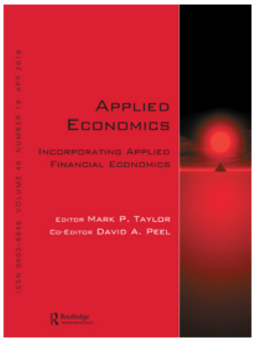

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The economics of BitCoin price formation

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ABSTRACT
This is the first article that studies BitCoin price formation by considering both the traditional determinants of currency price, e.g., market forces of supply and demand, and digital currencies specific factors, e.g., BitCoin attractiveness for investors and users. The conceptual framework is based on the Barro (1979) model, from which we derive testable hypotheses. Using daily data for five years (2009–2015) and applying time-series analytical mechanisms, we find that market forces and BitCoin attractiveness for investors and users have a significant impact on BitCoin price but with variation over time. Our estimates do not support previous findings that macro-financial developments are driving BitCoin price in the long run.

KEYWORDS
BitCoin; exchange rate; supply and demand; financial indicators; financial investment

JEL CLASSIFICATION
E31; E42; G12

I. Introduction

During the last decade, 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. BitCoin price has increased from zero value at the time of its inception in 2009 to around \$1100 at the end of 2013 (see Fig. 1). At the end of 2014, its price has dropped to around \$250, but is increasing again since then. Such market volatility with huge price movements (±8000%) is not usual for traditional currencies, suggesting that there must be other determinants of price formation, which are specific to digital currencies. The present article attempts to identify and assess the factors behind the BitCoin price formation.

Its 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; Bouoiyour, Selmi, and Tiwari (2014); and BitCoin price formation in particular (e.g. Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013; Bouoiyour and Selmi 2015). Several factors affecting BitCoin price have been identified in the previous literature: (i) market forces of BitCoin supply and demand (Buchholz et al. 2012; Bouoiyour and Selmi 2015); (ii) BitCoin attractiveness for investors (Kristoufek 2013; Bouoiyour and Selmi 2015); and (iii) global macro-financial development (van Wijk 2013). Our article is the first in the literature that studies BitCoin price formation by considering both the traditional determinants of currency price, such as market forces of supply and demand, and digital currency-specific factors, e.g., BitCoin attractiveness for investors.

Buchholz et al. (2012) find that an important determinant of BitCoin price (as price of any currency) is the interaction between BitCoin 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 for goods and services. Buchholz et al. find that, to a large extent, BitCoin price movements can be explained by interactions between its supply and demand.

According to Kristoufek (2013), the price formation of BitCoin cannot be explained by standard economic theories, such as future cash-flows model, purchasing power parity, or uncovered

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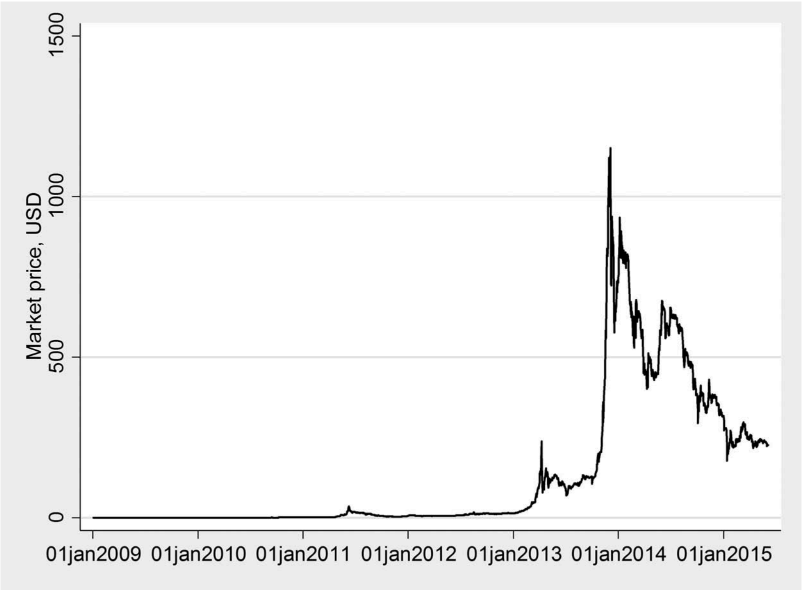

Figure 1. BitCoin price development, 2009–2015. Source: Blockchain.

interest rate parity, because several features of currency supply and demand, which usually form the basis of currency price, are absent on BitCoin markets. In particular, BitCoin is not issued by a specific central bank or government. Thus, it is detached from the real economy implying that there are no macroeconomic fundamentals that would determine its price formation. Similarly, findings of Bouoiyour and Selmi (2015) provide support that BitCoin is largely detached from macroeconomic fundamentals and rather behaves as a 'speculative bubble'. According to the Bouoiyour and Selmi estimates, the contribution of speculation (proxied by investors' attractiveness to BitCoin) to BitCoin price formation dominates other drivers such as market forces of supply and demand.

van Wijk (2013) stresses the role of global macro-financial development, captured, e.g., by stock exchange indices, exchange rates and oil price measures, in determining BitCoin price. van Wijk finds evidence that, for example, 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 separately at specific BitCoin price determinants, without considering interactions between them. A second shortcoming of previous studies is that they do not account for potential structural breaks in BitCoin price series which can lead to the biased results when performing econometric estimations. The present article attempts to close this research gap by accounting for all three types of BitCoin price determinants identified in the previous literature: market forces of supply and demand, attractiveness indicators and global macroeconomic and financial development to explain the formation of BitCoin price, and by accounting for interactions between them. Further, the present article tests for structural breaks in BitCoin price series and, based on the identified break, provides a more nuanced dynamics of BitCoin price formation over time.

In order to identify and assess the determinants of BitCoin price formation, first we derive an econometrically estimable model from the Barro (1979) model for gold standard. Second, based on previous studies on BitCoin price formation, we extend the canonical model to capture factors which are specific to digital currencies and formulate testable hypotheses. Finally, in order to test the BitCoin price formation hypotheses, we apply time-series analytical mechanisms to daily data for the period 2009–2015.

Our empirical results confirm that market forces of BitCoin supply and demand have an important impact on BitCoin price and their importance tends to increase over time. Second, we cannot reject the hypothesis that investors speculative behaviour affect BitCoin price in the short- and long run. The short-run price fluctuations are driven by online information search about BitCoin in the first years after its introduction, when it was little known. In the later years, when it became more established on financial markets, the impact of online searches seems to be minimal. Third, our estimates do not support previous findings that macro-financial indicators are driving BitCoin price. Furthermore, the results of our analysis underline the importance of analysing different drivers of BitCoin price simultaneously, as the results are likely to be biased when looking at one factor at a time.

The rest of the article is structured as follows. Section II provides background information about BitCoin, which is a relatively new digital currency with several features being different from traditional currencies. Section III introduces the underlying conceptual framework and formulates testable hypotheses of BitCoin price formation. Section IV outlines the econometric approach and discusses how we address the key estimation issues. Section V details the data sources used in the empirical analysis, the construction of the estimable model's variables and discusses the estimation results. The final section concludes.

II. 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 exchange of BitCoins. Access to the BitCoin network requires downloading a BitCoin software on a personal computer and joining the BitCoin network, which allows participants to engage in operations, as well as 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. 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. 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 growth rate of BitCoin will converge to zero, when the maximum amount of BitCoins in circulation will reach 21 million units; according to the current algorithm it will not change after 2140.

BitCoins can be used to buy goods or services worldwide, provided that the transaction partner accepts BitCoin as a mean of payment. A transaction implies that the owner of BitCoins transfers the ownership of a certain amount 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 beginning of 2015, there were more than 100 000 venues accepting BitCoins (Cuthbertson 2015).

III. Conceptual framework and testable hypotheses

The model

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 traditional government-controlled fiat currency, such as dollars. Similarly, we assume that users need to convert BitCoins into dollars or other traditional currencies, as they operate in economies using traditional currencies for purchasing goods and services.[1]

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). The total BitCoin money supply, M^S, is then given by $P^B B$:

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

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

[1]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.

of BitCoin economy, G, and the velocity of BitCoin circulation, V. The BitCoin velocity, V, measures the frequency at which one unit of BitCoin is used for purchasing goods and services, and it depends on the opportunity cost for holding it (inflation, opportunity interest rate).

$$M^D = \frac{PG}{V} \tag{2}$$

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

$$P^B = \frac{PG}{VB} \tag{3}$$

In perfect markets, the equilibrium price is 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 general price level.

Note that in the market equilibrium Equation 3 some variables, such as BitCoin price, P^B, the general price level of goods and services, P, and the size of the BitCoin economy, G, adjust simultaneously, which may cause endogeneity issues when estimating the price relationship econometrically. In standard regression models by placing particular variables on the right-hand side, the endogeneity of simultaneous variables sharply violates the exogeneity assumption of a regression equation. In order to address the endogeneity issue, we will apply time-series analytical mechanisms (see further).

Testable hypotheses

We 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; Kancs, Ciaian, and Rajcaniova 2015; Bouoiyour and Selmi 2015) to derive testable hypotheses of BitCoin price formation: (i) market forces of BitCoin supply and demand, (ii) BitCoin 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) and Bouoiyour and Selmi (2015), one of the key drivers of BitCoin price is the interaction between BitCoin supply and demand on BitCoin market. The demand for BitCoin is primarily driven by its value as a medium of exchange for goods and services, i.e., by its value in future exchange. The key difference between the gold standard and BitCoin is that the demand for BitCoins is driven by its value in future exchange, whereas the demand for commodity currency is driven both by 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 (fixed) in the long run. Note that, whereas BitCoin supply is exogenous, the supply of gold is endogenous in Barro's (1979) model for gold standard, as it responds to changes in production technology (e.g. mining technology for gold) and returns.

We can rewrite Equation 3 into an empirically estimable model of BitCoin price[2]:

$$p_t^B = \beta_0 + \beta_1 p_t + \beta_2 g_t + \beta_3 v_t + \beta_4 b_t + \epsilon_t \tag{4}$$

where ϵ_t is an error term. According to the underlying theoretical framework of Barro (1979), we expect that β_1 and β_2 would be positive, whereas β_3 and β_4 would be negative. In addition, given that BitCoin supply is largely predefined, the total stock of BitCoins in circulation, b, is a semi-exogenous variable, and implying that the impact of coefficient β_4 on BitCoin price should be small and/or statistically not significant.

Hypothesis 2: Investment attractiveness

BitCoin has been created relatively recently, particularly, when compared to standard currencies such as dollar or other investment goods, such as gold. As a result, there are several BitCoin-specific factors which, in addition to traditional currency price determinants, such as market supply and demand, determine investment demand for BitCoins (Barber

[2]We decided not to apply logarithmic transformation of the data because this would drop all zero observations for several variables used in estimations in particular for BitCoin days destroyed for any given transaction, Wikipedia views, page views, new posts, new topics, new members, and BitCoin price. Observations with zero values were frequent particularly in the first years (2009 – 2011) when BitCoin was not used widely.

et al. 2012; Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013; Bouoiyour and Selmi 2015).

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 future (Greco 2001).[3] 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 trust and credibility among market participants. The credibility of BitCoin is largely linked to the security the BitCoin system provides to its holders and when used in exchanges. Given that BitCoin transactions take place exclusively over Internet, cyber-security is its main challenge. Cyber-attacks may destabilize the whole BitCoin system and eventually lead to its collapse. Being a digital currency, BitCoin is more vulnerable to cyber-attacks than traditional currencies. Such attacks have been frequently occurring in the BitCoin system in the past (Barber et al. 2012; Moore and Christin 2013). Moore and Christin (2013) examined 40 BitCoin exchanges and found that 18 have been closed down after 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. Negative news about BitCoin system security, such as cyber-attacks on BitCoin exchanges, reduce BitCoin attractiveness for investors. In contrast, positive news about BitCoin system security, such as an upgrade to safer BitCoin network software, increase BitCoin attractiveness for investors.

Given that BitCoin is a relatively new currency, its attractiveness for investors and hence BitCoin price is determined by transactions costs for potential investors and users. According to Gervais, Kaniel, and Mingelgrin (2001); Grullon, Kanatas, and Weston (2004) and Barber and Odean (2008), potential investors' and users' decisions can be affected by an increase or decrease of attention in the news media. The role of information is particularly important in presence of many alternative investment opportunities, positive search costs and security concerns. Given that investment demand depends on the costs associated with searching for information for potential investment opportunities available on the market, such as, stock exchange, those investment opportunities which are under a particular attention in news media may be preferred by potential investors, because they reduce search costs. Similar holds for the information search cost for payment method to BitCoin users. The choice of the payment method (e.g. PayPal, Visa, MasterCard, BitCoin) used for exchanging goods and services depends on the costs associated with searching for information to potential users. Those payment methods which are under a particular attention in news media reduce search costs, and hence may be preferred by users. Overall, an increased demand for BitCoin due to higher attractiveness may exercise upward pressure on BitCoin price, whereas a lower attractiveness may imply a decrease in BitCoin demand and its 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 behaviour from both investors and users 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 investment attractiveness in BitCoin price formation, we extend the estimable model (4) as follows:

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

where a_t captures investment attractiveness. As discussed above, coefficient β_5 can be either negative or positive, as both positive and negative news attract attention. Neutral news would likely reduce search costs, increase BitCoin demand and hence its price.

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

Hypothesis 3: Global 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 price 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 a positive impact on BitCoin price.

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

According to Dimitrova (2005), there can also be a negative relation between a currency's price and macro-financial indicators. A decline in stock prices on stock exchange may induce foreign investors to sell the financial assets they hold. This in turn may lead to a depreciation of the respective currency, but may stimulate BitCoin 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 to BitCoin price.

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

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

where m_t captures macroeconomic and financial indicators. According to the previous findings discussed above, we expect β_6 to be either positive or negative.

IV. Econometric approach

The testable hypotheses derived in Section III contain mutually interdependent variables – BitCoin price and its explanatory variables. The estimation of non-linear interdependencies among interdependent time series in the presence of mutually correlated variables is subject to possible endogeneity biases (Lütkepohl and Krätzig 2004). To circumvent the issue of endogeneity, we follow the general approach in the literature to analyse the causality between endogenous time-series and specify a multivariate 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. In the first step, we test for the stationarity of time series, for which we use four unit-root tests: the augmented Dickey–Fuller (ADF) test, the Dickey–Fuller GLS (DF-GLS) test, the Zivot–Andrews (ZA) test and Clemente–Montañés–Reyes (CMR) test. The DF-GLS test is considered to be a more efficient test for autoregressive unit root recommended by Elliot, Rothenberg, and Stock (1996). Compared with the ADF tests, the DF-GLS test has the best overall performance in terms of sample size and power (Elliot, Rothenberg, and Stock 1996). However, as argued by Perron (1989), the existence of exogenous shock which has a permanent effect will lead to a non-rejection of the unit-root hypothesis with both ADF and DF-GLS test even though it is present. To account for the potential structural breaks in the series, which can lead to biased results in traditional tests, we also apply the ZA test and CMR test. The ZA test takes into consideration structural breaks in intercept, trend or both. The CMR unit-root test distinguishes between two types of breaks. In a model with additive outliers (AO model), changes are assumed to take place rapidly, allowing for break in the slope. In a model with innovative outliers (IO model), changes are assumed to take place gradually and allow for break both in intercept and slope. Testing for unit root while allowing for structural break in the series can prevent the test results to be biased towards unit root, and it can also identify the period when the structural break occurred (Perron 1989). The number of lags that we use for each dependent variable is determined by the Akaike Information Criterion (AIC).

The results of the unit-root tests may suggest three different outcomes: (i) all variables are non-stationary in levels but stationary in first differences (integrated of order 1), (ii) all variables are stationary in levels (integrated of order 0), and (iii) there is a mix of $I(0)$ and $I(1)$ variables in the model. If two or more series are stationary, then the standard OLS estimator can be used to estimate the model. If two or more individual time series are non-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 this case, the Vector Error Correction (VEC) model is suitable for estimation. With non-stationary and non-cointegrated variables, we need to turn to the VAR model using first differences. And finally, in the case when variables are both $I(0)$ and $I(1)$, the application of an autoregressive distributed lag (ARDL) model may be the most appropriate.

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* (Pantula 1989) to determine whether a time trend and a constant term should be included in the model.

Based on the results of the Johansen cointegration test, we decide whether to use VAR (no cointegration), ARDL (one cointegration relationship among $I(0)$ and $I(1)$ variables, or VEC (more than one cointegration relationships) model.

In the third step, we estimate a VAR model for non-stationary and non-cointegrated series, and derive an ARDL or VEC model for those series that are cointegrated. They include 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 into a VEC model as follows:

$$Z_t = \mu_1 + \delta_1 t + A_1 Z_{t-1} + \cdots + A_k Z_{t-k} + \varepsilon_t \qquad (7)$$

$$\Delta Z_t = \mu_1 + \delta_1 t + \Gamma_1 \Delta Z_{t-1} + \cdots + \Gamma_{k-1} \Delta Z_{t-p+1} + \pi \begin{pmatrix} \beta \\ \mu_2 \\ \delta_2 \end{pmatrix} (Z_{t-1} \quad 1 \quad t) Z_{t-1} + \varepsilon_t \qquad (8)$$

where Z_t is a vector of non-stationary variables, A are the matrices of different parameters, t is the time subscript, k is the number of lags, and ε_t is the error term assumed to follow *i.i.d.* process with zero mean and normally distributed $N(0, \sigma^2)$ error structure. Equation 7 can contain a constant with coefficient μ_1 and/or a trend variable with coefficient δ_1.

Equation 8 contains information on both short- and long-run adjustments to changes in Z_t via the estimates of Γ_i and Π, respectively. Π is decomposed in Equation 8 as $\Pi = \pi\beta'$, where π represents the speed of adjustment to disequilibrium, and β represents the long-run relationships between variables (Johansen and Juselius 1990). Equation 8 includes all possible options that can occur. In general, there are five different models that can be considered. Model 1 contains no intercept or trend in the cointegrating equation or VAR: $\delta_1 = \delta_2 = \mu_1 = \mu_2 = 0$. In Model 2, there is intercept but no trend is included in the cointegrating equation, and no intercept or trend in VAR: $\delta_1 = \delta_2 = \mu_1 = 0$. Model 3 considers intercept in the cointegrating equation and VAR, but no trend in the cointegrating equation or VAR: $\delta_1 = \delta_2 = 0$. Model 4 contains intercept in the cointegrating equation and VAR, a linear trend in the cointegrating equation, and no trend in VAR: $\delta_1 = 0$. And finally, in Model 5 there is intercept and quadratic trend in the cointegrating equation, or intercept and linear trend in VAR.

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–Bera test to check if the residuals in the VEC are normally distributed and a test of stability of the model. The order of lags is determined by the AIC.

In the case when some of the variables are stationary in levels, while others are difference stationary, we can get a 'trivial' cointegration equation and the cointegration rank is then augmented by one. To check whether this is the case, we re-estimate the number of cointegration relationships without $I(0)$

variable and treat it as an exogenous variable included in levels in the VEC model.

An advantage of the ARDL model of Pesaran, Shin, and Smith (2001) is that it can be applied irrespective of the order of integration of model variables (mix of $I(0)$ and $I(1)$ variables). The ARDL modelling framework estimates the following error correction model:

$$\Delta Y_t = \alpha_{0y} + \alpha_{1y} Y_{t-1} + \alpha_{2y} X_{t-1} + \sum_{i=1}^{n} \beta_i \Delta Y_{t-i} + \sum_{j=1}^{n} \gamma_i \Delta X_{t-j} + u_{1t} \quad (9)$$

where Y is the dependent variable, X contains independent variable(s), n is the number of lags, and Δ represents the differences. Cointegration between Y_t and X_t is tested using bounds test approach. Bounds test computes F-statistics to confirm the existence of long-run cointegration relationships between the underlying variables irrespective of whether those variables are $I(0)$ or $I(1)$ (Pesaran and Pesaran 2009).

V. Data and results

Data and variable construction

In order to construct the dependent variable, we use data for BitCoin price, P^B, denominated in US dollars (*BitCoin price*). We use the following proxies to capture market forces of BitCoin supply and demand as suggested by the price relationship (6). We use the historical number of total BitCoins (*number of BitCoins*), which have been mined, to account for the total stock of BitCoins in circulation, B. We use two alternative proxies for the size of BitCoin economy, G: the total number of unique BitCoin transactions per day (*number of transactions*), and the number of unique BitCoin addresses used per day (*number of addresses*). Following Matonis (2012), we proxy the monetary velocity of BitCoin circulation, V, by the days destroyed of any given transaction (*days destroyed*). This variable is calculated by taking the number of BitCoins in 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 US dollar and Euro (*exchange rate*) extracted from the Federal Reserve System. We use the exchange rate between the US dollar and euro, because in our data BitCoin price is denominated in the US dollars. For example, if the US dollar would appreciate against euro, most likely it would also appreciate against the BitCoin. Consequently, an increase in the exchange rate between euro and the US dollar would lead to a decrease in the amount of the US dollars that have to be paid for one BitCoin, which decreases its price.

In order to capture investment attractiveness, a, we follow Kristoufek (2013) and use the volume of daily BitCoin views on Wikipedia (*views on Wikipedia*).[4] According to Kristoufek (2013), the frequency of searches related to a digital currency is a good measure of potential investors' interest in the currency. However, the variable *Wikipedia views* may measure both investors' and users' interest in BitCoin, as it captures information demand about BitCoin, but it does not differentiate whether the information is used to guide investment decisions or BitCoin denominated exchanges (*purchases*) of goods and services. In addition, we also construct variables capturing the number of new members (*new members*) and new posts on online BitCoin forums (*new posts*) extracted from *bitcointalk.org*. As explained above, the variable *new members* captures the size of the BitCoin economy and also attention-driven behaviour of new BitCoin users/investors. The variable *new posts* captures the effect of trust, uncertainty and/or attention-driven behaviour, as it represents the intensity of discussions among members.

In order to capture the impact of macro-financial developments on BitCoin price, we follow van Wijk (2013) and we use oil price (*oil price*) and the Dow Jones stock market index (Dow Jones), which is an industrial average that captures 30 major corporations on either the NYSE or the NASDAQ. Both variables are often used in the literature to account for global macroeconomic and financial developments. Oil prices are extracted from the US Energy Information Administration, and Dow Jones index is extracted from the Federal Research Bank of St. Louis.

[4]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.

Specification tests

As explained above, we tested for stationarity of our data series using ADF, DF-GLS, ZA and CMR. The lags of the dependent variable in the tests were determined by the AIC. The test results are reported in Table 1–Table 4. Based on a visual inspection as well as the break dates identified by the tests (Table 3 and Table 4), we can observe two clearly different regimes of price formation: before October 2013 and after this breakpoint. To incorporate this information into our analysis, we split the data into two periods. The first regime covers the period from November 2009 to September 2013, whereas the second regime includes the period from October 2013 to May 2015.

While the unit-root hypothesis could not be rejected for all series in levels, the first differences were found to be stationary (Table 1–Table 4). The next step is to investigate whether the model variables share a common long-run relationship. To achieve this, we test the presence of the long-run relationship among variables. The results of the Johansen trace and max-eigenvalue tests for cointegration are summarized in Table 5. They indicate the number of cointegration relationships identified among variables (see Maximum rank in Table 5). We use VAR for not cointegrated time series; ARDL to model one cointegration relationship among $I(0)$ and $I(1)$ variables and VEC for more than one cointegration relationship.

Estimation results

Following the theoretical hypotheses, we estimate four sets of econometric models of BitCoin price. Differences in the specifications between the estimated models are summarized in Table 6. Models 1.1–3.1 consider the three types of divers of BitCoin price separately. Models 1.1–1.5 capture BitCoin supply–demand interactions and their impact on BitCoin price (hypothesis 1). Model 2.1 estimates the impact of BitCoin attractiveness for investors and users of buying/selling BitCoins (hypothesis 2). Model 3.1 estimates the impact of global macroeconomic and financial developments (hypothesis 3). General Models 4.1–4.9 consider the three types of BitCoin price determinants simultaneously (i.e. the combination of drivers as identified in hypothesis 1–3) to account for potential structural interaction between them. All models are estimated for two periods: for the 1st period from November 2009 to September 2013

Table 1. Augmented Dickey–Fuller test for unit root.

	Whole period			1st period			2nd period		
	None	Constant	Constant & trend	None	Constant	Constant & trend	None	Constant	Constant & trend
Levels									
BitCoin price	−1.186	−1.635	−2.142	0.865	0.282	−1.061	−0.813	−2.288	−2.857
number of transactions	2.074	0.631	−2.386	0.348	−0.571	−2.420	1.525	−0.431	−2.117
number of BitCoins	0.660	−1.040	−1.300	0.651	−2.550	1.062	2.292	−2.501	−2.292
days destroyed	−4.009***	−6.309***	−7.599***	−4.355***	−6.194***	−7.607***	−5.853***	−8.685***	−9.157***
Dow Jones	1.906	−0.354	−3.673**	1.442	−0.580	−2.932	1.178	−2.065	−4.569***
Views on Wikipedia	−5.995***	−6.997***	−7.768***	−2.797***	−3.326**	−3.874**	−5.484***	−6.653***	−6.861***
number of addresses	2.227	1.025	−1.518	0.981	−0.084	−2.210	1.233	−1.845	−2.334
oil price	−0.579	−1.428	−1.511	0.189	−2.398	−3.081	−1.086	−0.438	−1.137
exchange rate	−1.425	−1.504	−1.847	−0.680	−2.025	−2.680	−1.529	0.267	−1.886
new posts	−0.409	−1.164	−1.237	0.013	−0.826	−2.110	−0.297	−1.469	−3.266*
new members	−3.660***	−4.626***	−5.775***	−1.760*	−2.481	−2.948	−2.222**	−3.892***	−3.986***
1st differences									
BitCoin price	−10.933***	−10.935***	−10.933***	−7.827***	−7.920***	−8.050***	−6.014***	−6.009***	−6.149***
number of transactions	−12.903***	−13.074***	−13.038***	−10.363***	−10.444***	−10.459***	−7.102***	−7.249***	−7.260***
number of BitCoins	−2.986**	−6.139***	−6.172***	−3.387***	−4.550***	−5.777***	−2.215**	−3.672***	−6.571***
days destroyed	−15.899***	−15.895***	−15.892***	−14.840***	−14.835***	−14.831***	−10.313***	−10.304***	−10.296***
Dow Jones	−17.235***	−17.364***	−17.366***	−14.448***	−14.535***	−14.539***	−17.640***	−17.696***	−17.696***
views on Wikipedia	−15.284***	−15.280***	−15.277***	−9.786***	−9.783***	−9.780***	−9.101***	−9.093***	−9.087***
number of addresses	−12.554***	−12.817***	−12.991***	−8.919***	−9.028***	−9.072***	−6.950***	−7.239***	−7.243***
oil price	−45.990***	−45.982***	−46.001***	−37.277***	−37.269***	−37.256***	−18.482***	−18.593***	−18.580***
exchange rate	−43.802***	−43.830***	−43.820***	−37.056***	−37.051***	−37.074***	−16.432***	−16.586***	−16.640***
new posts	−10.611***	−10.624***	−10.635***	−7.398***	−7.451***	−7.475***	−7.330***	−7.325***	−7.770***
new members	−14.397***	−14.393***	−14.391***	−9.605***	−9.605***	−9.603***	−12.113***	−12.103***	−12.101***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root.

Table 2. DF-GLS unit-root test.

	Whole period		1st period		2nd period	
	Constant	Constant & trend	Constant	Constant & trend	Constant	Constant & trend
Levels						
BitCoin price	−1.163	−1.976	0.521	−1.165	−1.173	−1.359
number of transactions	1.763	−1.428	0.436	−1.587	0.337	−2.436
number of BitCoins	1.156	0.452	0.335	0.083	0.912	0.092
days destroyed	−3.143***	−6.810***	−2.847***	−6.194***	−8.415***	−8.672***
Dow Jones	1.142	−2.555*	0.778	−2.530	0.331	−2.703*
views on Wikipedia	−5.691***	−7.699***	−3.248***	−4.373***	−6.398***	−6.585***
number of addresses	2.612	−0.551	0.640	−1.817	0.949	−2.350
oil price	−1.423	−1.374	−1.320	−2.142	0.696	−0.937
exchange rate	0.503	−1.586	−0.749	−1.658	0.981	−0.992
new posts	−0.792	−1.740	−0.382	−2.288	−0.757	−0.650
new members	−3.084***	−5.959***	−1.793*	−2.638*	−2.745***	−3.225**
1st differences						
BitCoin price	−11.569***	−11.569***	−14.172***	−13.973***	−3.480***	−5.277***
number of transactions	−9.581***	−9.687***	−10.304***	−10.424***	−6.113***	−8.665***
number of BitCoins	−3.064***	−3.225**	−2.572**	−3.195**	−2.953***	−5.116***
days destroyed	−14.730***	−12.252***	−11.864***	−11.813***	−18.413***	−21.435***
Dow Jones	−7.053***	−8.971***	−5.674***	−5.359***	−3.133***	−5.017***
views on Wikipedia	−16.757***	−18.891***	−10.145***	−15.798***	−13.634***	−17.401***
number of addresses	−10.609***	−11.106***	−11.025***	−13.550***	−9.785***	−12.032***
oil price	−8.569***	−7.163***	−4.341***	−7.241***	−5.522***	−10.125***
exchange rate	−7.331***	−13.795***	−6.758***	−12.333***	−2.682***	−5.142***
new posts	−8.922***	−7.915***	−8.724***	−7.764***	−3.075***	−3.615***
new members	−26.932***	−20.317***	−17.075***	−17.149***	−14.450***	−14.340***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root.

Table 3. Zivot–Andrews unit-root test.

	Levels			1st differences		
	Break in intercept	Break in trend	Break in both intercept & trend	Break in intercept	Break in trend	Break in both intercept & trend
BitCoin price	−4.156	−2.960	−5.466**	−14.771***	−14.250***	−14.807***
	(3.10.2013)	(30.6.2014)	(4.11.2013)	(1.12.2013)	(6.10.2013)	(1.12.2013)
number of transactions	−4.131	−4.479**	−5.095**	−25.237***	−25.188***	−25.283***
	(22.11.2010)	(7.10.2011)	(3.5.2012)	(11.3.2013)	(1.6.2014)	(4.12.2013)
number of BitCoins	−2.043	−3.941	−3.931	−10.388***	−9.487***	−10.504***
	(6.10.2010)	(15.5.2011)	(9.7.2010)	(29.11.2012)	(23.9.2010)	(29.11.2012)
days destroyed	−14.577***	−14.110***	−14.538***	−26.685***	−26.621***	−26.740***
	(12.3.2014)	(22.12.2013)	(13.3.2014)	(11.3.2014)	(23.1.2013)	(11.3.2014)
Dow Jones	−6.000***	−4.921**	−6.056***	−18.318***	−18.252***	−18.349***
	(25.7.2011)	(19.5.2012)	(25.7.2011)	(4.10.2013)	(27.3.2013)	(17.10.2014)
views on Wikipedia	−12.343***	−12.101***	−12.542***	−26.658***	−26.642***	−26.653***
	(8.3.2014)	(10.1.2014)	(26.10.2013)	(13.4.2013)	(30.10.2013)	(13.4.2013)
number of addresses	−4.312	−4.816**	−5.603***	−27.967***	−27.921***	−28.007***
	(4.11.2013)	(28.11.2012)	(4.11.2013)	(7.3.2014)	(11.10.2013)	(7.3.2014)
oil price	−4.065	−3.463	−3.658	−46.063***	−46.007***	−46.250***
	(29.7.2014)	(28.3.2014)	(29.9.2014)	(23.6.2014)	(2.10.2010)	(29.9.2014)
exchange rate	−3.097	−3.444	−3.460	−16.959***	−17.027***	−17.179***
	(29.7.2014)	(6.5.2014)	(6.9.2013)	(7.5.2014)	(23.9.2010)	(14.6.2010)
new posts	−2.838	−2.353	5.539**	−23.904***	−23.718***	−23.928***
	(7.10.2013)	(27.5.2014)	(3.11.2013)	(27.1.2014)	(9.12.2013)	(7.10.2013)
new members	−8.530***	−7.964***	−8.947***	−26.904***	−26.557***	−27.139***
	(26.10.2013)	(20.5.2012)	(17.11.2013)	(11.3.2014)	(20.11.2013)	(11.3.2014)

Notes: Date of break in parenthesis, *** significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root with a structural break in the intercept/trend/both.

and for the 2nd period from October 2013 to May 2015.

The estimation results are reported in Table 7–Table 10. Table 7 and Table 8 summarize the short-run impacts of different determinants on BitCoin price.[5] Note that each variable has a maximum of 10 lags. The sign in parenthesis indicates the sign of estimated coefficients. The number is the count of statistically significant lags at least at 10% significance level. The reported significance level is that of the majority statistically sig-

[5]Detailed short-run estimates are reported in the Appendix.

Table 4. Clemente–Montańés–Reyes unit-root test.

	Additive Outlier (AO)		Innovational Outlier (IO)	
	Min t*	Optimal breakpoint	Min t**	Optimal breakpoint
BitCoin price	−3.022	1.12.2013	−4.426	12.10.2013
number of transactions	−1.671	23.12.2012	−1.648	2.12.2012
number of BitCoins	−2.215	6.9.2012	−6.962	12.7.2010
days destroyed	−9.231	5.3.2014	−10.888	6.3.2014
Dow Jones	−2.865	23.2.2013	−2.587	29.12.2012
views on Wikipedia	−12.268	1.3.2013	−12.124	10.4.2013
number of addresses	−2.314	2.11.2013	−2.486	3.11.2013
oil price	−3.449	29.11.2014	−3.900	27.9.2014
exchange rate	−3.568	9.1.2015	−3.338	16.8.2014
new posts	−1.729	29.3.2013	−2.749	5.10.2013
new members	0.099	8.3.2014	−8.977	9.3.2014

Notes: 'Min *t*' is the minimum *t* statistics calculated. * 5% crit. value −3.560 ** −4.270 (5% crit. value). The null hypothesis of this test is that the time series has a unit root.

nificant lags. For example, the result reported in Table 7 for the variable *number of transactions* in Model 1.1 implies that coefficients of four lags corresponding to this variable are statistically significant, most of these four coefficients are significant at 5% level.

The short-run effects represent the short-run dynamics of variables in the system, they describe how the series react when the long-run equilibrium is distorted. According to the results reported in Table 7 and Table 8, in the first period a number of variables have statistically significant short-run effects on BitCoin price. In particular, this is the case for BitCoin supply and demand drivers (*number of transactions, number of addresses, days destroyed*), and investment attractiveness drivers (*new posts, new members, views on Wikipedia*). In the second period, the impact of these variables on BitCoin price decreases (fewer of them are significant in Table 7 and Table 8). For BitCoin supply and demand drivers, only the variable *days destroyed* remains statistically significant in both periods. The rest of the supply and demand drivers (i.e. *number of transactions, number of addresses*) are significant only in the first period.

For attractiveness drivers, the *views on Wikipedia* and *new members* become statistically insignificant

Table 5. Johansen cointegration test.

Period	Model	Maximum rank	Trace statistics	5% critical value	Maximum rank	Max statistics	5% critical value	Lags	Model
1. Period	M 1.1	1	21.033***	24.31	1	13.953***	17.89	9	No constant
	M 1.2	1	31.152***	34.91	1	19.893***	22.00	10	No constant
	M 1.3	1	5.025***	19.96	1	4.752***	15.67	10	Restricted constant
	M 1.4	0	13.721***	24.31	0	10.301***	17.89	10	No constant
	M 1.5	0	14.858***	24.31	0	11.291***	17.89	10	No constant
	M 2.1	1	0.843***	3.84	1	0.843***	3.84	10	No constant
	M 3.1	0	28.204***	39.89	0	13.635***	23.80	6	No constant
	M 4.1	0	29.451***	39.89	0	14.907***	23.80	8	No constant
	M 4.2	3	45.167***	53.12	3	21.171***	28.14	4	Restricted constant
	M 4.3	4	4.326***	9.42	4	4.326***	9.24	5	Restricted constant
	M 4.4	1	12.434***	19.96	1	9.732***	15.67	9	Restricted constant
	M 4.5	2	1.943***	3.76	2	1.943***	3.76	10	Constant
	M 4.6	1	0.600***	3.84	1	0.600***	3.84	9	No constant
	M 4.7	1	8.135***	12.53	1	7.472***	11.44	10	No constant
	M 4.8	1	9.373***	12.53	1	9.229***	11.44	8	No constant
	M 4.9	1	17.099***	24.31	1	13.811***	17.89	7	No constant
2. Period	M 1.1	2	19.898***	19.96	2	14.391***	15.67	4	Restricted constant
	M 1.2	1	7.408***	12.53	1	5.935***	11.44	4	No constant
	M 1.3	2	9.231***	9.42	2	9.231***	9.24	4	Restricted constant
	M 1.4	0	28.582***	29.68	0	18.658***	20.97	8	Constant
	M 1.5	0	22.768***	24.31	0	17.741***	17.89	10	No constant
	M 2.1	1	0.082***	3.84	1	0.082***	3.84	7	No constant
	M 3.1	0	52.280***	53.12	0	28.022***	28.14	2	Restricted constant
	M 4.1	0	50.417***	53.12	0	25.404***	28.14	5	Restricted constant
	M 4.2	4	13.302***	15.41	5	9.203***	14.07	4	Constant
	M 4.3	4	0.208***	3.84	0	0.208***	3.84	6	No constant
	M 4.4	2	2.524***	9.42	2	2.524***	9.24	7	Restricted constant
	M 4.5	3	10.126***	12.53	3	9.410***	11.44	6	No constant
	M 4.6	1	0.082***	3.84	1	0.082***	3.84	7	No constant
	M 4.7	2	2.524***	9.42	2	2.524***	9.24	7	Restricted constant
	M 4.8	2	0.844***	9.42	2	0.844***	9.24	8	Restricted constant
	M 4.9	2	19.357***	19.96	2	15.209***	15.67	10	Restricted constant

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Maximum rank gives the number of cointegration relationships. VAR in first differences was used when 0 cointegration relationship was detected, ARDL was used to estimate 1 cointegration relationship and VEC models were used to model more than 1 cointegration relationships.

Table 6. Specification of the empirically estimated models.

		Models for hypotheses 1, 2 and 3							General 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	number of BitCoins	x	x	x						x	x		x				
	number of transactions	x				x										x	x
	number of addresses		x		x					x	x	x			x		
	days destroyed	x	x	x	x	x				x	x	x	x	x	x	x	x
	exchange rate	x	x	x	x	x		x	x	x							
BitCoin attractiveness for investors and users	views on Wikipedia						x		x	x	x	x		x		x	
	new members						x			x	x		x	x		x	x
	new posts						x			x	x	x	x	x	x	x	x
Macro-financial developments	Dow Jones							x	x	x	x						x
	oil price							x	x	x							

Table 7. 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
1. Period							
BitCoin price	8***	9***	8***	8***	8***	8***	6***
number of BitCoins	-	-	-	-	-	-	-
number of transactions	4**	-	-	-	5***	-	-
number of addresses	-	8**	-	4**	-	-	-
days destroyed	5**	4**	4**	5*	5**	-	-
exchange rate	1*	1*	1*	1*	1**	-	1**
views on Wikipedia	-	-	-	-	-	9***	-
new members	-	-	-	-	-	3***	-
new posts	-	-	-	-	-	4***	-
constant	-	-	-	-	-	-	-
2. Period							
BitCoin price	3***	2***	3***	5***	6**	3***	2***
number of BitCoins	-	-	-	-	-	-	-
number of transactions	1*	-	-	-	-	-	-
number of addresses	-	1*	-	1*	-	-	-
days destroyed	1*	1**	1*	1*	1*	-	-
exchange rate	-	-	-	-	-	-	-
views on Wikipedia	-	-	-	-	-	-	-
new members	-	-	-	-	-	-	-
new posts	-	-	-	-	-	1*	-
Dow Jones	-	-	-	-	-	-	-
oil price	-	-	-	-	-	-	-
constant	-	-	-	1*	-	-	-

Notes: The table shows the summary results of short-run estimates reported in detail in the Appendix. Each variable has a maximum of 10 lags. The number is the count of statistically significant lags at least at 10% significance level. The reported significance level is that of the majority statistically significant lags where *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. '-' indicates that the coefficient is not significantly different from zero.

in most models in the second period; only the variable *new posts* is statistically significant in both periods. This could be explained by the fact that the type of individuals searching for information about BitCoin on Wikipedia likely are investors/users with limited knowledge about BitCoin, because Wikipedia contains rather general information about BitCoin, which is usually known by experienced BitCoin investors/users. The demand for this information tends to be more important in the first period when BitCoin was introduced and thus was little known. The implied accumulation of knowledge

Table 8. 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
1. Period									
BitCoin price	7***	3***	4***	7***	9***	8***	9***	7***	6***
number of BitCoins	-	-	-	-	-	-	-	-	-
number of transactions	-	-	-	-	-	-	-	2**	1**
number of addresses	-	2**	2**	6**	-	-	7***	-	-
days destroyed	-	3***	3*	5**	3*	2*	2**	1**	1***
exchange rate	1*	-	-	-	-	-	-	-	-
views on Wikipedia	6***	3*	4***	8***	-	9***	-	6***	-
new members	-	3***	3***	-	5*	4***	-	4***	3**
new posts	-	2**	-	4**	5*	4***	5**	6***	3*
Dow Jones	-	-	-	-	-	-	-	-	2**
oil price	-	-	-	-	-	-	-	-	-
constant	-	-	-	-	-	-	-	-	-
2. Period									
BitCoin price	4**	3***	4***	5***	3***	4***	5***	4***	5***
number of BitCoins	-	1*	-	-	-	-	-	-	-
number of transactions	-	-	-	-	-	-	-	2**	2**
number of addresses	-	-	-	-	-	-	-	-	-
days destroyed	-	1**	2**	1*	2*	2**	-	2*	1*
exchange rate	-	-	-	-	-	-	-	-	-
views on Wikipedia	-	-	-	-	-	-	-	-	-
new members	-	1*	-	-	-	-	-	-	-
new posts	-	2**	4***	1***	3***	1**	1**	3***	3***
Dow Jones	1***	-	-	-	-	-	-	-	1*
oil price	2*	2*	-	-	-	-	-	-	-
constant	-	-	-	-	-	-	-	-	-

Notes: The table shows the summary results of short-run estimates reported in detail in the Appendix. Each variable has a maximum of 10 lags. The number is the count of statistically significant lags at least at 10% significance level. The reported significance level is that of the majority statistically significant lags where *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. '-' indicates that the coefficient is not significantly different from zero.

Table 9. 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
1. Period							
number of BitCoins	−2.7E-06	−4.78E-06	−7.74E-05***	-	-	-	-
number of transactions	0.004**	-	-	-	-	-	-
number of addresses	-	0.003***	-	-	-	-	-
days destroyed	−9.3E-06	−4.14E-06	−9.54E-07	-	-	-	-
exchange rate	12.085	14.367	119.595	-	-	-	-
views on Wikipedia	-	-	-	-	-	−0.002	-
new members	-	-	-	-	-	−0.213	-
new posts	-	-	-	-	-	0.023***	-
Dow Jones	-	-	-	-	-	-	-
oil price	-	-	-	-	-	-	-
trend	-	-	0.693***	-	-	-	-
constant	-	-	-	-	-	-	-
2. Period							
number of BitCoins	−0.006***	−0.001***	−0.003***	-	-	-	-
number of transactions	0.150***	-	-	-	-	-	-
number of addresses	-	0.043***	-	-	-	-	-
days destroyed	-	-	-	-	-	-	-
exchange rate	1166.965	1808.853	-	-	-	-	-
views on Wikipedia	-	-	-	-	-	0.002	-
new members	-	-	-	-	-	−0.078	-
new posts	-	-	-	-	-	0.035***	-
Dow Jones	-	-	-	-	-	-	-
oil price	-	-	-	-	-	-	-
constant	7.58E+04***	-	7.59E+04***	-		-	-

Notes: Dependent variable: BitCoin price. *** 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.

about BitCoin among investors and/or users impacted its price. The variable *new posts* captures the discussions among all types of investors/users with limited or advanced knowledge about BitCoin. The discussion thus likely reflects reactions to media reporting on BitCoin or personal perceptions and opinions about BitCoin of discussion participants. In line with our hypothesis, depending on the information contained in *new posts*, they impact BitCoin price either positively or negatively in both periods. For the variable *new members*, our results suggest that it affects BitCoin price in the first period, when the BitCoin economy was smaller and new members represented a larger share of total users exercising a stronger impact on its price. In the second period, the impact on *new members* is relatively minor in the short run.

Macroeconomic and financial drivers (*Dow Jones, exchange rate and oil price*) tend to have a relatively small impact on BitCoin price in the short run. *Exchange rate* has a statistically significant impact on BitCoin price in Models 1.1–3.1 in the first period. When we control simultaneously for all three types of drivers (supply–demand, investment attractiveness and macro-financial variables), macro-financial development are significant only in Models 4.1 and 4.9 in both periods and in Model 4.2 in the second period (Table 7 and Table 8).

Table 9 and Table 10 report the long-run impacts of the three types of BitCoin price determinants. According to these results, BitCoin price is in the long-run equilibrium relationship with a number of variables considered in the estimated models. In the following, we discuss the long-run results with respect to the three hypotheses of BitCoin price formation.

Hypothesis 1: Market forces of BitCoin supply and demand

The first major observation arising from the estimates reported in Table 9 and Table 10 is that the market forces of supply and demand have a strong impact on BitCoin price. Particularly, the demand side variables (e.g. *number of transactions, number of addresses*) appear to exert a more pronounced impact on BitCoin price than the supply side drivers (e.g. *number of BitCoins*). According to the results reported in Table 9, an increase in the stock of BitCoins (*number of BitCoins*) exerts an upward pressure on BitCoin price (Model 1.3 in the first period and Models 1.1., 1.2, 1.3 in the second period), whereas an increase in the size of the BitCoin economy (*number of addresses, number of transactions*) leads to an increase in BitCoin price (Models

Table 10. 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
1. Period									
number of BitCoins	-	−5.69E-06**	−9.46E-06**	-	−4.42E-06***	-	-	-	-
number of transactions	-	-	-	-	-	-	-	0.001*	0.001***
number of addresses	-	0.002***	0.003***	0.001**	-	-	0.001***	-	-
days destroyed	-	-	-	-	-	1.64E-06	-	−3.11E-06	−5.67E-06
exchange rate	-	101.410	-	-	-	-	-	-	-
views on Wikipedia	-	-	-	-	-	−0.002	-	−0.001	-
new members	-	-	-	-	-	−0.325	-	−0.145	0.038
new posts	-	0.028***	0.031***	0.013***	0.025***	0.028**	0.015***	0.015***	0.009**
Dow Jones	-	0.008	−0.008	-	-	-	-	-	−9.97E-05
oil price	-	0.640	-	-	-	-	-	-	-
constant	-	−175.820**	−107.689	6.271**	-	-	-	-	-
2. Period									
number of BitCoins	-	−0.001***	−0.001***	-	−6.22E-05***	-	-	-	-
number of transactions	-	-	-	-	-	-	-	0.013***	0.017**
number of addresses	-	0.029***	0.049***	0.004***	-	-	0.003***	-	-
days destroyed	-	-	-	-	-	1.95E-05	-	-	-
exchange rate	-	1585.792	-	-	-	-	-	-	-
views on Wikipedia	-	-	-	-	-	0.001	-	-	-
new members	-	-	-	-	-	−0.181*	-	-	-
new posts	-	0.036**	0.045**	0.066***	0.017**	0.031***	0.056***	0.090***	0.126***
Dow Jones	-	−0.078	−0.052	-	-	-	-	-	0.206**
oil price	-	-	-	-	-	-	-	-	-
constant	-	-	-	-	-	-	933.247***	1865.3***	632.205***

Notes: Dependent variable: BitCoin price. *** 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.

1.1, 1.2). These results are in line with our hypothesis. Contrary to our expectations, the variable that captures the velocity of BitCoin circulation (*days destroyed*) has a negative impact on BitCoin price in Models 1.1, 1.2 and 1.3. However, BitCoin velocity is not significant in these models, implying that its impact on the BitCoin price is negligible.

According to the general models reported in Table 10, the total stock of BitCoins in circulation (*number of BitCoins*) is always negative and statistically significant (Models 4.2, 4.3 and 4.5). This result is in line with our expectations. The magnitude is larger in the second period, when the number of BitCoins in circulation was larger compared to the first period. The size of the BitCoin economy (*number of transactions* and *number of addresses*) has always a positive and statistically significant impact on BitCoin price (Models 4.2, 4.3, 4.4, 4.8 and 4.9), which is also in line with our expectations. Again, the magnitude of coefficients is larger in the second period, when the size of BitCoin economy was considerably larger. The monetary velocity of BitCoin circulation (*days destroyed*) does not significantly affect BitCoin price in the long run (Models 4.6, 4.8 and 4.9), which is in line with the specific models' results (1.1, 1.2 and 1.3) and is robust in both periods.

Hypothesis 2: Investment attractiveness

The strongest and statistically the most significant impact of investment attractiveness on BitCoin price is estimated for the variable *new posts* (Models 2.1 and Models 4.2–4.9). Variable *new posts* has a positive impact on BitCoin price, reflecting an increasing acceptance and trust in BitCoin captured by the intensity of attention between BitCoin users. This may reflect declining transaction costs and uncertainty for investors, which increases investment demand for BitCoin and hence its price.

Note that the other two variables capturing the impact of investment attractiveness – *views on Wikipedia* and *new members* – were found to be stationary in levels and thus did not enter the long-run relationship in the estimated VEC models. However, they have a statistically significant impact on BitCoin price in the short run in period 1, as reported in Table 7. This could be explained by the fact that the type of information (rather basic) provided by Wikipedia becomes known for most users in the long run. As a result, the number of Wikipedia queries about BitCoin tends to decline over time (the variable *views on Wikipedia* becomes stationary), and it does not exercise any impact on BitCoin price in the long run. Only the variable *new posts* preserves an impact on BitCoin price in the long run. *New posts* may capture investors' interest in BitCoin, as it captures information's dilution (spread) about the currency among discussion participants. It may reflect changes in the knowledge about BitCoin between potential investors and users, thus leading to a higher demand for it. Assuming that these last two arguments hold, the estimated *new posts* effect represents the impact of the demand side of the BitCoin economy as given by variable G in Equation 6, though not necessarily capturing only attention-driven (speculative) behaviour of investors. On the one hand, *new posts* may capture attention devoted by potential users' and/or investors' to BitCoin as online forum discussions might be induced, among others, by their reaction to media reporting on BitCoin. The attention effect may impact either positively or negatively the BitCoin price depending on the type of news (discussions). The positive estimated coefficient associated with *new posts* variable implies that the impact of positive or neutral news (discussions) dominates.

Hypothesis 3: Global macroeconomic and financial developments

Our findings suggest that, in contrast to previous studies (i.e. van Wijk 2013), global macro-financial developments, such as the Dow Jones Index, exchange rate and oil price, do not significantly affect BitCoin price in the long run. Our estimation results imply that the estimates of van Wijk (2013) may be biased, as van Wijk does not account for market forces of supply and demand or investment attractiveness variables. When these factors are taken into consideration (Models 4.1–4.9), their impact is not significant in all estimated models. Hence, the results of our analysis underline the importance of analysing different drivers of BitCoin price simultaneously, as the results are likely to be biased when looking at one factor at a time.

VI. Conclusions

Due to a growing market share, a rapidly increasing price of BitCoin and its high price volatility, there is an increasing interest among BitCoin users, investors and economists in understanding the BitCoin system in general and its price formation in particular. This article attempts to shed light on the determinants of BitCoin price in the short- and long run. The present article analyses the impact of market forces of supply and demand, global macro-financial developments and investment attractiveness on BitCoin price. Our article is the first in the literature that studies BitCoin price formation by considering both the traditional determinants of currency price, e.g., market forces of supply and demand, and digital currency-specific factors, e.g., BitCoin attractiveness for investors, as well as interactions between different BitCoin price determinants. Further, the present article accounts for structural breaks in BitCoin price series and hence provides a more nuanced dynamics of BitCoin price formation over time.

In order to identify and assess the determinants of BitCoin price formation, first, we derive an econometrically estimable model from the Barro (1979) gold standard model. Based on previous studies on BitCoin price formation, we extend the canonical currency price model to capture factors which are specific to digital currencies and formulate testable hypotheses. In order to test the BitCoin price formation hypotheses, we apply time-series analytical mechanisms to daily data for the period 2009–2015.

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. In particular, the demand-side drivers, such as the size of the BitCoin economy, have a strong impact on BitCoin price. 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. The estimated magnitude of the BitCoin supply and demand drivers on BitCoin price tends to be larger in the period when BitCoin became more established (in the second period) – when the number of BitCoins in circulation was larger – compared to the first period when it was less widespread and known (the first period).

Second, we find that the arrival of new information impact BitCoin price positively, which may be a result of increasing trust among users. For the first period, our results suggest that, when BitCoin was little known, the online information queries about BitCoin (*views on Wikipedia*) exercised a stronger impact on

BitCoin price than in the later years, when it became more established on financial markets. In the long run, the online information queries about BitCoin (*views on Wikipedia*) have no impact on BitCoin price.

Third, we cannot reject the hypothesis that investor speculations are also affecting BitCoin price. The statistically significant short-run impact of *Wikipedia views* and *new posts* on BitCoin price could be an indicator of speculative short-run behaviour of investors, or it may capture the expansion of the demand side of the BitCoin economy. As such, speculative trading of BitCoins is not necessarily an undesirable activity per se, as it may generate benefits in terms of absorbing excess risk from risk adverse participants and providing liquidity on the BitCoin market. A downside of the short-run speculative investment is that it may increase price volatility and create price bubbles. The success of BitCoin thus also hinges 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 the global macro-financial development may be driving BitCoin price. In fact, we find a significant impact of global macro-financial development, captured by the Dow Jones Index, exchange rate and oil price, only in the short run. In contrast, in the long run they do not determine BitCoin price. These results imply that the estimates of van Wijk (2013), who does not account for market forces of supply and demand or investment attractiveness variables may be biased. When these factors are taken into consideration, the impact of global macro-financial development is not significant in all estimated models. Hence, the results of our analysis underline the importance of analysing different drivers of BitCoin price simultaneously, as the results are likely to be biased when looking at one factor at a time.

Understanding the BitCoin price formation is highly important both from a general monetary policy point of view and from a BitCoin ability to serve as a medium of exchange for global economy point of view. Our findings contribute to a better understanding of the determinants behind the enormous BitCoin 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 transactions. Our results suggest that this may not hold for BitCoin, at least in the short run. Large price movements alter the purchasing power potentially causing costs and risk to firms and consumers which use it as a medium of exchange in transaction of goods and services.

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