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Pavel Ciaian, Miroslava Rajcaniova, d'Artis Kancs

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**EERI**
**Economics and Econometrics Research Institute**
Avenue de Beaulieu
1160 Brussels
Belgium

Tel: +322 298 8491
Fax: +322 298 8490
www.eeri.eu

**The Economics of BitCoin Price Formation**[1]

Pavel Ciaian[1,2,3], Miroslava Rajcaniova[2,3,4], d'Artis Kancs[1,2,3]

[1]European Commission (DG JRC)

[2]Economics and Econometrics Research Institute (EERI)

[3]Catholic University of Leuven (LICOS)

[4] Slovenská Polnohospodárska Univerzita (SUA)

**Abstract**

This is the first paper that studies BitCoin's price formation by considering both the traditional determinants of currency price, e.g. market forces of supply and demand, and BitCoin-specific factors, e.g. digital currency's attractiveness for investors. The conceptual framework is based on the Barro's (1979) model, from which we derive testable hypotheses. Using daily data for five years (2009-2014) and applying time-series analytical mechanisms, we find that market forces of supply and demand and BitCoin's attractiveness for investors have a significant impact on BitCoin price. Our estimates do not support previous findings that macro-financial developments are driving BitCoin price in the long-run.

**Key words**: BitCoin, exchange rate, supply and demand, financial indicators, financial investment.

**JEL classification**: E31; E42; G12.

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[1] The authors are grateful to Tony Tam from for providing access to the BitCoin data of Bitcoinpulse. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

## 1 Introduction

Over the last few years, a wide range of digital currencies, such as BitCoin, LiteCoin, PeerCoin, AuroraCoin, DogeCoin and Ripple, have emerged. The most prominent among them is BitCoin, both in terms of its impressive price development and price volatility. The price has increased from zero value at the time of its inception in 2009 to around $1100 at the end of 2013 (see Figure 1). At the end of 2014, its price has dropped to around $250, but is increasing since then again. Such market volatility with huge price movements (±8000%) is not usual for traditional currencies, suggesting that there must be determinants of price formation, which are specific to BitCoin. The present paper attempts to identify and asses the factors behind BitCoin price formation.

It's rising popularity has attracted a growing interest in BitCoin in general (e.g. Grinberg 2011; Barber et al. 2012; Kroll, Davey and Felten 2013; Moore and Christin 2013), and BitCoin' price formation in particular (e.g. Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013). Several factors affecting BitCoin's price have been identified in the previous literature: (i) market forces of BitCoin supply and demand (Buchholz et al. 2012); (ii) attractiveness for investors (Kristoufek 2013); and (iii) development of global financial indicators (van Wijk 2013). Our paper is the first in the literature that studies BitCoin's price formation by considering both the traditional determinants of currency price, e.g. market forces of supply and demand, and BitCoin-specific factors, e.g. digital currency's attractiveness for investors.

Buchholz et al. (2012) note that an important determinant of BitCoin price (as price of any currency) is the interaction between BitCoins' supply and demand. The supply of BitCoin determines the amount of units in circulation and thus its scarcity on the market. The demand of BitCoin is mainly determined by transaction demand as a medium of exchange. Buchholz et al. argue that, to a large extent, BitCoin's price can be explained by interactions between its supply and demand. However, Buchholz et al. do not account for the fact that the demand (and supply) of BitCoin is driven also by investors' speculative behaviour, which is different than for traditional currencies, because there is no interest rate for digital currencies and thus profits can be earned only from price changes.

However, according to Kristoufek (2013), the price formation of BitCoin cannot be explained by standard economic theories,[2] because several market forces of supply and demand, which usually form the basis of currency price formation, are absent on BitCoin markets. In particular, BitCoin is not issued by a specific central bank or government and thus is detached from the real economy. Hence, BitCoin is a fiat currency without an intrinsic value. In contrast to standard government-backed fiat currencies, e.g. dollar, euro, BitCoin is developed outside of an underlying economy or issuing institution, implying that there are no macroeconomic fundamentals that would determine its price formation.

In addition, Van Wijk (2013) stresses the role of global financial development, captured e.g. by stock exchange indices, exchange rates, and oil price measures, in determining BitCoin price. Van Wijk finds evidence that the Dow Jones index, the euro-dollar exchange rate, and oil price have a significant impact on the value of BitCoin in the long-run.

An important shortcoming of previous studies is that they look at different BitCoin's price determinants separately; hence they do not consider interactions between them. The present paper attempts to close this research gap by accounting of all three types of BitCoin price determinants identified in the previous literature: market forces of supply and demand, investors' behaviour and global financial development to explain the formation of BitCoin price, and to account for their interactions.

In order to identify and assess the determinants of BitCoin's price formation, we apply time-series analytical mechanisms to daily data for the period 2009-2014. Our empirical results confirm that market forces of BitCoin supply and demand have an important impact on BitCoin price, implying that, to a large extent, the formation of BitCoin price can be explained in the Barro's (1979) model for gold standard. Supply and demand drivers have an important impact on BitCoin price formation and thus are among the key factors in determining its development. Second, we cannot reject the hypothesis that short-run investor speculations also affect BitCoin price. Finally, our estimates do not support previous findings that macro-financial indicators are driving BitCoin price.

Our findings contribute to a better understanding of the determinants behind the enormous BitCoin's price fluctuations experienced in the recent years. A desirable property of any monetary mean is that it holds its value over short-to-medium periods of time, in order not to

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[2] For example, future cash-flows model, purchasing power parity, or uncovered interest rate parity.

create distortion when used as a medium of exchange in transaction. Large price movements alter the purchasing power causing risk and costs to firms and consumers, which are using it as a medium of exchange in transaction of goods and services. Hence, understanding the price formation of BitCoin is highly relevant both from a general monetary policy point of view and from a BitCoin's ability to serve as a medium of exchange for global economy's point of view.

## 2 Background of BitCoin

BitCoin is a peer-to-peer payment system created in 2009. It is the first open source digital currency, as BitCoin is managed by an open source *software algorithm* that uses the global internet network both to create BitCoins as well as to record and verify its transactions. Being a cryptocurrency, BitCoin uses the principles of cryptography to control the creation and transfer of BitCoins. Access to the BitCoin network requires downloading a BitCoin software on personal computer and joining the BitCoin network, which allows participants to engage in operations, and update and verify transactions.

Compared to a standard fiat currency, such as dollars or euros, the key distinguishing feature of BitCoin is that the quantity of units in circulation is not controlled by a person, group, company, central authority, or government, but by a software algorithm.[3] A fixed amount of BitCoins is issued at a constant a-priori defined and publicly known rate, according to which the stock of BitCoins increases at a decreasing rate. In 2140 the BitCoin growth rate will converge to zero, when the maximum amount of BitCoins in circulation will reach 21 million units; it will not change after 2140.

BitCoins can be used to buy goods or services worldwide, provided that transaction partners accept BitCoin as a mean of payment. A transaction implies that the owner of BitCoins transfers their ownership of a certain number of BitCoins, in exchange for other currencies, goods and services. A continuously growing number of companies accept BitCoins as payments for their goods and services, at the end of 2014 there were more than 6000 venues accepting BitCoins (CoinDesk 2014, see Figure 2).

[3] BitCoins are created in a 'mining' process, in which computer network participants, i.e. users who provide their computing power, verify and record payments into a public ledger called blockchain. In return for this service they receive transaction fees and newly minted BitCoins.

## 3 Conceptual framework and testable hypothesis

BitCoin price formation can be analysed in an augmented version of Barro's (1979) model for gold standard. For the sake of comparability, we denominate the stock of money base of BitCoins in a standard government controlled fiat currency, such as dollars.[4] As in Barro, we assume that users need to convert BitCoins into dollars or other currencies, as they operate in economies using dollars or other currencies for the purchase production factors.[5]

Suppose that $B$ represents the total stock of BitCoins in circulation and $P_B$ denotes the exchange rate of BitCoin (i.e. dollar per unit of BitCoin), then the total BitCoin money supply, $M^S$, is given by:

(1) $$M^S = P^B B$$

The demand for circulating BitCoins in dollar denomination, $M^D$, is assumed to depend on the general price level of goods and services, $P$, the size of BitCoin economy, $Y$, and the velocity of BitCoin circulation, $V$. The BitCoin's velocity, $V$, measures the frequency at which one unit of BitCoin is used for purchase of goods and services, and it depends on the opportunity cost for holding it (inflation, opportunity interest rate).

(2) $$M^D = \frac{PY}{V}$$

The equilibrium between BitCoin supply (1) and BitCoin demand (2) implies the following equilibrium price relationship:

(3) $$P^B = \frac{PY}{VB}$$

In perfect markets the price equilibrium given by equation (3), which implies that the price of BitCoin decreases with the velocity and the stock of BitCoins, but increases with the size of BitCoin economy and the price level.

In the following, we will use the above outlined Barro's (1979) model for gold standard and insights from the previous empirical studies (Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013) to derive testable hypotheses of BitCoin price formation: (i) market forces of

[4] Note that goods and services are traded using dollars or other precious metals and not BitCoins.

[5] If all global transactions would be executed in BitCoins, then the monetary base would be fully BitCoin denominated and, in principle, its conversion to other currency would not be necessary.

BitCoin supply and demand, (ii) BitCoin's attractiveness for investors, and (iii) global macroeconomic and financial developments.

*Hypothesis 1: Market forces of BitCoin supply and demand*

According to Buchholz et al. (2012), one of the key drivers of BitCoin price is the interaction between BitCoin supply and demand on the BitCoin market. The demand for BitCoin is primarily driven by its value as a medium of exchange (i.e. by its value in future exchange). The key difference between the gold standard and BitCoin is that the demand for BitCoin is driven by its value in future exchange, whereas the demand for commodity currency is driven by both its intrinsic value and its value in future exchange. The supply is given by the stock of BitCoins in circulation, which is publicly known and is predefined in the long run. Hence, the supply of gold is endogenous; it responds to changes in production technology (e.g. mining technology for gold) and returns. In contrast, BitCoin supply is exogenous and is implemented by a predefined software algorithm.

Applying a logarithmic transformation to equation (3) and writing all log transformed variables in lowercase, we can rewrite equation (3) into an empirically estimable model of BitCoin price:

(4) $$p_t^B = \beta_0 + \beta_1 p_t + \beta_2 y_t + \beta_3 v_t + \beta_4 b_t + \epsilon_t$$

where $\epsilon_t$ is an error term. According to the underlying theoretical framework of Barro (1979), we expect that $\beta_1$ and $\beta_2$ would be positive, whereas $\beta_3$ and $\beta_4$ would be negative. In addition, given that BitCoin supply is largely predefined, it is a semi- exogenous variable, and implying that its impact on BitCoin price should be small and/or statistically not significant.

*Hypothesis 2: BitCoin's attractiveness for investors*

BitCoin has been created relatively recently, particularly, when compared to other investment goods, such as gold. As a result, there are several BitCoin-specific factors, which affect the behaviour of BitCoin investors, in addition to the traditional ones, such as market supply and demand (Barber et al. 2012; Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013).

First, BitCoin price may be affected by the risk and uncertainty of the whole BitCoin system. Given that BitCoin is a fiat currency and thus intrinsically worthless, it does not have an underlying value derived from consumption or its use in production process (such as gold). The value of a fiat currency is based on trust that it will be valuable and accepted as a medium of exchange also in the future (Greco 2001).[6] The expectations about trust and acceptance are particularly relevant for BitCoin which, being a relatively new currency, is in the phase of establishing its market share by building credibility among users.

Second, being a digital currency, BitCoin is more vulnerable to cyber-attacks, which can easily destabilise the whole BitCoin system and eventually lead to a collapse of BitCoin. Such attacks have been frequently occurring in the BitCoin system (Barber et al. 2012; Moore and Christin 2013). Moore and Christin (2013) examined 40 BitCoin exchanges and found that 18 have closed down due to cyber-attacks. For example, MtGox, once the world's biggest BitCoin exchange, collapsed in February 2014 due to a cyber-attack, which allegedly led to a loss of 850 thousand BitCoins.

Third, investors behaviour and hence BitCoin's price is also determined by transactions costs for potential investors. According to Gervais, Kaniel, and Mingelgrin (2001), Grullon, Kanatas, and Weston (2004) and Barber and Odean (2008), the preferences of new investors' decision may be affected by changes in the attention (e.g. attention in the news media), particularly, in the presence of many alternative investment choices and positive search costs. Investment behaviour depends on the costs associated with searching for information for potential investment opportunities available on the market, such as, the stock exchange. Investment opportunities under attention of news media may be preferred by new investors, because they reduce search costs, and hence increased demand for BitCoin may exercise upward pressure on BitCoin price. Indeed, Lee (2014) finds such evidence for BitCoin, whereby the alteration of positive and negative news generated high price cycles. This implies that the attention-driven investment behaviour can affect BitCoin price either positively or negatively, depending on the type of news that dominate in the media at a given point of time.

In order to account for BitCoin's attractiveness for investors in BitCoin price formation, we extend the estimable model (4) as follows:

$$p_t^B = \beta_0 + \beta_1 p_t + \beta_2 y_t + \beta_3 v_t + \beta_4 b_t + \beta_5 a_t + \epsilon_t \tag{5}$$

where $a_t$ captures BitCoin's attractiveness for investors. As noted above, coefficient $\beta_5$can be either negative or positive, as both positive and negative news attract investors' attention. Reduced search costs in turn increases demand and hence BitCoin price.

[6] Given that people consider a currency valuable if they expect others to do so, for a decentralised currency, such as BitCoin, that trust depends on a belief that the rules of the currency will be stable over time.

*Hypothesis 3: Macroeconomic and financial developments*

Van Wijk (2013) stresses the role of global macroeconomic and financial development, captured by variables such as stock exchange indices, exchange rates, and oil prices measures in determining BitCoin price. The impact of macroeconomic and financial indicators on BitCoin price may work through several channels. For example, stock exchange indices may reflect general macroeconomic and financial developments of the global economy. Favourable macroeconomic and financial developments may stimulate the use of BitCoin in trade and exchanges and thus strengthen its demand, which may have positive impact on BitCoin price.

Inflation and price indices are other sets of important indicators, capturing macroeconomic and financial developments. According to Krugman and Obstfeld (2003) and Palombizio and Morris (2012), oil price is one of the main sources of demand and cost pressures, and it provides an early indication of inflation development. Thus, if the price of oil signals potential changes in the general price level, this may lead to depreciation of BitCoin's price. Also the exchange rate may reflect inflation development and thus impact positively BitCoin's price as indicated above.

According to Dimitrova (2005), there could be also negative relation between a currency's price and macro financial indicators. A decline in stock prices induces foreign investors to sell the financial assets they hold. This leads to a depreciation of the respective currency, but may stimulate BitCoin's price, if investors substitute investment in stocks for investment in BitCoin. Generally, investors' return on stock exchange may capture opportunity costs of investing in BitCoin. Hence, the stock exchange indices are expected to be positively related with BitCoin price.

In order to account for macroeconomic and financial developments in the BitCoin price formation, we extend equation (5) as follows:

$$p_t^B = \beta_0 + \beta_1 p_t + \beta_2 y_t + \beta_3 v_t + \beta_4 b_t + \beta_5 a_t + \beta_6 m_t + \epsilon_t \tag{6}$$

where $m_t$ captures macroeconomic and financial indicators. According to the previous studies, we expect $\beta_6$ to be either positive or negative.

## 4 Econometric approach

The testable hypotheses derived in section 3 contain mutually interdependent variables – BitCoin price and its explanatory variables. The estimation of non-linear interdependencies among interdependent time series in presence of mutually cointegrated variables is subject to the endogeneity problem (Lütkepohl and Krätzig 2004). To circumvent the problem of endogeneity, we follow the general approach in the literature to analyse the causality between endogenous time-series and specify a Vector Auto Regressive (VAR) model (Lütkepohl and Krätzig 2004).

According to Engle and Granger (1987), regressions of interdependent and non-stationary time series may lead to spurious results. In order to avoid spurious regression, it is important to test the properties of the time series involved. Therefore, in the first step, the stationarity of time series is determined, for which we use two unit root tests: the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The number of lags that we use for each dependent variable is determined by the Akaike Information Criterion (AIC). If two individual time series are not stationary, their combination may be stationary (Engle and Granger 1987). In this special case, the time series are considered to be cointegrated, implying that there exists a long-run equilibrium relationship between them.

In the second step, we employ the Johansen's cointegration method to examine the long-term relationship between the price series. The number of cointegrating vectors is determined by the maximum eigenvalue test and the trace test. Both tests use eigenvalues to compute the associated test statistics. We follow the Pantula principle to determine whether a time trend and a constant term should be included in the model.

In the third step, we estimate a vector error correction model for those series that are cointegrated. It includes an error correction term indicating the speed of adjustment of any disequilibrium towards a long-term equilibrium state. Following Johansen and Juselius's (1990), we reformulate the vector autoregressive model and into a vector error correction model as follows:

(7) $$Z_t = A_1 Z_{t-1} + ... + A_k Z_{t-k} + \varepsilon_t$$

(8) $$\Delta Z_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Z_{t-i} + \Pi Z_{t-1} + \varepsilon_t$$

where $Z_t$ is a vector of non-stationary variables, $A$ are matrices of different parameters, $t$ is time subscript, $k$ is the number of lags and $\varepsilon_t$ is the error term assumed to follow *i.i.d*. process with a zero mean and normally distributed $N(0, \sigma 2)$ error structure. Equation (2) contains information on both short-run and long-run adjustments to changes in $Z_t$ via the estimates of $\Gamma_i$ and $\Pi$, respectively. $\Pi$ can be decomposed as $\Pi=\alpha\beta'$, where $\alpha$ represents the speed of adjustment to disequilibrium and $\beta$ represents the long-run relationships between variables (Johansen and Juselius's 1990).

As usual, in order to ensure the adequacy of the estimated models, we implement a series of specification tests: Lagrange-multiplier (LM) test for autocorrelation in the residuals; Jarque-Berra test to check if the residuals in the VEC are normally distributed and the test of stability of the model.

## 5 Data and results

### 5.1 Data and variable construction

We use the following proxies to capture market forces of BitCoin supply and demand as suggested by the price relationship 0. In order to construct the dependent variable, we use data for BitCoin price, $P^B$, denominated in US dollars (*mkpru*). We use the historical number of total BitCoins (*totbc*) which have been mined to account for the total stock of BitCoins in circulation $B$. We use two alternative proxies for BitCoin economy, $Y$: the total number of unique BitCoin transactions per day (*ntran*), and the number of unique BitCoin addresses used per day (*naddu*). Following Matonis (2012), we proxy the monetary BitCoin's velocity, $V$, by BitCoin days destroyed for any given transaction, *bcdde*. This variable is calculated by taking the number of BitCoins in a transaction and multiplying it by the number of days since those coins were last spent. All these data are extracted from *quandl.com*. To measure the price level of global economy, $P$, we use exchange rate between the U.S. dollar and the Euro (*exrate*) extracted from the European Central Bank.

In order to capture BitCoin's attractiveness for investors, $a$, we follow Kristoufek (2013) and use the volume of daily BitCoin views on Wikipedia, *wiki_views*, which measures investors' faith in BitCoin.[7] According to Kristoufek (2013), the frequency of searches related to the

[7] Kristoufek (2013) used also queries of BitCoin on Google Trends to measure investor faith/sentiment in BitCoin. These data are available only on weekly bases. Since we use daily data we do not use this proxy in our estimations.

digital currency is a good measure of potential investors' interest in the currency. Piskorec et al. (2014) argue that this measure may also capture speculative behaviour of investors. The online search queries, such as Wikipedia views, may measure investors' interest in BitCoin, as it captures information's demand about the currency. In addition, we also construct a variable capturing the number of new members (*new_members*) and new posts (*new_posts*) extracted from *bitcointalk.org*. As explained above, the variable *new_members* captures the size of the BitCoin economy but also attention-driven investment behaviour of new BitCoin members. The variable *new_posts* captures the effect of trust and/or uncertainty, as it represents the intensity of discussions among members.

To account for global macroeconomic and financial indicators, *m*, we follow van Wijk (2013) and use oil price, *oil_price*, and the Dow Jones stock market index, *DJ*.[8] The oil prices are extracted from the US Energy Information Administration and Dow Jones index is extracted from the Federal Research Bank of St. Louis.

### 5.2 Estimation results

Following the theoretical hypothesis, we estimate four sets of econometric models of BitCoin price (differences in the specifications between the estimated models are reported in Table 1). Models 1.1 to 1.5 capture BitCoin's supply-demand interactions and their impact on BitCoin price. Model 2.1 estimates the impact of BitCoin's attractiveness for investors of buying/selling BitCoins. Model 3.1 estimates the impact of global macroeconomic and financial developments. Models 4.1 to 4.9 interact the above three components.

The estimation results are reported in Table 3 - Table 6. Whereas Table 3 and Table 4 report the short-run impacts, Table 5 and Table 6 show the long-run impact of different determinants on BitCoin price. According to the results reported in Table 3 and Table 4, a number of variables have statistically significant short-run effect on BitCoin price adjustments. In particular, this is the case for own price effects, the stock of total BitCoins, *totbc*, BitCoin days destroyed, *bcdde*, and Wikipedia views, *wiki_views*. The short-run effects represent the short-run dynamics of variables in the cointegrated system. It describes how the time series react when the long-run equilibrium is distorted.

*Hypothesis 1: Market forces of BitCoin supply and demand*

[8] The Dow Jones Index is an industrial average that captures 30 major corporations on either the NYSE or the NASDAQ.

According to the results reported in Table 5 and Table 6, the long-run relationship between BitCoin price and the explanatory variables considered in the estimated models is stronger than the short-run impact. The first major observation arising from our estimates is that the market forces of supply and demand have a strong impact on BitCoin price. Generally, the demand side variables (e.g. *bcdde*, *naddu*) appear to exert a stronger impact on BitCoin price than the supply side drivers (e.g. *totbc*). According to the results reported in Table 5, an increase in the stock of BitCoins (*totbc*) leads to a decrease in BitCoin price (model 1.2), whereas an increase in the size of the BitCoin economy (*naddu*) and its velocity (*bcdde*) lead to a higher price (models 1.1, 1.2, 1.3, 1.4, 1.5, 4.3, 4.4, 4.7). Contrary to our expectations, the alternative variable that captures the size of the BitCoin economy (*ntran*) has negative impact on BitCoin price in models 1.1 and 1.5. However, this variable is not significant in the more general models (models 4.1-4.9).

Although, the sign of the estimated coefficients for market forces of BitCoin supply and demand is in line with our hypothesis (except for *ntran* in models 1.1 and 1.5), the statistical significance and magnitude of the estimated coefficients decreases in most models, when accounting for the impact of BitCoin's attractiveness for investors and global macroeconomic and financial developments (models 4.1 to 4.9 in Table 6). The supply-demand variables are statistically significant in models 4.3, 4.4 and 4.7, but have a considerably lower magnitude of the estimated impact than in models 1.1 to 1.5, which capture only market forces of supply and demand. This could be explained by the fact that part of the BitCoin's price variation explained by the supply-demand variables is absorbed by other variables in more general specifications (models 4.1 to 4.9).

*Hypothesis 2: BitCoin's attractiveness for investors*

The strongest and statistically most significant impact on BitCoin price is estimated for variables capturing the impact of BitCoin's attractiveness for investors: *wiki_views*, *new_members* and *new_posts* (models 2.1 and models 4.1 to 4.9). Variable *new_members* has negative impact on BitCoin price, implying that attention-driven investment behaviour of new members dominates. Variable *new_posts* has positive impact on BitCoin price, reflecting an increasing acceptance and trust of BitCoin captured by the intensity of discussion between BitCoin users. This may reflect declining transaction costs and uncertainty for investors, which increases investment demand of BitCoins and hence it's price.

Consistent with the findings of Kristoufek (2013), Wikipedia views have a statistically significant impact on BitCoin price. This variable is significant and has positive impact in all models (except for model 4.8). However, the interpretation of this variable is not straightforward, as it may capture various effects. On the one hand, this may reflect speculative behaviour of investors. For example, Kristoufek (2013) argues that, since the market forces of BitCoin supply and demand allowing for setting a ‘‘fair’’ price are missing, its price is driven by the investors’ faith in the future growth and is dominated by short-term investors, trend chasers, noise traders and speculators. On the other hand, Wikipedia views may measure investors' interest in BitCoin, as it captures information’s demand about the currency (Piskorec et al. 2014). It may reflect changes in the knowledge about BitCoin between users, thus leading to a higher acceptance and demand for it. Important is that the type of individuals searching information about BitCoin on Wikipedia are likely to be new BitCoin users/investors, because Wikipedia contains rather general information about BitCoin, which is known by incumbent investors or advanced BitCoin users. Assuming that these last two arguments hold, then the estimated Wikipedia effect represents the impact of the demand side of the BitCoin economy as given by variable $Y$ in equation (3) not necessarily capturing only speculative behaviour of investors.

*Hypothesis 3: Macroeconomic and financial developments*

Our findings suggest that, in contrast to previous studies (i.e. van Wijk 2013), macro-financial indicators such as the Dow Jones Index, exchange rate and oil price do not significantly affect BitCoin price in the long-run. Only in Model 3.1 the macro and financial variables (*dj*, *oil_price* and *exrate*) are statistically significant (Table 5). This is in line with the estimates of van Wijk (2013), who also finds statistically significant impact of macro-financial variables on BitCoin price. However, van Wijk (2013) does not account for market forces of supply and demand or BitCoin’s attractiveness for investors. When these factors are taken into consideration (models 4.1 to 4.9), their impact decreases considerably in all estimated models (except for model 4.1) (Table 6).

### 5.3 Robustness checks

Given that several explanatory variables are highly correlated, we estimate alternative model specifications (Table 1) by sequentially replacing those variables that are highly correlated.[9]

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[9] Note that we have tested for the stationarity of the data series using augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests. The lags of the dependent variable in the tests were determined by Akaike

According to robustness test results reported in Table 1, we found a particularly high correlation (corr. >0.8) for the total stock of BitCoin and the size of the BitCoin economy (*totbc – ntran, totbc – naddu, naddu – ntran*), the Dow Jones Index and the total stock of BitCoins, and the size of BitCoin economy (*totbc – dj, naddu – dj*) and the Wikipedia views with the Dow Jones Index and the size of BitCoin economy (*wiki_views – dj, wiki_views – naddu*) (Table 2).

## 6 Conclusions

Due to a growing market share, a rapidly increasing price of BitCoin and its high price volatility, there is an increasing interest among users and economists in understanding the BitCoin system in general and its price formation in particular. This paper attempts to shed light on drivers that determine BitCoin price in the short- and long-run. The present paper analyses the impact of market forces of supply and demand, global macro-financial developments, and BitCoin's attractiveness for investors on BitCoin's price. Hence, our paper is the first in the literature that studies BitCoin's price formation by considering both the traditional determinants of currency price, e.g. market forces of supply and demand, and BitCoin-specific factors, e.g. digital currency's attractiveness for investors.

In order to identify and assess the determinants of BitCoin's price formation, we apply time-series analytical mechanisms to daily data for the period 2009-2014. Our empirical results confirm that market forces of BitCoin supply and demand have an important impact on BitCoin price, implying that, to a large extent, the formation of BitCoin price can be explained in a standard economic model of currency price formation. Supply and demand drivers have an important impact on BitCoin price formation and thus are among the key factors in determining its development. In particular, the demand-side drivers, such as the size of the BitCoin economy and the velocity of BitCoin circulation, have a strong impact on BitCoin price. Hence, given that BitCoin supply is exogenous, likely, the development of the demand side drivers will be among the key determinants of BitCoin price also in the future.

Second, we cannot reject the hypothesis that investor speculations are also affecting BitCoin price. The statistically significant impact of Wikipedia views on BitCoin price could be an evidence of speculative short-run behaviour of investors, or it may capture the expansion of

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Information Criterion (AIC). Both tests show that all the time series are non-stationary in levels but stationary in first differences (results of the tests are available upon request from authors).

the demand side of BitCoin economy. Additionally, we find that also new information impact BitCoin price positively, which may be a result of an increased trust among users. As such, speculative trading of BitCoins is not necessarily an undesirable activity, as it may generate benefits in terms of absorbing excess risk from risk adverse participants and providing liquidity on the market. A negative side of the short-run speculative investment is that it may increase price volatility and create price bubbles. The success of BitCoin thus also hitches on its ability to reduce the potential negative implications of such speculations and expand the use of BitCoin in trade and commerce.

Finally, our estimates do not support previous findings that macro-financial indicators may be driving BitCoin price. In fact, once we control for supply-demand variables and BitCoin's attractiveness for investors linked to BitCoin, the impact of macro-financial indicators becomes statistically insignificant.

Our findings contribute to a better understanding of the determinants behind the enormous BitCoin's price fluctuations experienced in the recent years. A desirable property of any monetary mean is that it holds its value over short-to-medium periods of time, in order not to create distortion when used as a medium of exchange in transaction. Large price movements alter the purchasing power potentially causing costs and risk to firms and consumers using it as a medium of exchange in transaction of goods and services. Understanding the price formation of BitCoin is highly relevant both from a general monetary policy point of view and from a BitCoin's ability to serve as a medium of exchange for global economy's point of view.

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## Table 1: Specification of the empirically estimated models

| | | M 1.1 | M 1.2 | M 1.3 | M 1.4 | M 1.5 | M 2.1 | M 3.1 | M 4.1 | M 4.2 | M 4.3 | M 4.4 | M 4.5 | M 4.6 | M 4.7 | M 4.8 | M 4.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Supply-demand variables | totbc | x | x | x | | | | | | x | x | | x | | | | |
| | ntran | x | | | | x | | | | | | | | | | x | x |
| | naddu | | x | | x | | | | | x | x | x | | | x | | |
| | bcdde | x | x | x | x | x | | | | x | x | x | x | x | x | x | x |
| | exrate | x | x | x | x | x | | x | x | x | | | | | | | |
| BitCoin's attractiveness for investors | wiki_views | | | | | | x | | x | x | x | x | | x | | x | |
| | new_member | | | | | | x | | | x | x | | x | x | | x | x |
| | new_posts | | | | | | x | | | x | x | x | x | x | x | x | x |
| Macro-financial developments | dj | | | | | | | x | x | x | x | | | | | | x |
| | oil_price | | | | | | | x | x | x | | | | | | | |

**Table 2: Correlation coefficients**

| | ntran | totbc | bcdde | dj | wiki_views | naddu | oil_price | ex_rate | new_posts | new_members |
|---|---|---|---|---|---|---|---|---|---|---|
| ntran | 1 | | | | | | | | | |
| totbc | **0.92** | 1 | | | | | | | | |
| bcdde | 0.45 | 0.41 | 1 | | | | | | | |
| dj | 0.76 | **0.92** | 0.38 | 1 | | | | | | |
| wiki_views | 0.71 | 0.79 | 0.51 | **0.83** | 1 | | | | | |
| naddu | **0.92** | **0.95** | 0.47 | **0.91** | **0.86** | 1 | | | | |
| oil_price | -0.21 | 0.03 | -0.06 | 0.29 | 0.07 | -0.01 | 1 | | | |
| ex_rate | 0.19 | 0.44 | 0.19 | 0.59 | 0.50 | 0.42 | 0.50 | 1 | | |
| new_posts | 0.59 | 0.68 | 0.34 | 0.75 | 0.68 | 0.74 | 0.11 | 0.36 | 1 | |
| new_members | 0.40 | 0.45 | 0.24 | 0.51 | 0.59 | 0.53 | 0.01 | 0.25 | 0.66 | 1 |

## Table 3: Short-run effects on BitCoin Price for hypotheses 1, 2 and 3

| | M 1.1 | M 1.2 | M 1.3 | M 1.4 | M 1.5 | M 2.1 | M 3.1 |
|---|---|---|---|---|---|---|---|
| LD.mkpru | 0.147*** | 0.136*** | 0.149*** | 0.135*** | 0.145*** | 0.147*** | 0.143*** |
| L2D.mkpru | -0.017 | -0.021 | -0.017 | -0.020 | -0.014 | -0.020 | - |
| L3D.mkpru | -0.033 | -0.027 | -0.037 | -0.028 | -0.025 | -0.032 | - |
| L4D.mkpru | 0.054* | - | 0.051 | - | - | - | - |
| LD.totbc | -17.31 | -11.940 | -21.540 | - | - | - | - |
| L2D.totbc | 38.51 | 44.880* | 36.500 | - | - | - | - |
| L3D.totbc | -43.68* | -20.140 | -48.360** | - | - | - | - |
| L4D.totbc | 41.60** | - | 39.190* | - | - | - | - |
| LD.ntran | 0.001 | - | - | - | 0.000 | - | - |
| L2D.ntran | -0.002 | - | - | - | 0.003 | - | - |
| L3D.ntran | -0.016 | - | - | - | -0.018 | - | - |
| L4D.ntran | -0.011 | - | - | - | - | - | - |
| LD.naddu | - | 0.015 | - | 0.011 | - | - | - |
| L2D.naddu | - | 0.005 | - | 0.007 | - | - | - |
| L3D.naddu | - | -0.022 | - | -0.023 | - | - | - |
| L4D.naddu | - | - | - | - | - | - | - |
| LD.bcdde | -0.009** | -0.009** | -0.011*** | -0.009*** | -0.008** | - | - |
| L2D.bcdde | -0.007* | -0.006* | -0.008** | -0.006** | -0.006* | - | - |
| L3D.bcdde | -0.005 | -0.003 | -0.007* | -0.003 | -0.003 | - | - |
| L4D.bcdde | -0.002 | - | -0.003 | - | - | - | - |
| LD.exrate | -0.382 | -0.391 | -0.417 | -0.404 | -0.426 | - | -0.630 |
| L2D.exrate | 0.369 | 0.429 | 0.327 | 0.429 | 0.359 | - | - |
| L3D.exrate | 0.175 | 0.292 | 0.152 | 0.280 | 0.222 | - | - |
| L4D.exrate | -0.278 | - | -0.306 | - | - | - | - |
| LD.wiki_views | - | - | - | - | - | -0.005 | - |
| L2D.wiki_views | - | - | - | - | - | -0.012* | - |
| L3D.wiki_views | - | - | - | - | - | -0.015** | - |
| L4D.wiki_views | - | - | - | - | - | - | - |
| LD.new_members | - | - | - | - | - | 0.004 | - |
| L2D.new_members | - | - | - | - | - | 0.005 | - |
| L3D.new_members | - | - | - | - | - | -0.001 | - |
| L4D.new_members | - | - | - | - | - | - | - |
| LD.new_posts | - | - | - | - | - | -0.007 | - |
| L2D.new_posts | - | - | - | - | - | -0.002 | - |
| L3D.new_posts | - | - | - | - | - | 0.005 | - |
| L4D.new_posts | - | - | - | - | - | - | - |
| LD.dj | - | - | - | - | - | - | -0.046 |
| L2D.dj | - | - | - | - | - | - | - |
| L3D.dj | - | - | - | - | - | - | - |
| L4D.dj | - | - | - | - | - | - | - |
| LD.oilprice | - | - | - | - | - | - | 0.178 |
| L2D.oilprice | - | - | - | - | - | - | - |
| L3D.oilprice | - | - | - | - | - | - | - |
| L4D.oilprice | - | - | - | - | - | - | - |
| constant | - | - | 0.000 | - | - | - | - |

Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. "-" indicates either absence of a variable in the respective model or the coefficient is not significantly different from zero.

## Table 4: Short-run effects on BitCoin Price for general models

| | M 4.1 | M 4.2 | M 4.3 | M 4.4 | M 4.5 | M 4.6 | M 4.7 | M 4.8 | M 4.9 |
|---|---|---|---|---|---|---|---|---|---|
| LD.mkpru | 0.144*** | 0.136*** | 0.147*** | 0.146*** | 0.145*** | 0.149*** | 0.143*** | 0.148*** | 0.147*** |
| L2D.mkpru | - | -0.032 | -0.017 | -0.026 | -0.027 | -0.024 | -0.020 | -0.016 | -0.017 |
| L3D.mkpru | - | - | -0.021 | - | - | - | -0.022 | -0.033 | -0.028 |
| L4D.mkpru | - | - | - | - | - | - | - | 0.056* | 0.054* |
| LD.totbc | - | -20.930 | -15.524 | - | -16.637 | - | - | - | - |
| L2D.totbc | - | 26.010 | 44.028*** | - | 31.547 | - | - | - | - |
| L3D.totbc | - | - | -32.434 | - | - | - | - | - | - |
| L4D.totbc | - | - | - | - | - | - | - | - | - |
| LD.ntran | - | - | - | - | - | - | - | 0.001 | 0.001 |
| L2D.ntran | - | - | - | - | - | - | - | 0.006 | 0.002 |
| L3D.ntran | - | - | - | - | - | - | - | -0.018 | -0.020 |
| L4D.ntran | - | - | - | - | - | - | - | -0.009 | -0.007 |
| LD.naddu | - | 0.024 | 0.001 | 0.009 | - | - | 0.006 | - | - |
| L2D.naddu | - | 0.014 | -0.002 | 0.007 | - | - | 0.001 | | - |
| L3D.naddu | - | - | -0.022 | - | - | - | -0.026* | - | - |
| L4D.naddu | - | - | - | - | - | - | - | - | - |
| LD.bcdde | - | -0.003 | -0.004 | -0.005 | -0.005 | -0.004 | -0.009** | -0.006 | -0.009** |
| L2D.bcdde | - | -0.002 | -0.002 | -0.004 | -0.003 | -0.003 | -0.006* | -0.005 | -0.008* |
| L3D.bcdde | - | - | -0.001 | - | - | - | -0.003 | -0.003 | -0.005 |
| L4D.bcdde | - | - | - | - | - | - | - | -0.002 | -0.003 |
| LD.exrate | -0.644 | -0.488 | - | - | - | - | - | - | - |
| L2D.exrate | - | 0.370 | - | - | - | - | - | - | - |
| L3D.exrate | - | - | - | - | - | - | - | - | - |
| L4D.exrate | - | - | - | - | - | - | - | - | - |
| LD.wiki_views | -0.002 | -0.003 | -0.007 | 0.001 | - | 0.001 | - | -0.004 | - |
| L2D.wiki_views | - | -0.010 | -0.013* | -0.009 | - | -0.008 | - | -0.011 | - |
| L3D.wiki_views | - | - | -0.014** | - | - | - | - | -0.012* | - |
| L4D.wiki_views | - | - | - | - | - | - | - | 0.004 | - |
| LD.new_members | - | 0.003 | 0.003 | 0.003 | 0.003 | 0.004 | - | 0.004 | 0.002 |
| L2D.new_members | - | 0.005 | 0.005 | 0.004 | 0.004 | 0.005 | - | 0.005 | 0.002 |
| L3D.new_members | - | - | -0.001 | - | - | - | - | -0.001 | -0.003 |
| L4D.new_members | - | - | - | - | - | - | - | 0.001 | 0.000 |
| LD.new_posts | - | -0.006 | -0.005 | -0.006 | -0.005 | -0.007 | - | -0.007 | -0.006 |
| L2D.new_posts | - | -0.003 | -0.001 | -0.003 | -0.003 | -0.003 | -0.003 | -0.002 | -0.001 |
| L3D.new_posts | - | - | 0.006 | - | - | - | 0.001 | 0.004 | 0.004 |
| L4D.new_posts | - | - | - | - | - | - | 0.004 | -0.001 | -0.001 |
| LD.dj | -0.057 | -0.143 | 0.009 | - | - | - | - | - | 0.085 |
| L2D.dj | - | 0.088 | 0.008 | - | - | - | - | - | 0.010 |
| L3D.dj | - | - | -0.226 | - | - | - | - | - | -0.209 |
| L4D.dj | - | - | - | - | - | - | - | - | 0.094 |
| LD.oilprice | 0.181 | 0.212 | - | - | - | - | - | - | - |
| L2D.oilprice | - | -0.176 | - | - | - | - | - | - | - |
| L3D.oilprice | - | - | - | - | - | - | - | - | - |
| L4D.oilprice | - | - | - | - | - | - | - | - | - |
| constant | - | - | - | - | - | - | - | - | - |

Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. "-" indicates either absence of a variable in the respective model or the coefficient is not significantly different from zero.

**Table 5: Long-run effects on BitCoin Price for hypotheses 1, 2 and 3**

| | M 1.1 | M 1.2 | M 1.3 | M 1.4 | M 1.5 | M 2.1 | M 3.1 |
|---|---|---|---|---|---|---|---|
| totbc | -4.2 | -5.96*** | - | - | - | - | - |
| ntran | -3.99** | - | - | - | -3.42*** | - | - |
| naddu | - | 3.17*** | - | - | - | - | - |
| bcdde | 11.71*** | - | 5.07*** | 5.40*** | 10.84*** | - | - |
| exrate | - | - | 12.69 | - | 0.43 | - | 16.04*** |
| wiki_views | - | - | - | - | - | 1.94*** | - |
| new_members | - | - | - | - | - | - | - |
| new_posts | - | - | - | - | - | - | - |
| dj | - | - | - | - | - | - | 16.10*** |
| oil_price | - | - | - | - | - | - | - 4.52*** |
| constant | -62.14 | -66.73** | -77.35*** | -77.79*** | -124.98*** | -13.66*** | -133.79*** |

Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level
"-" indicates either absence of a variable in the respective model or the coefficient is not significantly different from zero.

**Table 6: Long-run effects on BitCoin Price for general models**

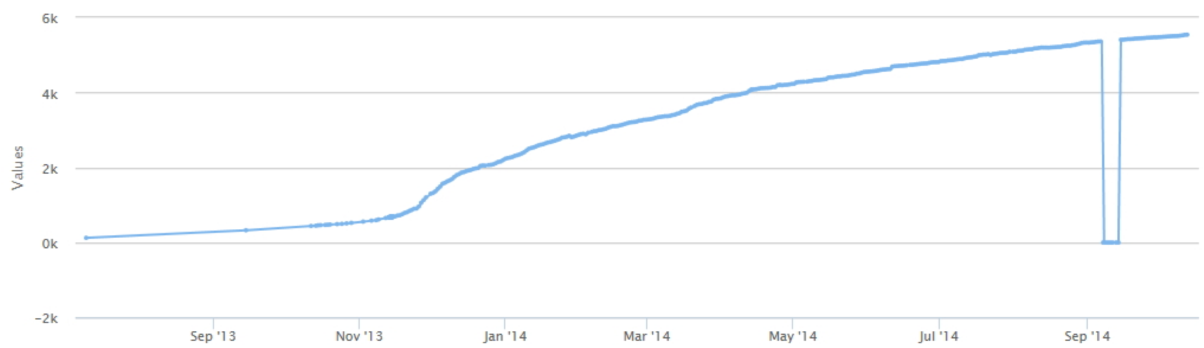
| | M 4.1 | M 4.2 | M 4.3 | M 4.4 | M 4.5 | M 4.6 | M 4.7 | M 4.8 | M 4.9 |
|---|---|---|---|---|---|---|---|---|---|
| totbc | - | - | - | - | - | - | - | - | - |
| ntran | - | - | - | - | - | - | - | - | - |
| naddu | - | - | 0.36 | 0.50*** | - | - | - | - | - |
| bcdde | - | - | 0.41*** | - | - | - | 0.28** | - | - |
| exrate | 0.63 | - | - | - | - | - | - | - | - |
| wiki_views | 1.38*** | 0.89*** | 0.90*** | 1.78*** | - | 1.93*** | - | - | - |
| new_members | - | -1.23*** | -0.26*** | -0.35*** | - | - | - | -0.46*** | -0.35*** |
| new_posts | - | 2.33*** | 1.21*** | - | 1.92*** | - | 1.99*** | 2.55*** | 2.44*** |
| dj | 4.79*** | - | - | - | - | - | - | - | - |
| oil_price | - | - | - | - | - | - | - | - | - |
| constant | -54.45*** | -17.44** | -15.64*** | -15.73*** | -11.89*** | -13.62*** | -17.23*** | -15.29*** | -14.96*** |

Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level
"-" indicates either absence of a variable in the respective model or the coefficient is not significantly different from zero.

**Figure 1. BitCoin price development, 2009-2014**


Source: Bitcoin Block Explorer – Blockchain.

**Figure 2. Number of venues accepting bitcoin, 2009-2014**




Source: http://www.bitcoinpulse.com/#/chart/coinmap/num_venues.