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What drives Bitcoin price?

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Abstract

The cryptocurrencies increased in popularity and have become nowadays well known to a wide audience. This article seeks to assess the issue of Bitcoin price formation from a novel perspective. We use a new technique called Empirical Mode Decomposition (EMD) with which a complicated data set can be disentangled into a small number of independent and concretely implicational intrinsic modes that admit well-behaved Hilbert transforms. Even though Bitcoin is usually labelled as a purely speculative asset, EMD views that it is extremely driven by long-term fundamentals (above one year).

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1. Introduction

Unlike the fiat currencies (dollar, euro and yen), Bitcoins are digital coins which are not issued by any government or legal entity. Bitcoins rely on cryptographic protocols and a distributed network of users to mint, store, and transfer. Instead, investors perform their business transactions themselves without any intermediary. The peer-to-peer network eliminates the trade barriers and makes business easier. The scheme was initially suggested in 2008 by Satoshi Nakamoto, and became operational in January 2009. Every passing day, the increase in the number of companies which accept Bitcoin is making its perceived value real. Nevertheless, security concerns, the inelastic money supply coded via mathematic formula and unsustainable volatility have deeply plagued this virtual currency. Despite its heaviest popularity, it was difficult to get accurate answers to simple questions such as: what determines Bitcoin's value? Is it a speculative bubble? Is it a future currency? Is it a long-term promise? Getting frequently asked underscores the complication of this phenomenon. The majority of studies on this issue supported that Bitcoin is likely to be a speculative bubble rather than a future currency or long-term investment (Bucholz et al. 2012; Kristoufek 2013; Ciaian et al. 2014; Yermack 2014; Bouoiyour et al. 2015; Bouoiyour and Selmi 2015).

Given the intrinsic complexity of crypto market, methodological problems arise when one wants to assess how evolves Bitcoin price over time. This concerns particularly the non-stationarity and non-linearity problems. In the literature, the Fourier spectrum has been largely used to decompose the initial process into various harmonic functions with fixed frequencies and amplitudes. Note that a transform basis does not depend on the nature of a transformed sequence. Also, the amplitude and frequency values of the derived harmonic components are constant. This implies that if the behavior of a given sequence changes over a specific period, such changes will not be adequately reflected in the outcomes. Unlike the Fourier transform, every component resulting from a wavelet approach has parameters that determine its scale and level over time which avoids the possible non-stationarity problem. But for empirical aims, it would be more effective to have a transform that would not only enable to deal with non-stationarity and nonlinearity problems, but would carry out an adaptive transform basis. This method is an intuitive econometric tool enables to look further into inner features driving such phenomenon, which the standard econometric techniques are malapropos and unbefitting. The Empirical Mode Decomposition (EMD), first, developed by Huang et al. (1998) explains the time-frequency evolution of such multi-component signals, without the weaknesses sketched above.

The outline of the paper is as follows. Section 2 discusses the methodology used and provides a brief overview of the data. Section 3 reports our results. The last section concludes.

2. Methodology and data

The signal-processing approaches such as Fourier and wavelet transforms provided generally distorted information about nonlinear and non-stationary variables, like for instance ground motion recording (Huang et al. 1998). To find more complete information from signals that might be hidden when employing standard econometric methods, the Empirical mode decomposition (EMD) may be useful. This technique is suited to extract mono-component and symmetric components, known as Intrinsic Mode Function (IMF), from wide bands of signals. The IMF denotes an oscillatory mode of a simple function with varying amplitude and frequency. By exploring data intrinsic modes, the EMD helps detecting possible hidden features in the data, and aims indeed at transforming the investigated time series to hierarchical structure by means of the scaling transformations. It offers appropriate frequency information evolving over time and quantifies the changeability captured via the oscillation under distinct scales and locations. In brief, the IMFs have well defined instantaneous frequencies, which give an idea about the instantaneous energy and frequency content of the signal. Determining the dependence between the focal variables via EMD consists of: (i) decomposing original time series into dissimilar intrinsic mode functions (IMFs) and one residue among different time scales, from high to low frequencies; (ii) composing these independent mode functions into fluctuating process, slowing varying component and a trend based on a fine-to-coarse reconstruction.

Step 1: Decomposition

The data was extracted 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 one 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. It must be mentioned here that 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 considered time series in order to identify the difference $d(t)$ between $x(t)$ and $m(t)$:

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

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 further IMFs.

Step 2: Composition

This step consists of detecting maxima and minima and connecting the local maxima with the upper envelope and the minima with the lower one. When residue successfully meets the conditions that the number of zero- crossings and extrema do not differ by more than one as mentioned above and the sifting process can be fully achieved if the total number of IMFs is limited to log2*N* (*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:

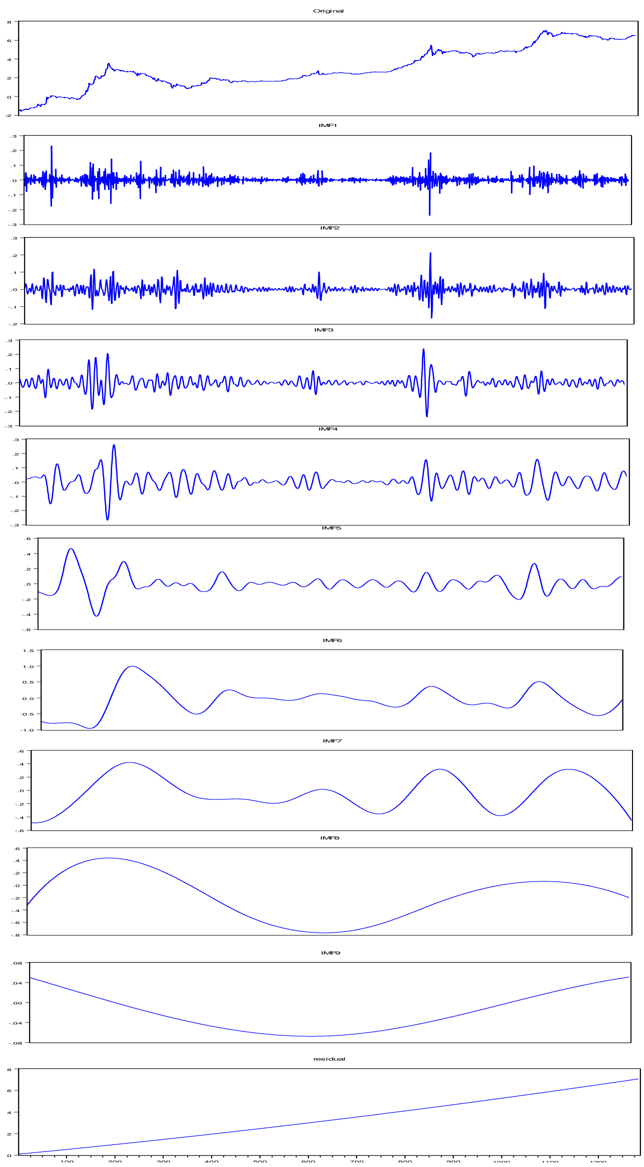
$$X(t) = \sum_{j=1}^{N} c_j(t) + r(t) \tag{3}$$

In the sifting process, the first component contains the shortest period component of the time series. The residue after extracting the quickly fluctuating component corresponds to the longer period fluctuations in the data. Briefly, EMD 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), consisting of: (i) computing the mean of the sum of c_i for each component (except for the residue); (ii) employing t-test to obtain for which *j* the mean departs from zero; (iii) once *j* 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 high frequency component. To effectively analyze Bitcoin price dynamics, we use daily time-series data related to Bitcoin price index (BPI) over the period from December 2010 to June 2015. These data were derived from Blockchain (https://blockchain.info/).

3. Results

Figure 1 shows that, via empirical mode decomposition, the Bitcoin price is decomposed into nine IMFs plus one residue. All the IMFs are listed from high (short-term) to low frequency (long-term), and the last one is the residue. Remarkably, the frequencies and amplitudes of all the IMFs move over time. As the frequency changes from high to low, the amplitudes of the IMFs become wider. The residue varies slightly around the long term mean. From highest to lowest frequency components, the amplitudes appear not the same with any harmonic. For example, the amplitudes of IMFs1-2 are larger than IMFs6-9. The residue follows a long term average.

Figure 1. The IMFs and residue for the Bitcoin price



We discuss in the following three main frequency components or scales: short-run, medium-run and long-run. Table 1 presents the time scale interpretation of empirical mode.

Table 1. Interpretation of scales based on EMD

modes	scales
IMF1	Short-run: less than 56 days
IMF2	
IMF3	
IMF4	Medium-run: above 56 and less than 315 days
IMF5	
IMF6	Long-run: above one year
IMF7	
IMF8	
IMF9	

On various time-scales, distinct modes may behave differently, possibly due to hidden factors that may determine the dynamic of Bitcoin price. Table 2 reports some measures which are given to assess IMFs features: mean period of each IMF, correlation between each IMF and the original data series and the 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. Two correlation coefficients, Pearson correlation and Kendall rank correlation coefficients are employed here to measure the relationships between IMFs and the original data. Because IMFs are intrinsically independent, it is possible to sum up the variances and use the percentage of variance to determine the contribution of each IMF to the total volatility of the original data set. Together, these measures reveal interesting insights. We show that the IMFs 7-8 (above one year) and the residue seem the dominant modes explaining the dynamic of Bitcoin price. In particular, the variance of IMF7 and IMF8 exceed respectively 38 % and 43%. The IMFs1-5 explain also the evolution of this digital money; such oscillations have weaker impact on Bitcoin price.

Table 2. Measures of IMFs and residue

	Mean period	Pearson correlation	Kendall correlation	variance as % of the sum of (IMFs+residue)
IMF1	1.17	0.068*	0.049***	0.13
IMF2	2.85	0.051**	0.038**	0.26
IMF3	3.96	0.123	0.061***	0.20
IMF4	5.04	0.082*	0.100**	0.17
IMF5	9.78	0.064**	0.075*	0.62
IMF6	11.95	0.032*	0.041**	0.35
IMF7	13.86	0.411**	0.329***	38.68
IMF8	16.17	0.310***	0.267***	43.92
IMF9	19.21	0.066	0.054	3.17
Residue		0.279***	0.238**	15.46

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

Table 3 gives more accurate information about the three mono-components yet identified. We usually note that the slowly fluctuating (long-term) component exerts more influence on Bitcoin price than quickly fluctuating (short-term) components, strengthening the validity of the previous outcomes.

Table 3. Correlations and variance of components

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

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

The nine IMFs may be grouped into three categories (as indicated in Table 1). Regarding the mean periods, the partial reconstruction with IMF1, IMF2 and IMF3 can be recognized as the shortest scales, IMF4 and IMF5 as the medium term scaling components, whereas the partial reconstruction with IMF6, IMF7, IMF8 and IMF9 can be treated as the longest time-scales (Figure 2). The first one corresponds to the Euclidean distance smaller than eight weeks or 60 days (high frequency component); the second one represents the Euclidean distance within eight weeks and less than twelve weeks (medium frequency component); the third one corresponds to the distance above fourteen weeks (low frequency component). While Bitcoin seems largely explained by long-run factors (IMFs 6–8) or more precisely by relevant market fundamentals; its value appears also driven by short-run features (IMFs 1–3) or normal market fluctuations possibly due speculative attacks.

Figure 2. The Euclidean distance via hierarchical clustering method

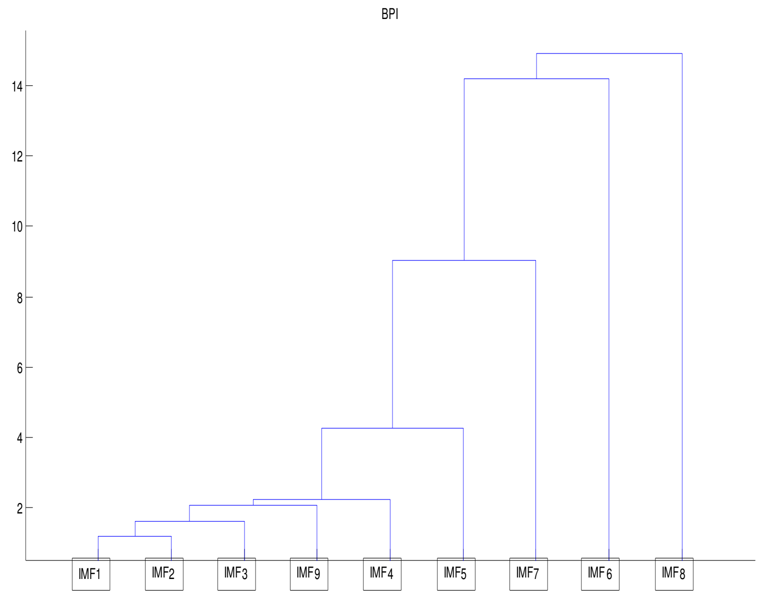
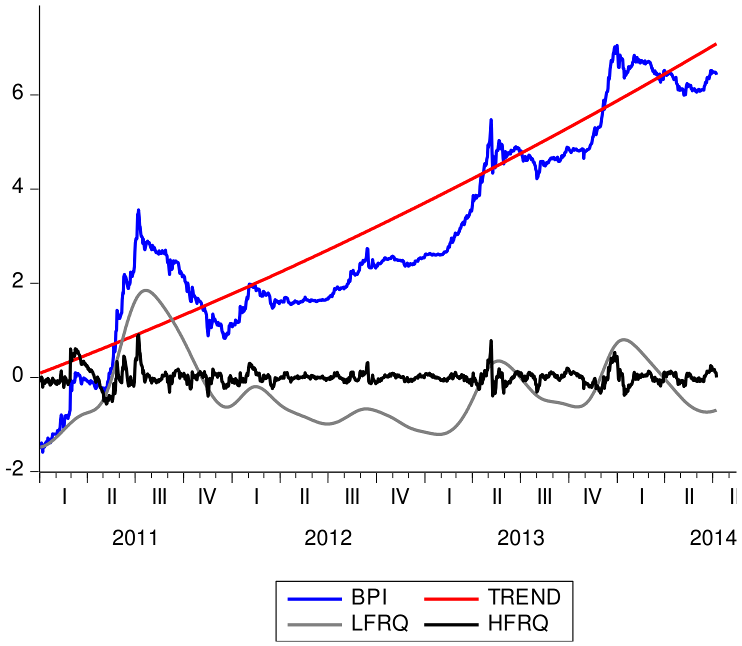


Figure 3 indicates that each component explaining the evolution of Bitcoin price has different characteristics. The residue is slowly varying around the long term mean and it is thus treated as the long term trend, the low frequency component reflects the extreme dependence of

Bitcoin value to long-term fundamentals. Nevertheless, the high frequency component contains essentially the market' short term fluctuations, highlighting its speculative nature.

Figure 3. The composition of IMFs into three components



Note: BPI: Bitcoin price index; LFRQ: Low Frequency Component (long-term); HFRQ: High Frequency Component (short-term).

4. Conclusions

Given an acute awareness that understanding the fundamentals of Bitcoin is not quite simple, this article seeks to gather fresh insights into this "complex" phenomenon. The main motivation of this study is to perform EMD for Bitcoin price analysis and try to interpret its formation mechanism from a new perspective.

Contrary to popular belief, this study suggests that although Bitcoin seems a speculative bubble (high frequency component), the long-term fundamentals (low frequency component) are likely to be the major contributors of Bitcoin price variation. On the basis of this article results, we must nuance our judgments concerning the speculative nature of this digital money. Although it is ubiquitous, the decomposition of Bitcoin series via EMD highlights the convolution of short-run and long-term fluctuations.

The short term variation can be explained by the fact that since its creation in 2009 Bitcoin has created tremendous media coverage and great speculation as to what will happen with this new virtual currency. Some researchers advocated that Bitcoin is likely to be a speculative foolery because there is no guarantee of repayment at any time (Kristoufek 2013; Yermack 2014; Bouoiyour et al. 2015).It is also not yet largely accepted as a payment system across wide markets and does not have an underlying value derived neither from consumption nor production process such as the precious metals including gold (Ciaian et al. 2014; Glaster et al. 2014). In addition, since the majority of users have not acknowledged about mathematical programs, and it is unknown for them how far it can go, Bitcoin seems vulnerable to cyber-attacks that may play a destabilizing role in the Bitcoin system (Bouoiyour et al. 2015). Further, the fact that this nascent currency can be anonymously used to conduct transactions between any account holders, anywhere and anytime across the globe, makes it very attractive to criminal activities. Bitcoin may be served to buy or sell illegal goods such as drugs. Thus, most countries have not clearly made determinations on the legality of Bitcoin. In brief, the attitude of regulators towards Bitcoin, coupled with the typical traders' lack of experience will prompt an intensive speculation.

This study appears also in line with the existing literature, supporting that Bitcoin price may be potentially determined by long-term fundamentals. In this context, van Wijk (2013), Ciaian et al. (2014), Kristoufek (2014), Bouoiyour et al. (2015) and Bouoiyour and Selmi (2015) argued that there are potential generators of Bitcoin price fluctuations in the long term. These contributors include supply-demand fundamentals, the exchange-trade ratio, the monetary velocity[1], equity market indices, exchange rates, oil prices and the estimated output volume. For example, Buchholz et al. (2012) argued that one of the most important determinants of Bitcoin price in the long-run is the interplay between Bitcoins' supply and demand. Besides, van Wijk (2013) stressed the significant role of global financial development (in particular, stock market indices, exchange rates, and oil prices measures) on the value of Bitcoin over longest time-horizons. Kristoufek (2014) added that an increase in the estimated output-reflecting the true volume of transactions- leads to a drop in Bitcoin price in the long term. Moreover, Ciaian et al. (2014) and Bouoiyour and Selmi (2015) found that the trade and exchange transactions expand the utility of holding Bitcoin, leading to an increase in its price in the long-run.

Even though it is a challenging task to perform signal processing techniques for non-stationary and noisy signals (Lin and Hongbing 2009), this study underscores the appropriateness of EMD for capturing hidden factors that may drive "complex" phenomena such as cyptocurrencies (in particular, Bitcoin price). While EMD, Fourier, and wavelets are all developed to disentangle signals, EMD seems fundamentally different. Unlike Fourier and wavelet transforms, EMD makes no assumptions a priori about the composition of the signal. Rather, it uses spline interpolation between maxima and minima to successively trace out intrinsic mode functions; hence, the outcomes might be more meaningful.

[1] By definition, the velocity of money is the frequency at which one unit of each currency is used to purchase tradable or non-tradable products for a given period.

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