What Determines Bitcoin's Value?

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ABSTRACT: Despite its great popularity and gradual worldwide acceptance, most people are still confused as to what a Bitcoin actually is. This paper tries to reach clearer knowledge about what determines the Bitcoin's value. . Due to the intrinsic complexity of crypto market, standard approaches often fail to capture the non-stationary and nonlinear properties and properly depict the moving tendencies. This problem can be solved by an objective data analysis method, i.e. Empirical Mode Decomposition. By decomposing Bitcoin price into intrinsic modes based on scale separation, we will be able to explain its generation from a novel perspective. Specifically, the intrinsic modes are composed into a fluctuating process, a slowly varying part and a trend. By doing so, the short-term fluctuations appear the major contributor of this new crypto-currency, without overlooking the power of long term trend. The first outcome suggests that Bitcoin is backed up by nothing other than the expectation of people' willingness to accept it and thus displays characteristics of purely speculative bubble. The second one implies that if traders appreciate risky investments, a trend can be identified and serious disappointments may await the unwary Bitcoiners.

Keywords: Crypto market; Bitcoin price; empirical mode decomposition.

1. INTRODUCTION

Since its creation in 2009 by a pseudonymous hacker calling himself Satoshi Nakamoto, particular attention has been given to Bitcoin. Every passing day, the number of companies who accept Bitcoin increases, thereby making the perceived value of this crypto-currency real. The surging popularity of Bitcoin forces a lot of questions requiring thorough responses. Some of them appear complex and technical, others are financial and economic, while few questions seem monotonous. Although the question of where the value of Bitcoin is decided emerges, up to now, there are no clear answers needed to better understand how behaves the world’s first completely virtual and decentralized currency. Most people are greatly disillusioned by the fiat currencies values, and they attempt to determine Bitcoin’s value in the same manner. However, Bitcoin is backed up by nothing other than the confidence of people in its value. Compared with official fiat currency backed by a sovereign entity or commodity money such as gold which has an intrinsic value, the Bitcoin is highly driven by self-fulfilling expectations. Unlike earlier crypto currencies that had some central controlling person or entity, the Bitcoin is the first fully decentralized digital money. The price of a Bitcoin is determined by supply and demand. When the interest to this nascent currency and thus the demand increases, the price increases, and when demand falls, the price falls. There is only a limited number of bitcoins in circulation, implying that demand must pursue the inflation level to avoid swelling volatility. As Bitcoin market remains small, the price of this crypto-currency seems extremely volatile.

Despite having a passionate following, Bitcoin is stilla complex phenomenon. The status of Bitcoin as an alternative currency, transactions tool or a speculative trap remains multi-sided and subject to on-going debate. The majority of researches on this phenomenon considered Bitcoin as speculative foolery due to its excessive volatility (Kristoufek 2013; Bouoiyour et al. 2015; Cheah and Fry 2015) rather than currency or payment system (Brandvold et al. 2015). Some others called it “evil” since it is neither controlled by central banks nor by governments (Glouderman 2014). Others show that with no intrinsic value, Bitcoin’s rising price constituted a speculative bubble (Buchholz et al. 2012; Ciaian et al. 2014). Recently, Bouoiyour and Selmi (2015) confirm the dominant speculative behavior of Bitcoin and its partial usefulness in economic reasons as business income. They also indicate that there is no sign of Bitcoin being a safe haven or a long-term promise.

Due to the complexity of crypto market, standard approaches often fail to properly depict non-stationary, nonlinear properties and moving tendencies. Besides, the dynamic and unstable Bitcoin market increases the difficulty of modeling. This problem can be solved by an objective data analysis method, i.e. Empirical Mode Decomposition (EMD), initiated by Huang et al. (1998). EMD is proposed especially for nonlinear and non-stationary data. The aim of EMD is to decompose data into nearly periodic intrinsic modes based on local characteristic scale. Each derived intrinsic mode is dominated by scales in a narrow range and as a result the implications of each mode can be highlighted. For example, for an intrinsic mode derived from the original time series under a scale of two months can be depicted as seasonal component. By exploring data's intrinsic modes, EMD helps substantially display the main features of the data. EMD has been largely applied for research of ocean waves, biomedical engineering and health monitoring. However, very few studies considered this technique to decompose financial data and to examine the changeability of the markets (Huang et al. 2003; Cummings et al 2004; Zhu et al. 2015). In the present research, we apply EMD to crypto-currency data and find that it can help greatly interpret the formation of Bitcoin price from a new perspective. This technique enables to appropriately explain the driving forces that move the focal virtual currency. To our best knowledge, this study is the first that applies this technique to investigate crypto market changeability. For this purpose, the price of Bitcoin is initially decomposed into different independent intrinsic modes, from high to low frequency. Then, the intrinsic modes are composed into a fluctuating process, a slowly varying part and a trend through a fine-to-coarse reconstruction.

The remainder of the article proceeds as follows: Section 2 presents the adopted methodology, i.e., Empirical Mode Decomposition. Section 3 describes the data, reports and discusses the main findings. Section 4 concludes.

2. EMPIRICAL MODE DECOMPOSITION

The concept of Empirical Mode Decomposition (EMD) has attracted the attention of several academic researchers in many disciplines since Huang et al. (1998)'s study. It is an adaptive time-frequency data analysis method. It is a very fruitful and valuable tool for signals' extraction from data generated in nonlinear and non-stationary processes (Huang and Attoh-Okine, 2005). Accordingly, Zhang et al. (2009) highlight the meaningfulness of EMD as local, self-adaptive, implicational and efficient approach. The main focus of EMD is to decompose data into different independent and nearly periodic intrinsic modes through local characteristics. This method provides effective frequency information evolving over time and quantifies the changeability captured via the oscillation under different scales and locations. The EMD method consists of:

(1) Decomposing original time series into different intrinsic mode functions(IMFs) and one residue among different time scales, from high to low frequency;

(2) Composing these independent mode functions into fluctuating process, slowing varying component and a trend based on a fine-to-coarse reconstruction.

2.1. Decomposition

This step consists of extracting complicated data into independent IMFs. An IMF denotes an oscillatory mode of a simple function with varying amplitude and frequency. It satisfies at least two requirements: The first one relies on the fact that functions should have the same numbers of extrema and zero-crossings or differ at the most by one. The second requirement consists in the need of symmetrical functions with respect to local zero mean. Given these last conditions, the IMF is a nearly periodic function and the mean is set to zero. Basically, the IMF are decomposed by determining the maxima and minima of time series $x(t)$, generating then its upper and lower envelopes ($e_{\min}(t)$ *and* $e_{\max}(t)$), with cubic spline interpolation. To do so, we initially measure the mean ($m(t)$) under different points from upper and lower envelopes:

$$m(t) = (e_{\min}(t) + e_{\max}(t))/2 \tag{1}$$

Then, we decompose the mean of the time series in order to highlight the difference $d(t)$ between $x(t)$ and $m(t)$:

$$d(t) = m(t) - x(t) \tag{2}$$

It seems important to mention that in the case of the IMF, we present $d(t)$ as the i^{th} IMF and we replace $x(t)$ with the residual $r(t) = x(t) - d(t)$. If not, we replace $x(t)$ with $d(t)$. We repeat the same steps until the residual requires the stopping criterion when the residue becomes a monotonic function and data cannot be decomposed into supplementary IMFs.

2.2. Composition

This step consists essentially on detecting maxima and minima and connecting then the local maxima with the upper envelope and the minima with the lower one. This step allows us to determine the first component through the difference between the data and the local mean of the two envelopes. The final obtained difference can be denoted by c_j (the components). When residue successfully meets the conditions that the number of zero-crossings and extrema do not differ by more than one and the sifting process can be fully achieved if the total number of IMFs is limited to log2N (N denotes the length of a data series) or when the residue (r) becomes a monotonic function and data cannot be extracted into further intrinsic mode functions (Huang et al., 2003), the original time series can be expressed as the sum of some IMFs and a residue:

$$X(t) = \sum_{j=1}^{N} c_j(t) + r\ (t) \tag{3}$$

In the sifting process, the first component, c_1 contains the the shortest period component of the time series. The residue after extracting c_1 corresponds to the longer period fluctuations in the data. Thus, the mode functions are extracted from high frequency to low frequency. Empirical mode decomposition is carried out here as a filter to separate high frequency (fluctuating process) and low frequency (slowing varying component) modes. Basically, this procedure corresponds to high-pass filtering by adding fastest oscillations (i.e., IMFs with smaller index) to slowest oscillations (i.e., IMFs with larger index). More precisely, we follow the following procedure:

(1) Computing the mean of the sum of c_1 to c_i for each component (except for the residue);

(2) Employing t-test to accurately determine for which i the mean departs from zero;

(3) Once i is determined as a relevant change point, partial reconstruction with IMFs from this to the end is considered as the slow-varying component and the partial reconstruction with other IMFs is identified as the fluctuating process or high frequency component.

3. APPLICATION

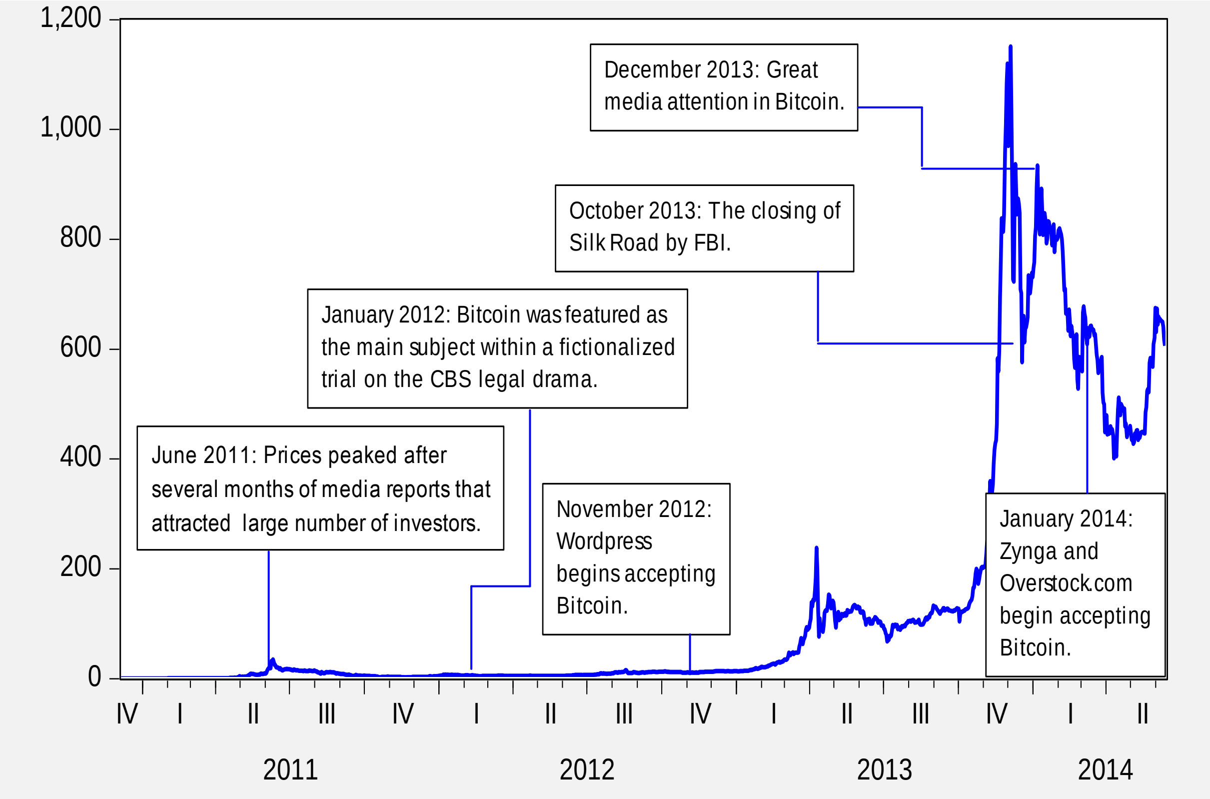
3.1. Decomposition

3.1.1. Data

The daily data of the Bitcoin price index (BPI) has been used in our investigation. Bitcoin's price has been volatile since its creation in 2009, subject to sharp appreciations and precipitous depreciations in value. Figure-1 clearly indicates that Bitcoin experienced several jumps and excessive swings over the period spanning between 2010 to 2014. It was 1.14 dollars on 01/06/2011 and becomes more than 900 dollars on 11/01/2014. A peak is sharply noticeable in 2011 due to a lot of months of media exposure. Bitcoin prices ended the year (December 2011) at $4.50, and increase to $7.20 in early January 2012. Bitcoin prices appear more than doubled in November 2012. The prices reach a record of $15.76 when Word Press begins to accept Bitcoin. 2013 starts by a Bitcoin boom. By the beginning of March, Bitcoin prices doubled again compared to its level in November 2012. In the end of March, the prices slightly collapsed, dropping to $34 before increasing to $45. Thereafter, a bug in the software of this new crypto-currency in the beginning of April has prompted a sharp fall in prices from $48 to $36.50. The Bitcoin's upward price trajectory remains until the end of September 2013, reaching high levels, i.e., above $500. After this date, Bitcion transactions have undergone several events such as the closing of the Silk Road[1] by the FBI influencing substantially the price of Bitcoin. The closing of this rotating-platform of drug has led to a drop by about 40% of Bitcoin's value, from $230 in 09/04/2013 to $123 in 02/10/2013. Notably, the starting of big companies like Zynga[2] and Overstock[3] to accept Bitcoin in early 2014 leads again to the rise of Bitcoin prices.

Figure-1: Bitcoin price evolution

[1] A rotating-platform of drug on which transactions were through Bitcoin.
[2] Zynga is a recent company of social games, founded in 2007 in California. It works specifically on mobile phone platforms such as AppleiOS and Android.
[3] Overstock is an American online retailer lunched in 1999. It sales products from individuals or businesses to the end-user.

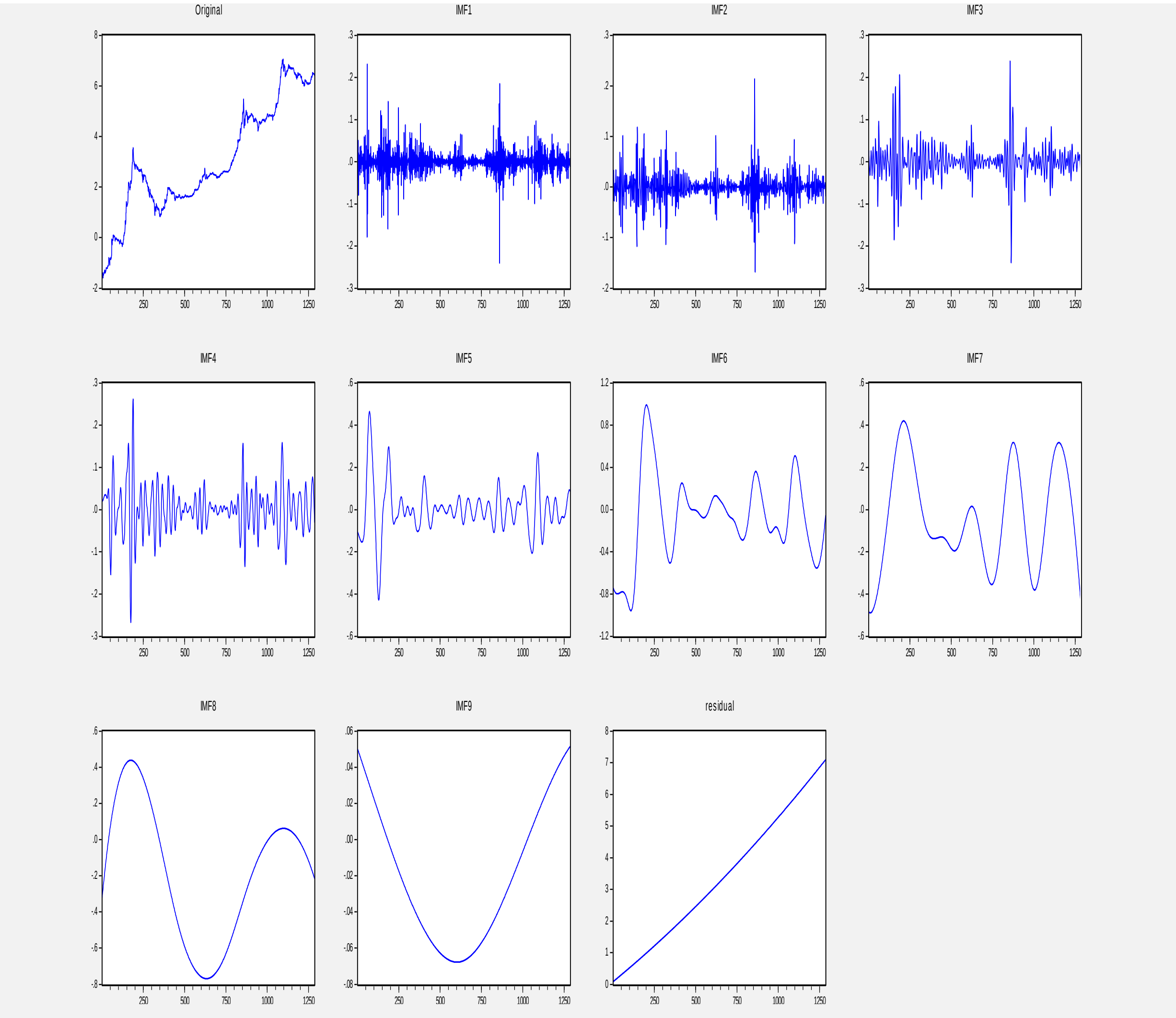


(Source) Blockchain: https://blockchain.info/

3.1.2. IMFs

The IMFs and the residue derived by applying EMD to Bitcoin price is well shown in Figure-2. Since the number of IMFs is limited and will be restricted to log2N where N is the length of data, the sifting processes produce 9 IMFs plus one residue. All the IMFs are listed in the order in which they are extracted, that is, from the highest frequency to the lowest frequency. The obtained intrinsic mode functions clearly indicate a changeability in frequencies and amplitudes (Figure-2), which differ substantially from low to high scales (the frequencies and amplitudes appear not the same with any harmonic). Remarkably, by moving from high to low frequency, the amplitudes of the IMFs are becoming smaller. For example, the majority of amplitudes of IMF1 are larger than IMF6, IMF7, IMF8 and IMF9. The residue slightly follows a long term average.

Figure-2: The IMFs and residue for the Bitcoin price



3.1.3. IMFs statistics

Table-1 reports some measures which are given to assess IMFs: mean period of each IMF, correlation between each IMF and the original data series, the variance and variance percentage of each IMF. The mean period corresponds to the value derived by dividing the total number of points by the number of peaks for each IMF since the frequency and the amplitude of an IMF may change considerably over time. Two correlation coefficients, Pearson correlation and Kendall rank correlation coefficients are applied here to determine the co-movement between IMFs and the observed data. Moreover, because IMFs are intrinsically independent, it is possible to sum up the variances and employ the percentage of variance to measure the contribution of each IMF to the total volatility of the original data set. The obtained findings reveal that the IMF7 and IMF8 as well as the residue seem the dominant modes explaining the dynamic of Bitcoin price. More precisely, both Pearson and Kendall correlation coefficients between the last IMFs and the original Bitcoin price reach high and significant levels. The variance of IMF7 and IMF8 appears about 41.30% (as an average). In addition, the Pearson and Kendall coefficients between the residue and the original data reach more than 27% and 23%, respectively. At the same time, variances of the residue account for more than 15% of the total variability. In sum, the residue is perceived as the deterministic long term behavior. Notably, the IMF1, IMF2, IMF3 and IMF5 play a minor role in explaining the evolution of this digital money. They account for only 1.768% of total variance, which means that the first IMFs or the slow oscillations (IMFs with larger index) have no great influence on Bitcoin price changes.

Table-1: Measures of IMFs and residue

	Pearson correlation	Kendall correlation	variance as percentage of the sum of IMFs and residue
IMF1	0.068*	0.049***	0.138
IMF2	0.051**	0.038**	0.265
IMF3	0.123	0.061***	0.209
IMF4	0.082*	0.100**	0.174
IMF5	0.064**	0.075*	0.628
IMF6	0.032*	0.041**	0.354
IMF7	0.411**	0.329***	38.68
IMF8	0.310***	0.267***	43.92
IMF9	0.066	0.054	0.172
Residue	0.279***	0.238**	15.46
Sum			100

(Note) *, **, ***: Correlations are significant at the levels of 0.01, 0.05 and 0.1, respectively (2-tailed).

3.2. Composition

After providing the decomposition outcomes of Bitcoin price data set and basic analysis of the different IMFs, in this sub-section, we decompose the IMFs into high frequency and low frequency parts and trend.

Figure-3 reports the Euclidean distance via a hierarchical clustering outcomes (partial composition). When the Euclidean distance appears smaller than 6, IMFs can be recognized as the low frequency component (IMF1, IMF2, IMF3 and IMF4). The group representing the Euclidean distance between 6 and 14 or precisely the IMFs treated as a high frequency component (IMF5, IMF6, IMF7 and IMF8). Another group can be added also corresponding to the Euclidean distance more than 14 defined as the trend component (the residue).

Figure-3: The Euclidean distance via hierarchical clustering method

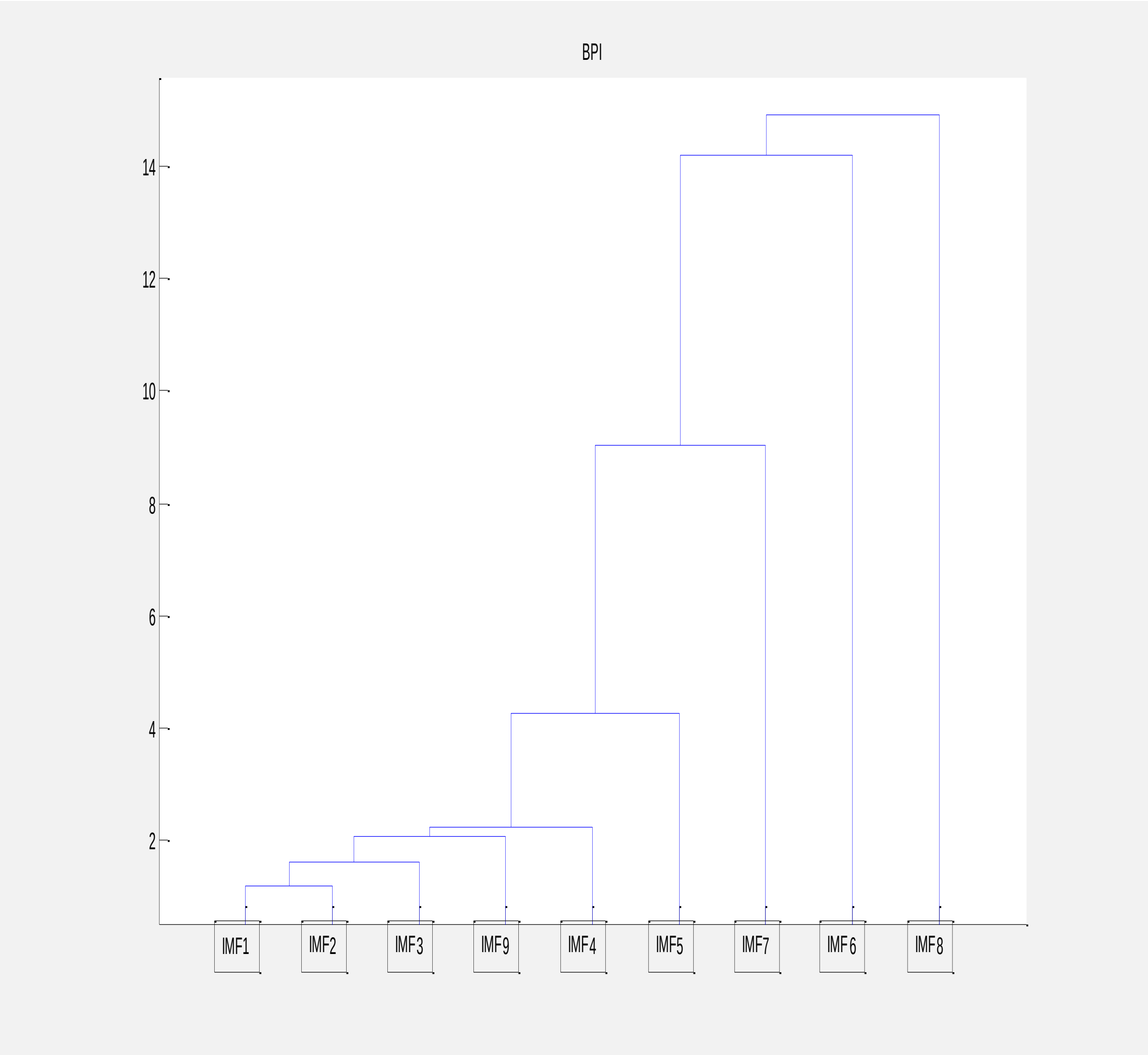
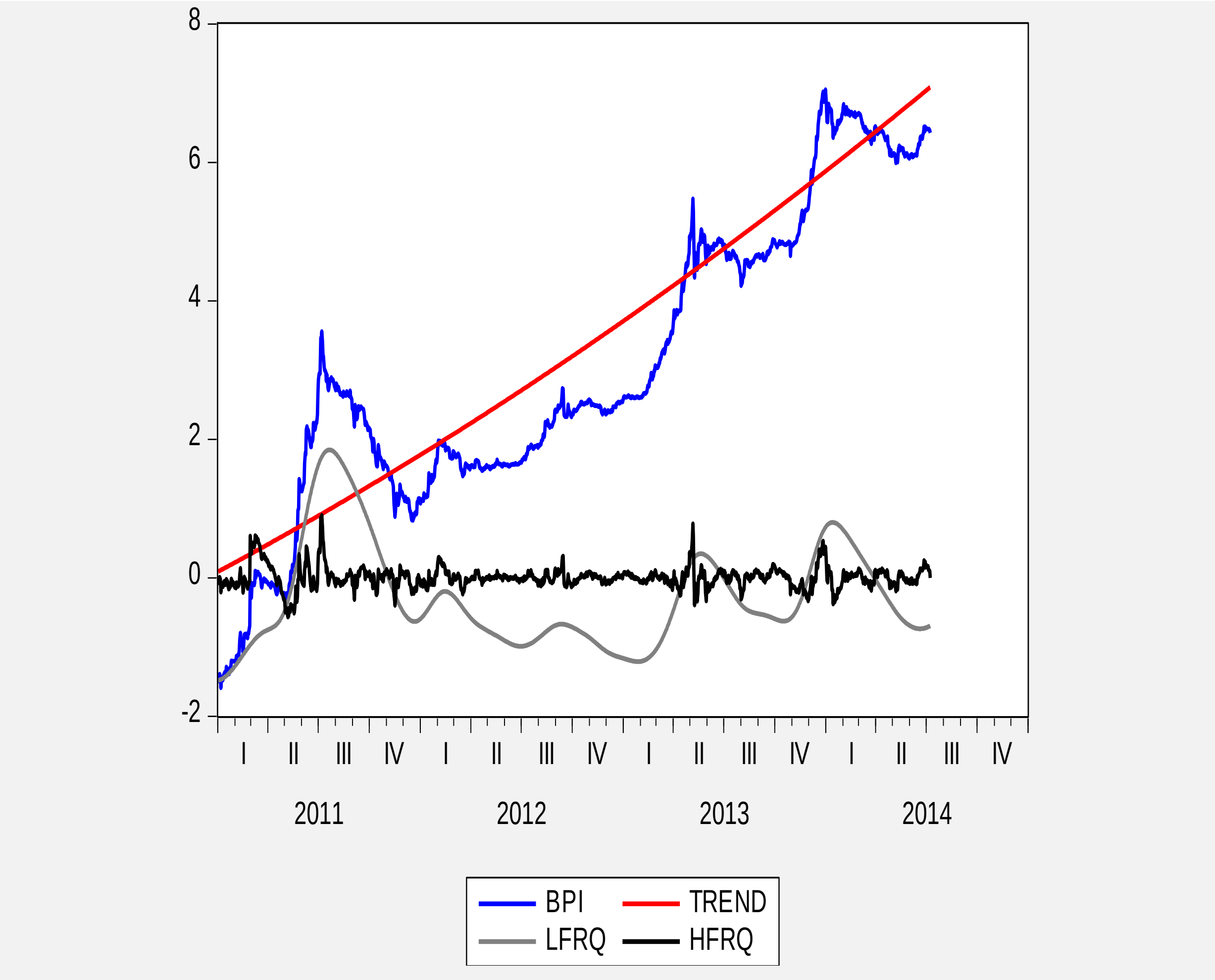


Figure-4 worthy depicts the three components (low frequency, high frequency and trend). Each component has distinct characteristics. The residue is slowly varying around the long term mean and it is thus treated as the long term trend during the evolution of Bitcoin price; the low frequency component is perceived as a representative of significant events, while the high frequency component contains essentially the market' short term fluctuations. Table-2 gives more information about the components of interest (statistical measures via Pearson and Kendall correlations and the variance as percentage of the sum of IMFs and residue). The trend seems a potential driver of Bitcoin. Additionally, the correlation coefficients between the high frequency component and the original Bitcoin price appear stronger than those of low frequency and trend components. They reach significant levels, i.e., 0.823 and 0.679 (Pearson and Kendall correlations, respectively).

Figure-4: The composition of IMFs into three components



(Notes) LFRQ: Low Frequency Component; HFRQ: High Frequency Component.

Table-2: Correlations and variance of components

	Pearson correlation	Kendall correlation	variance as percentage of the sum of IMFs and residue
High frequency component	0.823**	0.679***	57.18
Low Frequency component	0.159*	0.114*	2.53
Trend	0.346**	0.285**	41.07

(Note) *, **, ***: Correlations are significant at the levels of 0.01, 0.05 and 0.1, respectively (2-tailed).

3.2.1. The low frequency component

The low frequency component holds a weaker correlation with the Bitcoin price, since it explains less than 3% of its variability (Table-2). Normally and based on previous studies (Huang et al. 2003 and Zhang et al. 2009), the low frequency component is treated as the significant events that affect considerably the focal time series. From a first visual comparison between the observed Bitcoin price, the low and high frequency components and the trend (Figure-4), we clearly see that, although Bitcoin fluctuates widely due to significant events especially the closing of Road Silk, it would return to the trend after the influence of this event is over (for instance, in the end of 2013 after the closing drug platform by FBI).

3.2.2. The high frequency component

The high frequency component is treated as a collection of events with short term impact on Bitcoin price. The latter can be deeply influenced by rampant hacking attacks that may discourage momentary users or people interested in this digital money. Since Bitcoin depends on computer algorithms, it is unfamiliar with the majority of users, who have very little experience in mathematical programs. This structural problem may create uncertainty and then great speculation. The fact that the dynamics of the focal digital money is uncertain notoriously creates speculative bubbles. Without thoroughly tackling the causes, the virtual currency seems highly correlated to the behaviors of investors or people who hold it. Nobody is able to estimate the true value and the specific form Bitcoin will take since the technological development is unpredictable and the crypto market seems very open and thus may be challenged by new rivals or new forms of competition.

3.2.3. The trend

The trend displays a stronger correlation with the Bitcoin price (original time series), since it accounts for more than 41% of its variability (Table-2). This highly suggests that trend seems a deterministic force for Bitcoin evolution in the long-run. The continuing rising trend is consistent with the increased attention to Bitcoin as nascent phenomenon. The great media attention to this new digital money substantially pushes Bitcoin to an all-time increase. This new digital currency has attracted a huge number of users due to its lower transaction fees and deflationary bias. The upward trend may be more notable since biggest world companies as Zynga and Overstock begun accepting Bitcoin. In addition, relevant fundamentals (recorded in literature) including the exchange-trade ratio, the monetary velocity, Chinese stock market index and the hash rate (Kristoufek 2014 and Bouoiyour and Selmi 2015) may also explain this trend. In other way, if traders appreciate risky investments, a trend can also be identified and serious disappointments may await the unwary users.

4. CONCLUSIONS

Bitcoin seems a complicated phenomenon that requires thorough research. Compared with official fiat currency backed by a sovereign entity or commodity money such as gold which has an intrinsic value, the Bitcoin's value depends substantially on self-fulfilling expectations. Viewed from this perspective, the majority of people are still confused as to what a Bitcoin actually is. The present research attempts to reach clearer knowledge and better paths about what determines the Bitcoin's value. For this purpose, the Bitcoin data is decomposed into several independent intrinsic mode functions among different frequencies, bringing out interesting characteristics of the prices of this new virtual currency. The IMFs and the residue are summed up into three main components through a fine-to-coarse reconstruction. By doing so, the Bitcoin price can be appropriately explained as the composite of significant event effects (low frequency component), short-run fluctuations (high frequency component) and a long term upward trend. The short term fluctuations have the strongest correlation with the focal variable and then seem the major contributor of the variability of Bitcoin. Otherwise, the evolution of Bitcoin price is slightly impacted by significant events. Although Bitcoin moves largely due to some events like the closing of Road Silk, it returns to the trend after the influence of this event is over. Specifically, this nascent money appears determined by the trend, which changes continuously and stays around the long term mean.

While our results clearly highlight the difficulty to reach the real value of Bitcoin, it accurately indicates what determine this value. The obtained findings clearly reveal that Bitcoin price is mainly driven by short-run fluctuations and long term upward trend, which are themselves highly associated to speculation. This means that despite its passionate following, there is a possibility that Bitcoin collapses in the future rather than becomes an internationally recognized medium of exchange.

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