0.02	-0.01	-0.01	0.01	0.00	-0.01	-0.03	0.05
sp5r		1.00	0.92	0.05	0.04	0.15	0.18	0.06	0.14	-0.03	-0.20	-0.41	0.36	0.01	-0.06	-0.48	0.32
sp6r			1.00	0.06	0.05	0.12	0.14	0.04	0.10	-0.02	-0.16	-0.37	0.32	0.00	-0.08	-0.45	0.24
gldr				1.00	0.81	0.33	0.38	-0.24	0.34	-0.14	-0.29	-0.29	0.05	0.06	0.04	-0.03	0.06
silvr					1.00	0.33	0.42	-0.12	0.34	-0.15	-0.32	-0.29	0.09	0.07	0.06	-0.04	0.14
eurr						1.00	0.55	-0.22	0.65	-0.24	-0.80	-0.51	0.14	0.05	0.07	-0.12	0.16
audr							1.00	-0.22	0.50	-0.20	-0.59	-0.55	0.18	0.03	0.10	-0.15	0.32
jpyr								1.00	-0.21	0.09	0.09	0.25	-0.04	-0.03	-0.02	-0.05	0.06
gbpr									1.00	-0.21	-0.57	-0.43	0.15	0.05	0.05	-0.13	0.20
cnyr										1.00	0.20	0.21	-0.02	-0.11	0.00	0.05	-0.04
hufr											1.00	0.48	-0.16	-0.03	-0.06	0.15	-0.24
twus												1.00	-0.37	-0.06	-0.19	0.15	-0.31
wtir													1.00	0.12	-0.03	-0.24	0.19
hhr														1.00	-0.01	-0.04	-0.01
cbr															1.00	0.64	0.25
tbr																1.00	-0.12
hbr																	1.00

3.2.3 *Predictability and Explosive Price Processes*

Since Bitcoin is relatively young and volatile, it would not be surprising if Bitcoin returns showed some predictability and thus potential inefficiencies. Indeed, the Box-Pierce and Ljung-Box tests show highly significant test statistics at the 1% level indicating the presence of autocorrelation. Moreover, the first-lag return autocorrelation is 0.058 and statistically different from zero at the 1% level of significance. Figure 4 presents the 120-day rolling first-lag autocorrelation coefficients and the days on which they are statistically significant at the 10% level (grey vertical lines). The graph shows that Bitcoin return predictability is time-varying with values regularly above 0.1 and even reaching values above 0.4. The results suggest that there are significant profit opportunities for momentum traders. We have also employed a recently developed bubble test (Phillips and Yu, 2011) and found clear evidence for a bubble in 2013 as displayed in Figure 5.

Figure 4: Rolling (4-months) autocorrelation of Bitcoin returns

The grey-shaded areas indicate autocorrelation coefficients that are statistically different from zero at the 95% confidence level.

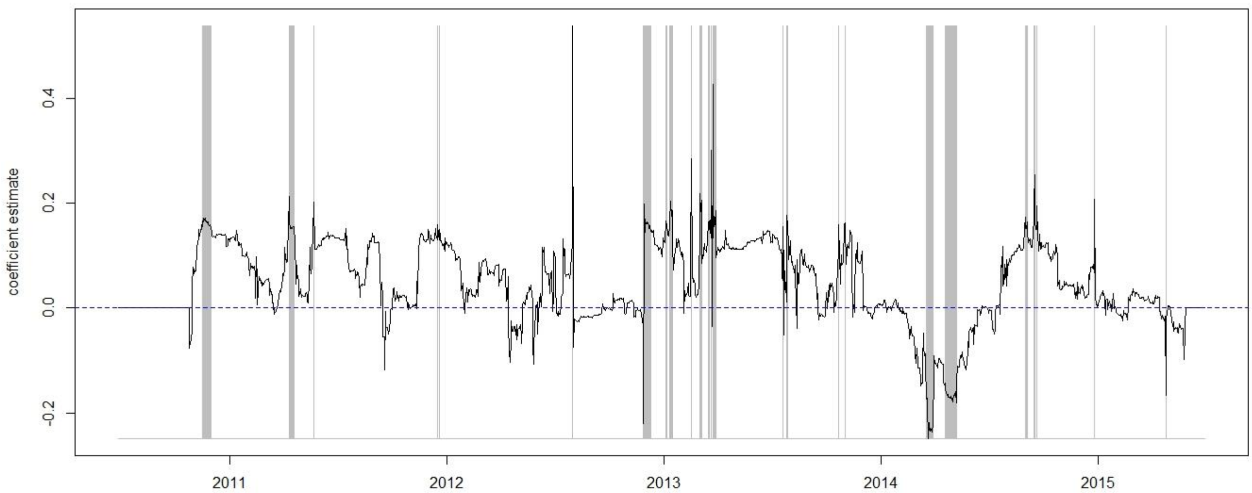
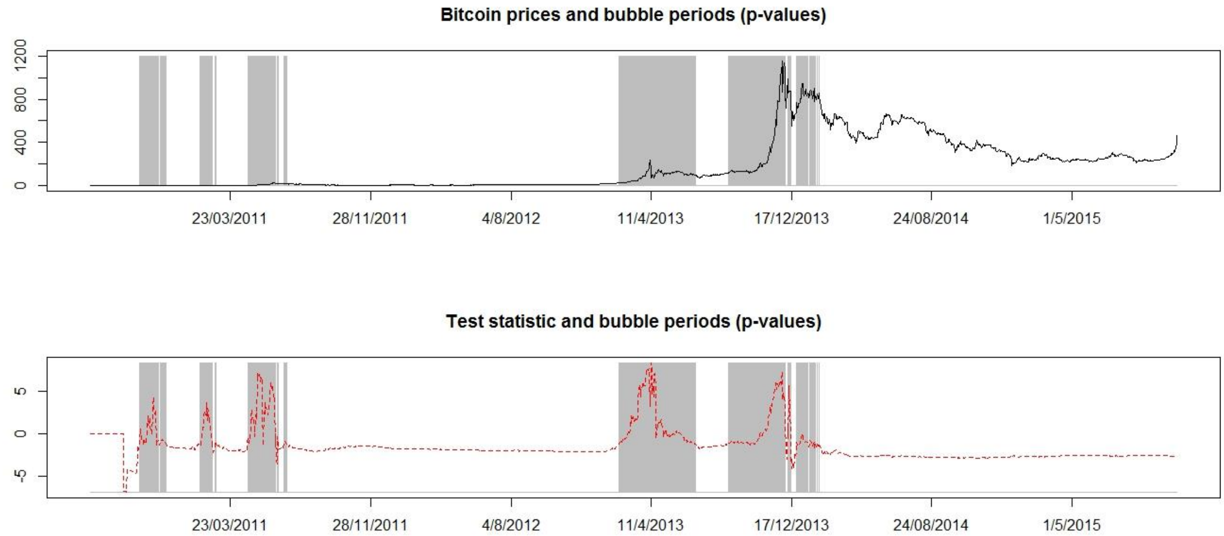


Figure 5: Recursive bubble-test on Bitcoin prices

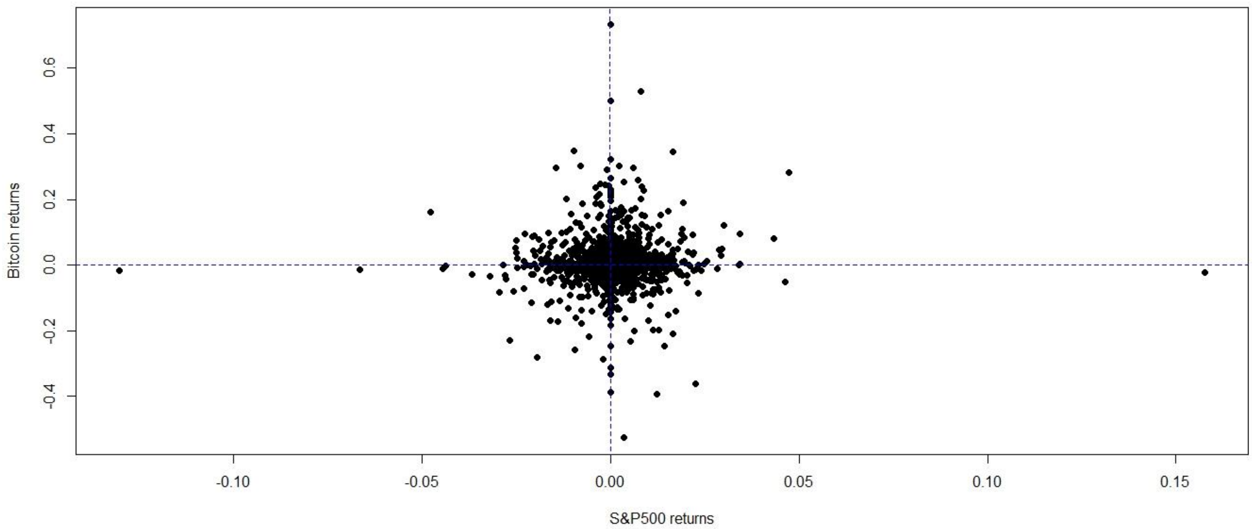
The grey-shaded areas indicate statistically significant periods of explosive, bubble-like, price processes.



3.2.4 *Safe Haven*

Bitcoin is often compared to gold since it shares some crucial characteristics such as the limited supply and supply growth through mining and the non-centrality and independence of central banks or government authorities. Since Bitcoin is segmented from the current fiat money system, it is also possible that it is a safe haven against financial turmoil or against the collapse of the financial system despite its excess volatility compared to other currencies and gold. Arguments for Bitcoin as a safe haven are that Bitcoin does not yet play an important role in the financial system and thus may be uncorrelated with extreme negative stock returns and financial system turmoil. Moreover, Bitcoin could function as an alternative to a rapidly depreciating currency and serve as a temporary store of value. The scatterplot of Bitcoin returns and S&P500 returns in Figure 6 indeed indicates that there is no positive relationship between S&P500 returns and Bitcoin returns. More specifically, for negative or extreme negative S&P500 returns, Bitcoin returns are uncorrelated which renders Bitcoin a weak safe haven (Baur and McDermott, 2010).

Figure 6: Scatter plot Bitcoin returns and S&P500 returns



This conclusion derived from a visual inspection is confirmed by a regression analysis of Bitcoin returns on S&P500 returns and interaction terms with dummies for extreme values of S&P500 and FX volatility returns. The model is similar to the one that Ranaldo and Söderlind (2010) use:

$$bitret_t = a_0 + (b_0 + b_1 * p90\_FXVol + b_2 * p95\_FXVol + b_3 * p99\_FXVol) * FXVol_t + (c_0 + c_1 * p10\_SP500 + c_2 * p5\_SP500 + c_3 * p1\_SP500) * SP500_t + d_0 * lag1bitret_t + e_0 * lag1FXVol_t + f_0 * lag1SP500_t + \varepsilon_t \quad (13)$$

where $bitret_t$, $FXVol_t$ and $SP500_t$ are daily Bitcoin returns, foreign exchange (FX) volatility and S&P 500 (total) returns. $lag1bitret_t$, $lag1FXVol_t$ and $lag1SP500_t$ denote the prior day values of Bitcoin return, FX volatility and S&P 500 returns, respectively. p90_FXVol, p95_FXVol and P99_FXVol are indicator variables for days in the sample where FX Volatility are in the 90^{th}, 95^{th} and 99^{th} percentiles. These represent the days where volatility is the highest. Analogously, *p10_SP500*, *p5_SP500, p1_SP500* are indicator variables for days when the S&P 500 returns are in the 10^{th}, 5^{th} and 1^{st} percentiles, respectively. FX Volatility is average daily realized volatility across CHF/USD, EUR/USD, JPY/USD and GBP/USD pairs using 5-minute midpoint quotes. If Bitcoin returns act as a hedge to FX volatility and the S&P 500 then we should find b_0 positive and statistically significant and c_0 negative and statistically significant, respectively. If Bitcoin acts as a safe haven to FX volatility and S&P 500 returns we expect to find b_1, b_2 or b_3 positive and statistically significant and c_1, c_2 or c_3 negative and statistically significant.

The estimation results are presented in Table 4 Panel A and show that Bitcoin is both uncorrelated with FX volatility and the S&P500 on average and in periods of extreme volatility/losses. This empirical finding of Bitcoin not being a strong safe haven is also consistent with the excess volatility of Bitcoin and indications that assets with no history as a safe haven asset are unlikely to be considered "safe" in an economic or financial crisis.

Our results using explicit crisis event dates interactions instead of percentiles yield similar conclusions. We adopt the method of Ranaldo and Söderlind (2010) and run the following regression model:

$$bitret_t = a_0 + (b_0 + b_1 * Financial + b_2 * Natural + b_3 * Terror) * FXVol_t + (c_0 + c_1 * Financial + c_2 * Natural + c_3 * Terror) * SP500_t + d_0 * lag1bitret_t + e_0 * lag1FXVol_t + f_0 * lag1SP500_t + \varepsilon_t \quad (14)$$

where *Financial*, *Natural* and *Terror* is an indicator variable of 1 for the event date and subsequent seven days from the start of a financial, natural disaster or terrorism/war related event, respectively. The dates that we use are in Appendix 1. If Bitcoin acts as a safe haven in crisis events we would expect b_1, b_2, b_3 to be positive and statistically significant and c_1, c_2, c_3 to be negative and statistically significant. We are particularly interested in Bitcoin's movements during financial crisis events as an advantage of Bitcoin is that it is not tied to governments and therefore may act as a safe haven.

Table 4 Panel B reports our results. Similar to the percentile regression we find no strong effect of crisis events for FX volatility. For the S&P500 we find a positive and statistically significant effect for natural disasters and a negative and weakly significant effect for terrorism/war. The positive effect for natural disasters suggests that Bitcoin and S&P500 become more positively correlated during these events. The negative coefficient for terrorism/war suggests there is some safe haven effect. However the lack of an effect for financial crisis is inconsistent with Bitcoin acting as a safe haven for sovereign risk as proponents of Bitcoin would suggest.

3.3. Bitcoin User Analysis

In this section we classify Bitcoin users into user types and investigate the wallet characteristics of these user types. We categorise user types to determine whether Bitcoin is predominantly used for investing or as a currency. Section 3.3.1 shows how we classify user types; Section 3.3.2 reports the total Bitcoin balance and Section 3.3.3 reports wallet characteristics of the user types (mean balance, number of transactions and transaction size).

3.3.1 *Categorising User Types*

We define users into four categories by their lifetime activity up to the balance date. In the below definitions 'sending Bitcoin' refers to a user transmitting their Bitcoin to another user (e.g. in exchange for fiat currency or a good/service) while 'receiving Bitcoin' refers to a user being transmitted from another user

Active investor - More than two transactions and only sends Bitcoin in greater than USD$2,000 transactions.

Passive investor - More than two transactions and only receives Bitcoin in greater than USD$100 transaction with no sending of Bitcoin; or has made only one receiving Bitcoin transaction of greater than USD$100.

Currency user - Makes more than one transaction, has made both sending and receiving transactions and sending transaction sizes are less than USD$2,000.

Tester - Makes only one transaction of less than USD$100.

Miner – A user that has ever mined for Bitcoin as identified by a user receiving newly generated Bitcoin.

Hybrid user - All other users not categorised.

Bitcoin transaction sizes in USD use the Bitcoin to USD price on the day of the transaction as per Mt Gox or WinkDex's trade-weighted price. Prior to 16th July 2010 we set all transaction as being worth USD$0 as there is no USD exchange price during this period.

Our categorisation system attempts to distinguish between those users that are investing in Bitcoin by building up Bitcoin balances over time and either not sending Bitcoin (*passive investor*) or only making large send transactions (*active investor*). In contrast, users that send small amounts of Bitcoins are exchanging Bitcoin for goods and services (*currency user*). *Miners* are special Bitcoin users that earn new Bitcoin from adding transaction records to Bitcoin's public ledger through computationally intensive mathematical problems. We also group users that are just testing the system and so are neither investors nor currency users (*tester*) and those that appear to do both currency users and investors (*hybrid user*).

We take three snapshots of user type balances on 31/12/11, 31/12/12 and 28/12/13 (the end of our sample period). We use these three snapshots to see whether there are trends in users purely investing or using Bitcoin as a medium of exchange. We also graph the daily balances of each user over time in comparison to the Bitcoin price.

3.3.2 Total Bitcoin Balances of User Types

Table 5 reports the total Bitcoin balances in Bitcoin and USD across user types for our three snapshot dates. Total Bitcoin value in USD has risen dramatically due to the rapid rise in price of Bitcoin and from the mining of Bitcoin which increases the total number of Bitcoins available. The total value in USD as at the end of 2013 is $8.8 billion dollars which is small relative to other assets such as shares where trillions of dollars are invested.

We find that the *active investors*, *passive investors* and *hybrid user* group total balances have increased over time while *currency user, miner* and *tester* have fallen over time. There has also been a dramatic increase in total users over time from 720,705 users as at the end of 2011 to 6.7 million users as at the end of 2013. The largest group of users by share of Bitcoin and user numbers are *hybrid* from 34.49% in 2011 to 44.59% in 2013 which is expected as hybrid users would consist of a mix of investors, merchants and consumers who hold Bitcoin to purchase goods and services.

The second largest user type is *passive investors* who hold 29.86% of all Bitcoins as at 2013 end despite being the second smallest group by user numbers. The fact that such users remain dominant strongly suggests that Bitcoin is mainly a vehicle for investment rather than for trade and has continued to be as such during our sample period.

Miners are the third largest group as at 2013 end of 17.81% although as at end of 2011 had a similar share of Bitcoin as the largest group *Hybrid.* This shows that *Miners* typically sell down their holdings of Bitcoin to others rather than accumulate it. *Tester* is the smallest group its share of balances has fallen from 1.91% at 2011 end to 1.22% at the end of 2013. Such a fall is expected as Bitcoin gains recognition over time. However *currency user* holdings declined from 5.1% of total Bitcoins in 2011 to 2.25% in 2013 which suggests that Bitcoin's usage purely for purchasing goods and services has diminished.

We conclude that there are very few users that use Bitcoin purely as a medium of exchange and a dominant group of users that use Bitcoin for investment.

Table 5
Total Bitcoin Balances by User Types

This table reports the total Bitcoin balances of various user types as at the end of 2011, 2012 and 2013. User types are defined in Section 3.3.1. The data is transaction data from the Bitcoin public ledger from 9th January 2009 to 28th December 2013. Bitcoin to USD values are from Mt Gox and WinkDex.

Total Balances (millions)												
Balance Year End	**2011**				**2012**				**2013**			
User Types	Bitcoin	USD Value	% Share	No. Of Users	Bitcoin	USD Value	% Share	No. Of Users	Bitcoin	USD Value	% Share	No. Of Users
Active Investor	0.29	1.38	3.64	18,940	0.28	3.73	2.62	82,621	0.52	376.11	4.27	1,035,596
Passive Investor	1.66	7.84	20.63	32,996	2.46	32.96	23.16	86,304	3.64	2,630.26	29.86	319,988
Hybrid	2.78	13.11	34.49	425,347	4.39	58.82	41.34	1,529,848	5.43	3,928.32	44.59	4,044,719
Currency User	0.41	1.94	5.10	31,780	0.74	9.89	6.95	116,986	0.27	198.19	2.25	464,397
Miner	2.76	13.02	34.23	93,304	2.58	34.58	24.30	119,010	2.17	1,568.60	17.81	135,187
Tester	0.15	0.73	1.91	118,338	0.17	2.31	1.63	256,072	0.15	107.65	1.22	722,451
Total	8.05	38.02	100	720,705	10.62	142.29	100	2,190,841	12.18	8,809.13	100	6,722,338

3.4. User Type Bitcoin Wallet Characteristics

In this section we investigate the wallet characteristics of our user group classifications. First, at the individual user level, we calculate the mean wallet characteristic across all transactions until the snapshot date. Then we calculate statistics based on the user mean wallet characteristics for each user type.

Table 6 reports mean and standard deviations of individual user wallet characteristics for various user types and as at the end of our snapshot periods. The wallet characteristics are user mean Bitcoin balances in USD (Panel A), user mean number of Bitcoin trades (Panel B) and user mean transaction size (Panel C).

In Table 6 Panel A we find *passive investors* generally have the largest mean and standard deviation of Bitcoin balances in USD amongst all groups over all time snapshots. at the end of 2013, *Miners* held the largest mean balances. *Active investors* and *currency users* keep small balances. *Testers* keep small balances prior to 2012 although in 2013 their balances are larger reflecting early adopters who only did one trade when the Bitcoin price was low. Overall we find that *passive investors* and *miners* while small groups in number of users, tend to hold large balances compared with other groups. Our findings are consistent with Surowiecki (2011)'s observation that Bitcoin is being hoarded rather than being used as medium of exchange.

In Table 6 Panel B we find that *currency users* trade the most frequently having a mean of 41.08 trades as at 2013. *Active investors* trade the least of all groups, even compared with *buy only investors*. Combined with evidence in Table 6 Panel A this suggests that *active investors* appear to be 'all-in' investors rather than active traders of Bitcoin. *Miners* have the largest standard deviation in number of Bitcoin transactions of up to 25,155.50 as at 2013 end suggesting that they actively trade Bitcoin and earn fees from confirming transactions.

In Table 6 Panel C we find that *active investors* make large transactions with a mean transaction size of $18,177 and standard deviation of $156,617.70. This group thus appears to make large receiving and sending transactions to enter and completely exit out of Bitcoin. *Currency users* have the second smallest transaction sizes consistent with consumers making many small transactions in order to purchase goods and services. *Hybrid users* as at 2011 made larger transactions than *passive investors* although by 2013 the mean and standard deviation of transaction sizes are similar.

Table 6
Bitcoin Wallet Characteristics by User Types

This table reports the wallet characteristics of various user types as at the end of 2011, 2012 and 2013. User types are defined in Section 3.3.1. The data is transaction data from the Bitcoin public ledger from 9th January 2009 to 28th December 2013. Bitcoin to USD values are from Mt Gox and WinkDex. Panel A reports statistics for individual account Bitcoin balances, Panel B for number of Bitcoin trades and Panel C for transaction size across various user types.

Panel A. Bitcoin Balances in USD by User Types

	2011			2012			2013		
User Type	Mean	Std	N Users	Mean	Std	N Users	Mean	Std	N Users
Active Investor	72.99	5,829.86	18,940	45.19	2,822.77	82,621	363.18	40,616.52	1,035,596
Passive Investor	237.69	5,114.44	32,996	381.90	9,706.49	86,304	8,219.87	374,934.07	319,988
Hybrid	30.83	1,346.69	425,347	38.45	2,141.67	1,529,848	971.22	72,261.73	4,044,719
Currency User	61.08	943.16	31,780	84.55	3,126.09	116,986	426.76	57,947.40	464,397
Miner	139.50	3,104.37	93,304	290.55	2,887.79	119,010	11,603.16	88,465.65	135,187
Tester	6.14	68.47	118338	9.04	129.63	256072	149.01	3995.37	722451

Panel B. Number of Bitcoin Trades by User Types

	2011			2012			2013		
User Type	Mean	Std	N Users	Mean	Std	N Users	Mean	Std	N Users
Active Investor	2.76	3.61	18,940	2.72	3.53	82,621	3.24	18.68	1,035,596
Passive Investor	10.21	30.45	32,996	13.06	56.55	86,304	11.05	39.78	319,988
Hybrid	2.82	18.83	425,347	3.46	290.84	1,529,848	5.38	580.30	4,044,719
Currency User	32.01	91.79	31,780	61.51	535.73	116,986	41.08	382.00	464,397
Miner	8.39	161.04	93,304	60.54	10,722.55	119,010	136.83	25,155.50	135,187
Tester	1.00	0.00	118,338	1.00	0.00	256,072	1.00	0.00	722,451

Panel C. Transaction Size in USD by User Types

	2011			2012			2013		
User Type	Mean	Std	N Users	Mean	Std	N Users	Mean	Std	N Users
Active Investor	17,222.21	107,642.35	18,940	8,905.80	54,987.26	82,621	18,177.20	156,617.70	1,035,596
Passive Investor	116.36	3,627.24	32,996	56.83	1,035.59	86,304	781.48	37,241.27	319,988
Hybrid	228.62	1,978.57	425,347	239.84	1,221.45	1,529,848	677.32	34,169.70	4,044,719
Currency User	61.86	154.03	31,780	79.86	176.88	116,986	131.61	392.13	464,397
Miner	144.09	331.89	93,304	186.32	340.69	119,010	309.11	1,906.62	135,187
Tester	4.74	28.25	118,338	3.80	17.58	256,072	7.87	39.87	722,451

Finally, we relate changes in the Bitcoin balances of user types to the past return performance of Bitcoin and the volatility of Bitcoin returns. To do this we regress the log percentage changes in Bitcoin total balances for each user type (i.e. active investor, passive investor, hybrid, etc.) on lagged daily/weekly returns, lagged daily/weekly volatility and a time trend. We should expect active investors to increase holdings when past returns or volatility are high. Testers are also expected to increase holdings when past volatility is high due to Bitcoin become more attention grabbing (e.g. Kristoufek (2013)). In contrast currency and hybrid users are expected to reduce holdings when past volatility is high as volatility reduces the appeal of using Bitcoin as a currency. Table 7 reports the regression results. Some user types have a lower number of observations due to the user type not existing in the early stages of the sample period. We find that *active investors* increase their holdings after higher daily past returns (positive and significant *lag1bitret* coefficient). This suggest that they are momentum (positive trend) traders. They also reduce balances with higher weekly volatility which suggests such investors are sensitive to longer term volatility in Bitcoin. *Passive investors* react to positive lagged daily volatility with a reduction in their holdings. *Hybrid, Currency* and *Miner* balances are unrelated to returns and volatility consistent with such users not being speculators. Finally, *testers* are contrarian investors and increase holdings with lower past returns (negative and significant *lagwbitret* coefficient). They also increase Bitcoin holdings with higher volatility consistent with testers being attracted by large fluctuations in Bitcoin prices. These findings lead to the conclusion that the user groups display wallet characteristics consistent with the user classifications and that Bitcoin is rather a speculative asset than an alternative currency and money. It also shows that users that use Bitcoin as a means of exchange do not react to past returns or volatility. The investor types however react to the volatility in Bitcoin returns.

Table 7
Determinants of User Type Bitcoin Balances

Every day we classify each Bitcoin user by user types based on Section 3.3.1. We then aggregate the Bitcoin balances by user type and calculate the log daily percentage change in balance. The data is transaction data from the Bitcoin public ledger from 9th January 2009 to 28th December 2013. The table reports coefficient estimate regress the log percentage changes in Bitcoin total balances for each user type (i.e. active investor, passive investor, hybrid, etc.) on lagged daily/weekly returns, lagged daily/weekly volatility and a time trend. *Active investors* have a lower number of observations due to the category type not existing in the early stage of Bitcoin. ***, **,* denote statistical significance at the 1, 5 or 10 percent level, respectively.

	Active Investors			Passive Investors			Hybrid			Currency			Miner		
Parameter	Estimate	*t*		Estimate	t		Estimate	t		Estimate	t		Estimate	t	
Intercept	-0.096	-1.15		-0.225	-7.46	***	-0.575	-9.44	***	0.019	0.94		-0.015	-2.02	**
lag1bitret	1.649	2.55	***	0.228	1.05		0.320	1.44		0.000	-0.01		-0.120	-1.62	
lagwbitret	0.018	0.10		-0.200	-2.06		0.032	0.27		-0.040	-1.11		0.006	0.23	
lag1bitvol	1.166	1.46		-0.604	-1.99	**	-0.175	-0.73		0.063	0.77		-0.096	-0.83	
lagwbitvol	-0.456	-2.30	**	-0.001	-0.01		0.180	1.03		-0.030	-0.65		-0.040	-0.95	
Daily Time Trend	Yes			Yes			Yes			Yes			Yes		
Adjusted R-squared	0.0167			0.0195			0.0234			0.0052			0.0108		
N	966			1,251			1,249			1,251			1,251		

Table 7 continued

	Tester		
Parameter	Estimate	*t*	
Intercept	-1.486	-13.8	***
lag1bitret	-0.072	-0.17	
lagwbitret	-0.305	-2.32	**
lag1bitvol	0.143	0.26	
lagwbitvol	0.948	4.05	***
Daily Time Trend	Yes		
Adjusted R-squared	0.4553		
N	1,250		

3.5. Turnover Velocity

Turnover velocity (TV) is generally used to work out how often the entire stock market is turned over. We calculate TV as the number of Bitcoins transacted on the day over the day's supply of Bitcoin. Consequently, a high TV means that there is considerable trading relative to the size of the market. Since the Bitcoin supply grows at a steady pace, by using TV we adjust for this natural growth by using supply as the denominator.[10] TV may be seen as a measure of liquidity. If TV is positively related to past extreme returns or volatility it suggests speculative trading rather than transactional motives. On the other hand a large and negative relationship with volatility would suggest that greater price swings in Bitcoin reduces trading activity if currency users dominate trading. We regress TV on different realizations of extreme Bitcoin returns on the previous day (one lag) or the previous week (excluding the previous day to avoid overlapping with the day lag). The regression model is:

$$\begin{aligned} TV_t = \; & a_0 + (b_0 + b_1{*}p1\_lag1bitret + b_2{*}\,p5\_lag1bitret + b_3{*}\,p10\_lag1bitret + b_4{*}p90\_lag1bitret + \\ & b_5{*}\,p95\_lag1bitret + b_6{*}\,p99\_lag1bitret\,){*}lag1\_bitret_t + \\ & (b_0 + b_1{*}p1\_lagwbitret + b_2{*}\,p5\_lagwbitret + b_3{*}\,p10\_lagwbitret + b_4{*}p90\_lagwbitret + \\ & b_5{*}\,p95\_lagwbitret + b_6{*}\,p99\_lagwbitret\,){*}lagw\_bitret_t + \\ & c_0{*}lag1bitvol_t + d_0{*}lagwbitvol_t + \varepsilon_t \qquad (15) \end{aligned}$$

where TV_t is turnover velocity calculated as the Bitcoin exchanged by unique users (excluding mined Bitcoin) over the total Bitcoin in existence on a given day. $lag1bitret_t$ is the prior day's Bitcoin return, $lagwbitret_t$ is the prior week's Bitcoin return (excluding the prior day to avoid overlap). The percentile rankings (i.e. p1_lag1bitret, p5_lag1bitret, etc) represent dummies for when Bitcoin daily or weekly returns are at the extreme percentiles. $lag1bitvol_t$ is the absolute value of prior day's Bitcoin return and $lagwbitvol_t$ is the square root of the sum of squared daily Bitcoin returns over the prior week (excluding the prior day). If the coefficients for prior returns and volatility are positive and statistically significant then this suggests speculative elements in Bitcoin trading. If the coefficients are negative and statistically significant then this suggests that currency users influence trading of Bitcoin.

Table 8 reports our coefficient estimates. We find the coefficients lagged daily (*lag1bitret)* and weekly (*lagwbitret*) returns are positive and statistically significant suggesting that high past returns of Bitcoin attract more trading. Looking at interactions with extreme price movements we find *lag1bitret*p10_lag1bitret* and *lagwbitret*p99_lagwbitret* to both be negative and statistically significant. This suggests if the past day's return is very low (at the tenth percentile) or the past week's return is extremely high (at the 99th percentile) then TV will be lower. This suggests that extreme

[10] The average TV varies significantly around the mean of 0.14 with a standard deviation of 0.29 and a maximum value of 4.46 reached in September 2012.

fluctuations in the Bitcoin price reduces Bitcoin trading beyond the reduction caused by Bitcoin volatility.

Our evidence on volatility shows a negative effect for lagged daily volatility and a positive effect for lagged weekly volatility. This suggests that there are different effects on a daily and weekly basis most consistent with speculators rather than currency users affecting Bitcoin trading. Our findings differ to Surowiecki (2011)'s observation that high past Bitcoin returns reduce trading activity in Bitcoin. The difference may be due to the longer sample period used in this analysis and also due to the fact that we control for the past volatility of Bitcoin returns. Once past volatility is controlled for we find higher past Bitcoin returns increase turnover velocity rather than decrease it. Our findings are consistent with Bitcoin trading having a speculative element.

Table 8
Determinants of Bitcoin Turnover Velocity

The table reports a regression of daily turnover velocity in Bitcoin on lagged Bitcoin returns and volatility, including interactions for extreme quantiles. Bitcoin to USD values are from Mt Gox and WinkDex. Turnover velocity is calculated from the public Bitcoin ledger as number of Bitcoin made by unique users over total Bitcoin outstanding on the day. The sample period is from 9th January 2009 to 28th December 2013. ***, **,* denote statistical significance at the 1, 5 or 10 percent level, respectively.

Parameter	Estimate	Std. Error	*t*-value	Pr > |t|	
intercept	-2.630	1.470	-1.79	0.07	*
lag1bitret	1.064	0.323	3.29	<0.001	***
lag1bitret*p1_lag1bitret	-0.416	0.258	-1.61	0.11	
lag1bitret*p5_lag1bitret	-0.402	0.548	-0.73	0.46	
lag1bitret*p10_lag1bitret	-2.022	0.774	-2.61	0.01	***
lag1bitret*p90_lag1bitret	0.185	0.424	0.44	0.66	
lag1bitret*p95_lag1bitret	0.095	0.258	0.37	0.71	
lag1bitret*p99_lag1bitret	0.136	0.228	0.59	0.55	
lagwbitret	0.383	0.120	3.20	<0.001	***
lagwbitret*p1_lagwbitret	-0.091	0.150	-0.60	0.55	
lagwbitret*p5_lagwbitret	-0.230	0.162	-1.42	0.16	
lagwbitret*p10_lagwbitret	-0.097	0.212	-0.46	0.65	
lagwbitret*p90_lagwbitret	-0.179	0.117	-1.53	0.13	
lagwbitret*p95_lagwbitret	-0.103	0.076	-1.35	0.18	
lagwbitret*p99_lagwbitret	-0.193	0.058	-3.31	<0.001	***
lag1bitvol	-1.600	0.503	-3.18	<0.001	***
lagwbitvol	0.275	0.114	2.41	0.02	**
Day Fixed Effects	Yes				
Month Fixed Effects	Yes				
Year Fixed Effects	Yes				
Daily Time Trend	Yes				
Adjusted R-squared	0.2102				
Number of Observations	1,251				

4. Summary and Concluding Remarks

This paper theoretically analysed the question if virtual currencies crowd-out fiat currencies and developed a model inspired by the heterogeneous agents literature. We showed that, if anything, fiat currencies crowd out virtual currencies and that the design and size of virtual currencies deprives the currency from its intended use as a medium of exchange. More specifically, the demand for virtual currencies by potential users increases its price thereby also attracting speculators who drive the price further up reducing the currency's property as a medium of exchange.

The competition or co-existence of virtual currencies with fiat currencies is often discussed with reference to Gresham's law that predicts that bad money drives out good money. Unfortunately, Gresham's law cannot be applied to virtual currencies in most cases as the price of virtual currencies is generally not fixed to existing fiat currencies. Since this paper demonstrated that changes in the price of virtual currencies caused by the demand of potential users and speculators deprives the currencies from its intended usage, one could argue that its design is driving itself out. Fixing the price to fiat currency with an implicit government-backing could alleviate the problem and also allow an application of Gresham's law. However, whilst a fixed price may solve one major problem it would not be consistent with the decentralized, libertarian and free-market designs of most virtual currencies. Regional currencies are an example of a virtual currency that is fixed to an existing currency but those types of alternative currencies are neither decentralized nor global.

We extend the theoretical analysis and empirically investigate the question of whether the most prominent virtual currency, Bitcoin, is a currency or an asset. We find Bitcoin's return properties are very different from traditional asset classes and thus offer great diversification benefits. Analysing the Bitcoin public ledger, we find about a third of Bitcoins are held by investors, particularly users that only receive Bitcoin and never send to others. A minority of users, both in number and Bitcoin balances, appear to use Bitcoin as a medium of exchange. This suggests that at present Bitcoins are held for investment purposes rather than being used for transactions.

Since the size of Bitcoin investments and transactions can be characterised as small relative to other assets we do not see an immediate risk or even threat for financial or monetary stability. However, if the acceptance of Bitcoin or similar virtual currencies increased significantly on a global level, it could affect the behaviour of consumers and producers and as a consequence change the relevance of monetary policy. Given Bitcoin's global decentralized nature and independence from any central bank or supranational authority, regulatory oversight may be difficult and challenging.

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Appendix 1
Crisis Event Dates

The following table lists the dates used in our regression of Bitcoin returns on S&P 500 and FX volatility interacted with crisis event dates.

Event	**Event Date**	**Type**
Greece Bailout I	3/05/2010	Financial
Ireland Bailout	29/11/2010	Financial
2011 Tohoku Earthquake and Tsunami	11/03/2011	Natural
Syrian Civil War	15/03/2011	Terrorism/War
Portugal Bailout	15/05/2011	Financial
Greece Bailout II	21/07/2011	Financial
Thailand Floods	5/08/2011	Natural
Spanish Banks Bailout	11/06/2012	Financial
Hurricane Sandy	28/10/2012	Natural
Cyprus Bailout	16/03/2013	Financial
Boston Marathon Bombings	15/04/2013	Terrorism/War
Tropical Storm Thelma	8/11/2013	Natural
Crimean Crisis	20/02/2014	Terrorism/War
France Attacks	7/01/2015	Terrorism/War
Nepal Earthquake	25/04/2015	Natural