What Does Crypto-currency Look Like? Gaining Insight into Bitcoin Phenomenon

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13 August 2014

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Abstract: The present paper seeks to effectively address the following question: What Bitcoin looks like? To do so, we regress Bitcoin price on a number of variables (Bitcoin fundamentals recorded in the literature) by applying an ARDL Bounds Testing approach for daily data covering the period from December 2010 to June 2014. Our findings highlight the speculative nature of Bitcoin. We also provide insightful evidence that Bitcoin may be used for economic reasons but there is any sign of being a safe haven. By considering the Chinese trading bankruptcy and the closing of Road Silk by FBI, the contribution of users' interest stills sharply dominant, indicating the robustness of our results.

Keywords: Bitcoin; ARDL Bounds Testing method; innovative accounting approach; VEC Granger causality test.

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1. Introduction

Since its creation in 2009 by Satoshi Nakamoto-pseudonym, the Bitcoin has experienced multiple peaks and successive ups and downs. Is it a safe haven or a speculative trap? Is it a short-term hedge? Is it a poor long-term investment or a long-run promise? The opinions about this nascent currency have drawn a substantial attention from investors, advisers and market regulators. The fact that questions get frequently and heavily asked indicates the very prime importance of this phenomenon.

Bitcoin is virtual money with zero intrinsic value issued by computer code in electronic portfolios, which is not convertible into anything and not have the backing of any Central Banks and any government. The value of a Bitcoin is neither a convertible tangible asset (such as gold) nor a fiat currency (such as dollar). It is determined by the interplay of supply and demand. This nascent crypto-currency fulfills various functions. It facilitates business transactions from person to person worldwide without any intermediary, reduces trade barriers and increases the productivity. Nevertheless, Bitcoin remains far from certain because of its sizeable price volatility, the inelastic money supply coded by mathematic formula and the lack of legal security. Bitcoin is a digital currency in a nascent stage closely associated to multiple risks stemming from its extra volatility and its speculative nature.

Despite its sharp popularity, there still very few works analyzing Bitcoin phenomenon. These researches seem insufficient to appropriately address the huge amount of questions around it. For instance, the study of Kristoufek (2013) focuses only on assessing whether Bitcoin is a “speculative bubble” by exploring the link between Bitcoin and users’ interest. In addition, Glaser et al. (2014) have attempted to evaluate if Bitcoin is an asset or a currency. Besides, Kristoufek (2014) has tried to investigate whether Bitcoin is more driven by technical, financial or speculative factors by applying coherence wavelet. This technique allows it to consider the interconnection between each two variables without considering the possible interaction with other time series. In other words, this analysis is incomplete and may lead to biased results. More accurately, wavelet coherence may not be considered usually as perfect technique. On the one hand, it may lead to confuse outcomes since the occurrence of noise cannot be heavily neglected, disrupting then the studied relationship (Ng and Chan, 2012). On the other hand, wavelet decomposition is generally applied to assess the periodicity and the multiple signals that happen over time. Moreover, when we consider only two variables in wavelet analysis, we generally fall on the problem of simple regression without control variables. This highlights the inability of this technique to capture proper and accurate outcomes since it may distort the estimate. In that context, Aguiar-Conraria and Soares (2011) argue that the findings change intensely when we move from wavelet investigation with two variables for conditional wavelet estimation (with more than two variables or by adding other explanatory time series). This implies that the use of large-scale parameters of each two variables as the case of Kristoufek (2014)’s study may prompt inconclusive results in terms of the interaction dynamic between Bitcoin price and its main drivers. This reinforces the need to take into account the control variables to confirm the obtained findings.

Due to the complexity of this new digital currency, the Bitcoin phenomenon demands a deeper investigation. Hence, the present paper attempts to address several questions in order to elucidate readers’ information about Bitcoin: What this crypto-currency looks like? Is it a safe haven or a speculative trap? Is it a business income? Is it a short-term hedge? Is it good idea to invest in Bitcoin? Is it a long term promise?

To find better paths, our contribution to this debate is to check the robustness of the previous results and to answer further questions by adding additional explanatory variables and by carrying out convenient method that considers the interaction dynamic between several variables and captures the shocks of own series with others. To this end, we regress Bitcoin price on investors' attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price, oil price, Dow Jones and Shangai market indices. We apply an ARDL Bounds Testing approach, innovation accounting by simulating variance decomposition and impulse response function and VEC Granger causality test for daily data for the period spanning between December 2010 and June 2014.

We show interesting outcomes: In the short-run, the investors attractiveness, the exchange-trade ratio and the Chinese market index affect positively and significantly the Bitctoin price, while the monetary velocity, the estimated output volume, the hash rate, the gold price, the oil price and the Dow Jones index have no influence. In the long-run, the speculative nature of Bitcoin and the Chinese stock market index which play the major role in the short-run appear without statistically significant impact on Bitcoin price. The influence of exchange-trade ratio becomes less strong, whereas the effects of the monetary velocity, the estimated output volume, the gold price and the oil price still insignificant. The hash rate and the USA stock market performance play a significant determinant role on explaining the dynamic of this nascent virtual currency. These findings appear solid and unambiguous since there is a very slight change when incorporating two dummy variables relative to the bankruptcy of Chinese trading company and the closing of Road Silk by FBI. Beyond the nuances of short and long terms, this research confirms the speculative nature of Bitcoin and its partial usefulness in economic reasons without forgetting the utmost importance of accounting for Chinese stock market and the processing power of Bitcoin network when analyzing the Bitcoin price dynamic. This new digital money seems far from being a safe haven and a long-term promise.

The remainder of the article proceeds as follows: Section 2 presents a brief literature survey. Section 3 describes our data and presents our methodological framework. Section 4 reports our main results and discusses them. Section 5 focuses on robustness check. Section 6 concludes and offers policy implications that may be fruitful for investors and regulators.

2. Brief literature survey

Bitcoin has engaged the attention of Medias and researchers, acknowledging the complexity of this new digital currency. Some researchers considered Bitcoin as financial instrument rather than currency or payment system. Others called it "evil" since it is not controlled nor by central banks nor by governments. Some economists defined it as "a speculative trap" because of its extreme volatile behavior (Buchholz et al. (2012), Kristoufek (2013, 2014), Bouoiyour et al. (2014) and Ciaian et al. (2014)). Others showed that with the absence of hedging instruments able to appropriately prevent Bitcoin volatility, this digital money can behave as a speculative trap (Yermack, 2014). Consistently, Glouderman (2014) argue that "economists scoffed at Bitcoin as more of a financial experiment than a legitimate payment system. Some economists denounced it as evil, because its value is not backed by any government nor can it be used to make pretty things as can gold. Others show that with no intrinsic value, Bitcoin's rising price constituted a speculative bubble".

The study of Kristoufek (2014) attempts to determine whether Bitcoin is likely to be safe haven, speculative bubble or transactions tool by analyzing the potential sources of Bitcoin price fluctuations including supply-demand fundamentals, speculative and technical drivers. Wavelet coherence has been carried out to investigate properly and effectively the evolution of correlations between the considered variables at different time frequencies. The obtained results reveal that the fundamental factors such as exchange-trade ratio play substantial roles in the long-run (short frequencies). The Chinese index seems an important source of Bitcoin price evolution, while the contribution of gold price dynamic appears minor and sometimes unclear. He finds also that Bitcoin prices are mainly influenced by investors' interest and thus by the speculative behaviors of businesses. This interconnection is most dominant at lower frequencies (higher time scale). Intuitively, the findings reveal that during the explosive prices period, the investors' attractiveness to this nascent currency drives this currency price up, while it drives it down during rapid declines period.

Glaser et al. (2014) have tried to address what intentions are businesses and investors following when moving their currency's usage from domestic ones into a crypto-currency like Bitcoin. By applying an Autoregressive Conditional Heteroskedasticity model, they show that the motivation of investors to Bitcoin and their intention to gather proper and additional information about its development has a great effect on this crypto-currency exchange volume, while the nexus between Bitcoin and users' interest seems insignificant when considering the volume within the Bitcoin system. These observed outcomes may be owing to the fact that exchange users prefer usually to keep their Bitcoins in their exchange wallet to avoid speculation and cyber-attacks without any intention to use them in economic reasons (trade transactions, for example).

Bouoiyour et al. (2014) attempt to appropriately address whether Bitcoin is a business income or risky investment. They use Granger causality to assess the relationship between Bitcoin price and exchange-trade ratio to answer the first question and the link between Bitcoin price and investors' attractiveness to address the second one. These tests have been carried out within a frequency domain framework (unconditional versus conditional causality) by applying a Breitung and Candelon's (2006) approach. Their results reveal that Bitcoin price Granger-causes exchange-trade ratio in the medium- and long-run. Besides, the investors' attractiveness Granger-cause Bitcoin price in the short term. These relationships change substantially when considering the Shangai index and the hash rate (i.e. conditional causality), highlighting therefore the complexity of evaluating what exactly Bitcoin looks like. To sum, the focal studied links seem bidirectional and cyclical. These cycles can be short, medium or long depending to directional causality in question. Their research provides insightful evidence by confirming the extremely speculative nature of Bitcoin without neglecting its great usefulness in economic reasons. The conditional causality through the consideration of the Shangai index and the hash rate appears valuable since it has succeeded to reach solid findings connecting further Bitcoin to the speculative behavior of investors.

3. Data and methodology

The existing literature on Bitcoin price suggests different factors that may play important roles in explaining its evolution including the Bitcoin' attractiveness of investors, the global macroeconomic and financial indicators and the technical drivers. To measure the users' attractiveness to Bitcoin, we follow Kristoufek (2013) by using daily Bitcoin views from wikipedia as it allows us to capture the speculative behavior of investors. In order to detect Bitcoin economy, we use two respective indicators which are exchange-trade ratio, the monetary Bitcoin's velocity determined by the Bitcoin days destroyed for given transactions and the estimated output volume. Technical drivers have been also considered to explain the dynamic of Bitcoin measured through the hash rate available at Blockchain. We consider also the global macroeconomic and financial indicators following the studies of Ciaian et al. (2014) and Kristoufek (2014) including the gold price, the oil price, the Dow Jones index and the Chinese or Shangai stock market index. Before beginning our analysis, it seems highly important to give some details about these considered variables:

- The Bitcoin price (*BPI*): As stated previously, the Bitcoin is new digital money that has recently attracted Medias and a wide range of people. It is an alternative currency to the fiat currencies including dollar, euro and yen, with several advantages like lower transactions fees and transparent information about the trade transactions. It has also some drawbacks where the most damageable are the lack of legal security, the extra volatility and the speculation (Kristoufek, 2014).
- The investors' attractiveness (*TTR*): To effectively determine the investors' attractiveness to Bitcoin, we can use daily Bitcoin views from Google[2] as it able to depict properly the speculative character of Bitcoin' users (Kristoufek, 2013). Likewise, Bouoiyour et al. (2014) have chosen to use the number of times a key word search term in relation to this famous crypto-currency is entered into the Google engine.
- The exchange-trade ratio (*ETR*): The trade transactions and exchanges expand the utility of holding the currency that may prompt an increase in Bitcoin price. The exchange-trade ratio is measured as a ratio between volumes on the currency exchange market and trade. It can be considered as measure of transactions (Kristoufek, 2014), or to address whether Bitcoin is business income (Bouoiyour et al. 2014).
- The monetary Bitcoin velocity (*MBV*): 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. Because of the sharply large daily fluctuations of Bitcoin, the velocity of the economy of this new crypto-currency has stayed relatively stable.
- The estimated output volume (*EOV*).: Basically, there is a negative relationship between the estimated output volume and Bitcoin price, i.e. an increase in output volume leads to a drop in Bitcoin price especially in the long-run (Kristoufek, 2014).
- The Hash rate (*HASH*): The emergence of the famous virtual money has provided new approaches concerning Bitcoin payments. Hence, some new words have emerged such as the hash rate. It may be considered as an indicator or measure of the processing power of the

[2] The views from Google used here as indicator of users' interest is determined via the frequency of the online Google search queries related to new digital money generally and Bitcoin particularly. Piskorec et al. (2014) highlight the great usefulness of this proxy to accurately describe the behavior of Bitcoin investors.

Bitcoin network. For security goal, Bitcoin network must make intensive mathematical operations, leading to an increase in the hash rate itself heavily connected with an increase in cost demands for hardware. This may affect widely Bitcoin purchasers and thus expands the demand of this new currency and in turn their prices. Theoretically, the hash rate is associated positively to Bitcoin price (Bouoiyour et al. 2014).
- The gold price (*GP*): Bitcoin does not have an underlying value derived from consumption or production process such as the precious metals including gold. Arguably, Ciaian et al. (2014) put in evidence that there is any sign of Bitcoin being a safe haven.
- The oil price (*OP*): Palombizio and Morris (2012) find that oil price is a potential factor that may affect intensely the inflation outcomes. If the price of oil indicates great ups and downs (i.e. sizeable volatility), the Bitcoin depreciates. Besides, the exchange rate may reflect inflationary pressures affecting positively the prices of this crypto-currency.
- The Dow Jones index (*DJI*): The relationship between Bitcoin price and the Dow Jones index appears complex, since the two variables seem sometimes correlated but not usually. After the announcement of American satellite TV provider that it would start accepting Bitcoin as payment tool, the prices of this digital money increased approximately by $40 touching the level of $ 600, while the Dow Jones Index was down by 300 points. A perfect example of how the Bitcoin and the American markets have been initially unrelated. Nevertheless, the offshoots of Al-Qaeda over different cities in Iraq and the Obama's declaration (i.e. America will not send the military in order to fight off the terrorist organizations) have affected Bitcoin price and simultaneously Dow Jones index. Due to the sizeable connection between the turmoil and Bitcoin's value, the price of Bitcoin started dropping and as response the Dow Jones index started falling by 200 points[3]. This implies that there is some connection between both variables.
- The Chinese market index (*SI*): The Chinese market index is considered as the biggest player in Bitcoin economy and then it may be a potential source of Bitcoin price volatility. Kristoufek (2014) takes an important example that may confirm this evidence, which is the development around Baidu that may be considered as a potential determinant of the Chinese online shopping. The announcement that Baidu is accepting Bitcoin has influenced substantially the price dynamic of this virtual currency. Arguably, Bouoiyour et al. (2014) provides insightful evidence that Bitcoin is likely to be a speculative trap rather than business income, but this is conditioning upon the performance of Chinese market.

During the period between 05/12/2010 and 14/06/2014, this study disentangles the existence of long-run cointegration between the above mentioned variables by considering two dummy variables denoting respectively the bankruptcy of Chinese trading company (it amounts 1 from 02/2013 and 0 otherwise) and the closing of the Silk Road[4] by the FBI (it amounts 1 from 23/10/2013 and 0 otherwise). All these data are extracted from Blockchain[5] and quandl[6]. To improve the precision power of results, we carry out a log-linear specification that incorporates *TTR, ETR, MBV, EOV, HASH, GP, OP, DJI* and *SI.*

[3] For more details, you can refer to: http://coinbrief.net/bitcoin-price-news-analysis/
[4] It is a roating-platform of drug on which transactions were through Bitcoin.
[5] https://blockchain.info/
[6] http://www.quandl.com/

$$LBPI_t = a_0 + a_1 LTTR_t + \alpha_2 LETR + a_3 LMBV_t + a_4 LEOV_t + a_5 LHASH_t + \alpha_6 LGP_t + \alpha_7 LOP_t + \alpha_8 LDJI_t + \alpha_ç LSI_t + \varepsilon_t \quad (1)$$

$$LBPI_t = \beta_0 + \beta_1 LTTR_t + \beta_2 LETR + \beta_3 LMBV_t + \beta_4 LEOV_t + \beta_5 LHASH_t + \beta_6 LGP_t + \beta_7 LOP_t + \beta_8 LDJI_t + \beta_ç LSI_t + \beta_{10} DV1 + \xi_t \quad (2)$$

$$LBPI_t = \varsigma_0 + \varsigma_1 LTTR_t + \varsigma_2 LETR + \varsigma_3 LMBV_t + \varsigma_4 LEOV_t + \varsigma_5 LHASH_t + \varsigma_6 LGP_t + \varsigma_7 LOP_t + \varsigma_8 LDJI_t + \varsigma_ç LSI_t + \varsigma_{10} DV2 + \zeta_t \quad (3)$$

Where ε, ξ, ζ are the error terms with normal distribution, zero mean and finite variance. The letter *L* preceding the variable names indicates Log. Kristoufek (2013, 2014) and Bouoiyour et al. (2014) assume that an increased users' interest searching for information about Bitcoin leads to an increase in Bitcoin prices. Then, we expect $a_1, \beta_1, \varsigma_1 > 0$. The exchange-trade ratio denotes the ratio between volumes on the currency exchange market and trade. Theoretically, the price of the currency is positively associated to the use of transactions as it expands the utility of holding the currency, increasing then Bitcoin price (Kristoufek, 2014). So, it is expected that $a_2, \beta_2, \varsigma_2 > 0$. The monetary Bitcoin velocity is measured by taking the number of Bitcoin in a transaction and multiplying it by the number of days where coins are already spent. Greater is Bitcoin velocity, greater will be Bitcoin prices (Ciaian et al. 2014). We expect $a_3, \beta_3, \varsigma_3 > 0$. An increase in the estimated output volume affects negatively Bitcoin price in the long term (Kristoufek, 2014). We expect therefore $a_4, \beta_4, \varsigma_4 \prec 0$. The hash rate is associated positively to Bitcoin price. According to Bouoiyour et al. (2014), an increase in Bitcoin price generates the intention of market participants to invest and to mine, leading to a higher hash rate. We expect that $a_5, \beta_5, \varsigma_5 > 0$. Kristoufek (2014) reveals that Bitcoin is not heavily interacted with gold price, while it is positively interacted with oil price (Ciaian et al., 2014). Palombizio and Morris (2012), gold price and the oil price may be considered as the main sources of demand and cost pressures and then seems a contributor of inflation development and thus affect positively Bitcoin price. We expect $a_6, \beta_6, \varsigma_6 > 0$ and $a_7, \beta_7, \varsigma_7 > 0$. The Chinese market index is considered as a substantial player in digital currencies and in particular Bitcoin. The Dow Jones index is an indicator of US economic performance. According to Kristoufek (2014) and Ciaian et al. (2014), the Bitcoin price is correlated with well Chinese and US performing economies. We expect thus that $a_8, \beta_8, \varsigma_8 > 0$ and $a_9, \beta_9, \varsigma_9 > 0$. The Chinese trading bankruptcy and the closing of the Road Silk may affect considerably Bitcoin price since Chinese market is one of the Biggest Bitcoin market and The Road Silk use only Bitcoin in their transactions. These two events have led to a remarkable drop in the prices of Bitcoin (Bouoiyour et al. 2014). Indeed, it is well expected that $\beta_{10}, \varsigma_{10} \prec 0$.

3.1.The ARDL Bounds Testing Method

The ARDL bounds testing approach introduced by Pesaran and Shin (1999) allows us to see whether there is a long-run relationship between a group of time-series, some of which may be stationary at level, while others are not. This method has various advantages: First, the time series are assumed to be endogenous. Second, it obviates the need to classify the time series into I(0) or I(1) as Johansen cointegration. Third, it allows us to assess simultaneously the short-run and the long-run coefficients associated to the variables under consideration.

This paper applies this technique to investigate the relationship between Bitcoin price and the aforementioned determinants on the one hand (Equation 1) and by incorporating then dummy variables that denote respectively the bankruptcy of Chinese trading company and the closing of the Road Silk on the other hand (Equation 2 and Equation 3) to check the robustness of our results. The ARDL representation of equations (1), (2) and (3) are formulated as follows:

$$DLBPI_t = a_0 + \sum_{i=1}^{n} a_{1i} DLBPI_{t-1} + \sum_{i=0}^{m} a_{2i} DLTTR_{t-1} + \sum_{i=0}^{l} a_{3i} DLETR_{t-1} + \sum_{i=0}^{h} a_{4i} DLMBV_{t-1} + \sum_{i=0}^{v} a_{5i} DLEOV_{t-1} + \sum_{t=0}^{r} a_{6i} DLHASH_{t-1} + \sum_{t=0}^{s} a_{7i} DLGP_{t-1} + \sum_{i=0} a_{8i} DLOP_{t-1} + \sum_{i=0}^{r} a_{9i} DLDJI_{t-1} + \sum_{i=0}^{z} a_{10i} DLSI_{t-1}$$
$$+ b_1 LBPI_{t-1} + b_2 LTTR_{t-1} + b_3 LETR_{t-1} + b_4 LMBV_{t-1} + b_5 LEOV_{t-1} + b_6 LHASH_{t-1} + b_7 LGP_{t-1} + b_8 LOP_{t-1} + b_9 DJI_{t-1} + b_{10} LSI_{t-1} + \varepsilon'_t \quad (4)$$

$$DLBPI_t = c_0 + \sum_{i=1}^{n} c_{1i} DLBPI_{t-1} + \sum_{i=0}^{m} c_{2i} DLTTR_{t-1} + \sum_{i=0}^{l} c_{3i} DLETR_{t-1} + \sum_{i=0}^{h} c_{4i} DLMBV_{t-1} + \sum_{i=0}^{v} c_{5i} DLEOV_{t-1} + \sum_{t=0}^{r} c_{6i} DLHASH_{t-1} + \sum_{t=0}^{s} c_{7i} DLGP_{t-1} + \sum_{i=0} c_{8i} DLOP_{t-1} + \sum_{i=0}^{r} c_{9i} DLDJI_{t-1} + \sum_{i=0}^{z} c_{10i} DLSI_{t-1}$$
$$+ d_1 LBPI_{t-1} + d_2 LTTR_{t-1} + d_3 LETR_{t-1} + d_4 LMBV_{t-1} + d_5 LEOV_{t-1} + d_6 LHASH_{t-1} + d_7 LGP_{t-1} + d_8 LOP_{t-1} + d_9 DJI_{t-1} + d_{10} LSI_{t-1} + d_{11} DV1 + \xi'_t \quad (5)$$

$$DLBPI_t = e_0 + \sum_{i=1}^{n} e_{1i} DLBPI_{t-1} + \sum_{i=0}^{m} e_{2i} DLTTR_{t-1} + \sum_{i=0}^{l} e_{3i} DLETR_{t-1} + \sum_{i=0}^{h} e_{4i} DLMBV_{t-1} + \sum_{i=0}^{v} e_{5i} DLEOV_{t-1} + \sum_{t=0}^{r} e_{6i} DLHASH_{t-1} + \sum_{t=0}^{s} e_{7i} DLGP_{t-1} + \sum_{i=0} e_{8i} DLOP_{t-1} + \sum_{i=0}^{r} e_{9i} DLDJI_{t-1} + \sum_{i=0}^{z} e_{10i} DLSI_{t-1}$$
$$+ f_1 LBPI_{t-1} + f_2 LTTR_{t-1} + f_3 LETR_{t-1} + f_4 LMBV_{t-1} + f_5 LEOV_{t-1} + f_6 LHASH_{t-1} + f_7 LGP_{t-1} + f_8 LOP_{t-1} + f_9 DJI_{t-1} + f_{10} LSI_{t-1} + f_{11} DV2 + \zeta'_t \quad (6)$$

Where D denotes the first difference operator; $\varepsilon', \xi', \zeta'$ are the usual white noise residuals. To evaluate whether there is a cointegration or not depends upon the critical bounds tabulated by Pesaran et al. (2001, pp.300). There is a cointegration among variables if calculated F-statistic is more than upper critical bound. If the lower bound is superior to the computed F-statistic, we accept the null hypothesis of no cointegration. Moreover, if the F-statistic seems between lower and upper critical bounds, the cointegration outcomes are inconclusive. The stability of ARDL approach is assessed by carrying out various diagnostic tests and the stability analysis. The diagnostic tests include the adjustment R-squared, the standard error regression, Breush-Godfrey-serial correlation and Ramsey Reset test. The stability of short-run and long-run estimates is checked by applying the cumulative sum of recursive residuals, the cumulative sum of squares of recursive residuals and the recursive coefficients.

3.2.The innovative accounting approach and VEC Granger causality

The majority of empirical studies on the nexus between macroeconomic variables use the standard Granger causality test augmented with a lagged error correction term. Nevertheless, this method may be ineffective since it is unable to properly detect the possible effects of shocks. To resolve these limitations, we explore an innovative accounting approach by simulating variance decomposition and impulse response function. The purpose here is to assess whether Bitcoin seems a safe haven, risky investment, business income, speculative trap or long-run promise. Using variance decomposition, we decompose forecast error variance for Bitcoin price following a one standard deviation shock to investors' attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price, oil price, Dow Jones and Shangai market indices. This technique enables to test the strength of its impact on the series. The impulse response function captures the shock of the own series (the focal variable) with others series in the studied specifications. In an effort to identify whether there is a short-run causality between the variables in question, the Granger causality/Block Exogeneity Wald tests based upon VEC model may be useful and, to some extent, the most convenient. It determines if the lags of any time series does not

Granger cause any other variable in the system using LM-test. The null hypothesis is accepted or rejected based on chi-squared test based on Wald criterion to properly capture the joint significance of the restrictions under the null hypothesis already mentioned above.

4. Results and discussion

4.1.ARDL results

To determine the most potential driver of Bitcoin price dynamic and what this crypto-currency looks like, we start by reporting the descriptive statistics (Table-1). We clearly show a substantial data variability, highlighting the very prime need to use robust models. The coefficient of kurtosis appears inferior to 3 for all variables (except *LTTR, LETR, LMBV* and *LEOV*), indicating that the distribution is less flattened than normal distribution. The Skewness coefficient is positive for all time series (except *LETR, LGP* and *LOP*), indicating that the asymmetrical distribution is preferable. The Jarque- Bera test revealed high and significant values, leading to reject the assumption of normality for the concerned variables.

Table-1: Summary of statistics

	LBPI	*LTTR*	*LETR*	*LMBV*	*LEOV*	*LHASH*	*LGP*	*LOP*	*LDJI*	*LSI*
Mean	3.052919	1.574058	13.41844	15.01983	13.69757	10.83858	7.319273	4.562011	9.512864	7.744138
Median	2.507972	1.565531	13.32571	14.95729	13.68825	9.846016	7.357317	4.567884	9.481399	7.717494
Maximum	7.048386	4.804185	18.09288	18.97052	17.10051	18.45453	7.547765	4.728538	9.737782	8.022789
Minimum	-1.480693	-1.033161	4.057230	11.58991	10.64887	4.528026	7.084017	4.335983	9.273813	7.568131
Std. Dev.	2.078718	0.918618	2.235922	1.019057	1.033003	3.263868	0.120834	0.073901	0.118224	0.114295
Skewness	0.203586	0.201630	-0.668879	0.116808	0.009475	0.687444	-0.243169	-0.282292	0.253780	0.761047
Kurtosis	2.280162	3.326236	4.017153	3.887130	3.684876	2.922190	1.703855	2.578585	1.870213	2.590701
Jarque-Bera	21.23110	8.362903	87.78542	26.12393	14.57141	58.86658	59.57174	15.42809	47.68292	77.22019
Probability	0.000025	0.015276	0.000000	0.000002	0.000685	0.000000	0.000000	0.000447	0.000000	0.000000

Before proceeding ARDL estimation, we determine the degree of integration of variables. To this end, we apply Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results are reported in Table-2. We notice that the variables are integrated either at level or at first difference. Given this finding, the ARDL bounds testing approach can be carried out to test the cointegration hypothesis among the considered variables. According to the ARDL bounds testing approach, lag order of the variables is important for the model specification. Hence, we determine the lag optimization based on lag-order selection using various information criteria including Akaike Information Criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn criterion (HQ). Since AIC has superior power properties for sample data compared to any lag length criterion, we show that the optimum lag is zero (Table-3).

Table-2: Results of ADF and PP Unit Tests

Variables	ADF test		PP test	
	Level	First difference	Level	First difference
LBPI	---	-15.8916***	---	-32.5107***
LTTR	-5.8908**	---	-15.5010***	---
LETR	-2.9074**	---	-31.0877***	---
LMBV	-5.5649***	---	-25.8706***	---
LEOV	-3.7443**	---	---	-72.5447***
LHASH	---	-29.0159***	---	-13.7236***
LGP	---	-26.9126***	---	-23.3523***
LOP	-3.1624**	---	---	-23.5743***
LDJI	---	-30.3262***	---	-24.3422***
LSI	---	-28.5842***	---	-18.5978***

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively ; The numbers within parentheses for the ADF and PP statistics represents the lag length of the dependent variable used to obtain white noise residuals ; The lag lengths for the ADF and PP tests were selected using Akaike Information Criterion (AIC).

Table-3: Lag-order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3678.627	NA*	2.36e-06*	-10.11759*	-10.04801*	-10.09074*
1	3678.644	0.032814	2.37e-06	-10.11488	-10.03897	-10.08558
2	3678.673	0.057395	2.38e-06	-10.11220	-10.02997	-10.08046
3	3678.675	0.003638	2.38e-06	-10.10945	-10.02089	-10.07527

Notes: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Using ARDL Bounds testing approach, we show interesting results (Table-4): The impact of users' interest to Bitcoin or investors attractiveness plays a significant role in explaining Bitcoin price formation. Indeed, an increase by 10% in *TTR* expands the *BTP* by about 1.22%. The exchange-trade ratio affects positively and significantly the price of Bitcoin. An increase by 10% of *ETR* leads to an increase by 1.15% of *BPI*. Bitcoin velocity and estimated output volume have no significant impact on Bitcoin price formation. The influence of technical driver (HASH) seems positive and significant but minor. We notice that an increase by 10% of *HASH* prompts an increase by 0.05% in the prices of Bitcoin. Gold and oil prices have no influence on Bitcoin price, while Dow Jones and Shangai market indices contribute positively and significantly to *BPI* with remarkable superiority of Chinese market performance compared to that of US market (i.e. an increase by 10% of *SI* and *DJI* leads to an increase by 1.46% and 0.35% of *BPI*, respectively).

Table-4: The ARDL Bounds Testing Analysis

Dependent variable: $DLBPI_t$	
C	-2.4325* (-1.7278)
$DLBPI_{t-1}$	0.1185** (3.0231)
$DLTTR_{t-1}$	0.1222** (3.1537)
$DLETR_{t-1}$	0.1153** (3.0589)
$DLMBV_{t-1}$	-0.1222 (-0.2482)
$DLEOV_{t-1}$	0.0030 (0.3763)
$DLHASH_{t-1}$	-0.0141 (-0.5719)
$DLGP_{t-1}$	0.1559 (0.5900)
$DLOP_{t-1}$	-0.1043 (-0.5383)
$DLDJI_{t-1}$	-0.1268 (-0.3857)
$DLSI_{t-1}$	0.1468* (2.000)
$LBPI_{t-1}$	0.0186* (1.6551)
$LTTR_{t-1}$	-0.0162 (-1.5979)
$LETR_{t-1}$	0.0158* (2.2800)
$LMBV_{t-1}$	0.0032 (0.5693)
$LEOV_{t-1}$	0.0026 (0.4453)
$LHASH_{t-1}$	0.0056* (1.8862)
LGP_{t-1}	-0.0534 (-0.9023)
LOP_{t-1}	-0.0161 (-0.2627)
$LDJI_{t-1}$	0.0355* (2.2728)
LSI_{t-1}	0.0762 (1.3060)
Diagnostic tests	
R-squared	0.54
SE regression	0.8881
Breush-Godfrey serial correlation	0.6231 [0.4097]
Ramsey Reset test	0.2664 [0.6058]

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively; [.]: p-value.

In addition, we depict from Table-5 that the value of F-statistic exceeds the upper bound at the 10% significance level, implying that there is evidence of a long-run relationship among variables at this level of significance. These results seem insufficient to capture accurately the evidence of long-term linkage because ARDL bounds test is unable to detect structural breaks stemming in the time series under consideration. Given its inability to account for nonlinearity, we believe that it is substantial to apply the method of Gregory and Hansen (1996) to re-explore this nexus. This technique is based on an unknown structural break in the focal variables with respect to Engle-Granger residual. This test reinforces the fact that there is a long-run cointegration between Bitcoin price and its drivers and highlights the great importance to consider structural breaks in the interaction dynamic process of *BPI* as well as its main determinants (Table-6).

Table -5: The ARDL Bounds Testing Analysis

Estimated model	Optimal lag length	F-statistic	Prob.
F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*	3, 3,4, 1, 0, 0, 0, 0	4.5711*	0.0659
Significance level	Critical values: T=21		
	Lower bounds I(0)	Upper bounds I(1)	
1%	6.84	7.84	
5%	4.94	5.73	
10%	4.04	4.78	

Notes: ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively; Critical values were obtained from Pesaran et al. (2001).

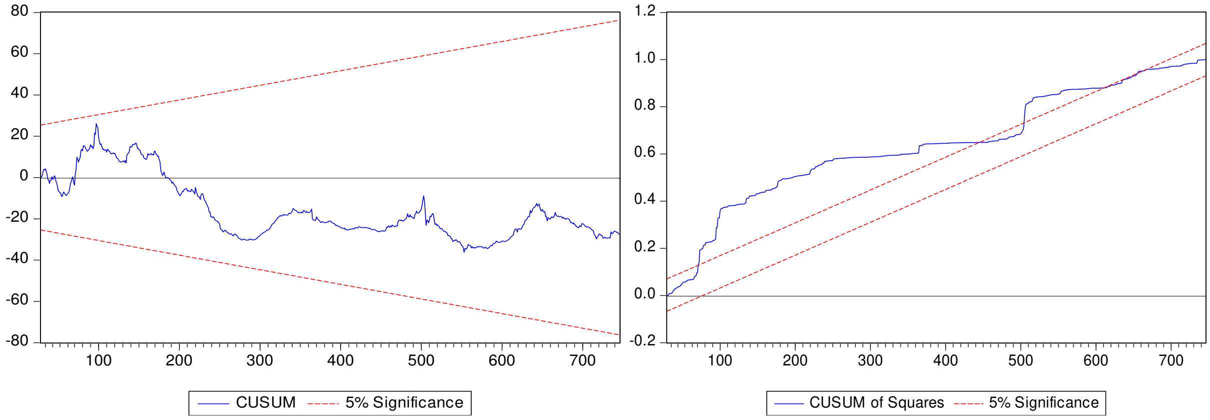
Table-6: Gregory-Hansen Structural Break Cointegration Test

Estimated model	F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*
Structural break year	23/10/2013
ADF-test	-5.9234***
Prob.values	0.0015
Significance level	Critical values of the ADF test
1%	-5.8652
5%	-4.9271
10%	-4.8135

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively.

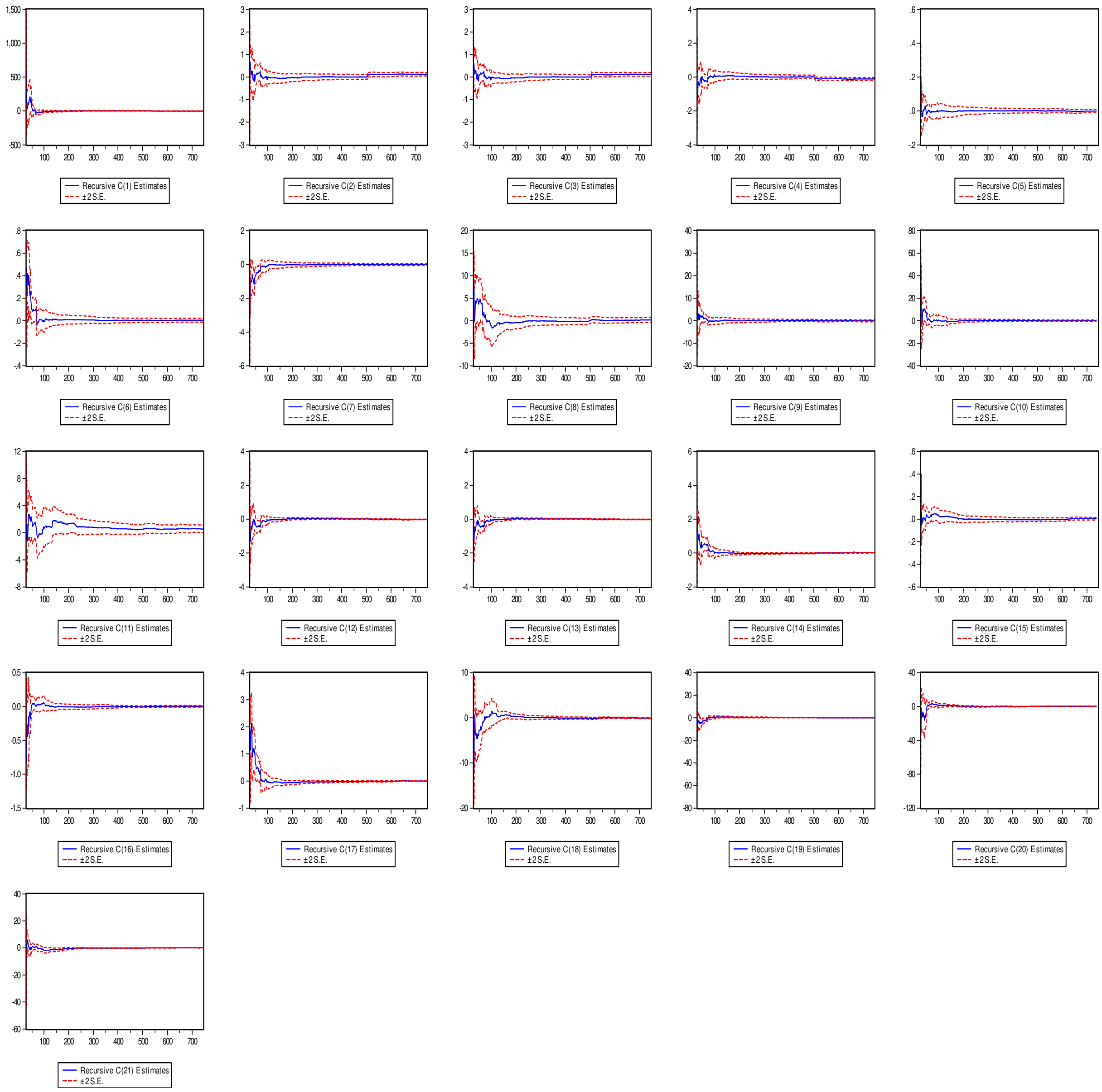
The diagnostic tests show that there is no evidence of serial correlation. The Ramsey reset test statistic reveals the performance of the short-run model (Table-4). The CUSUM test shows the adequacy of the considered models at 5% level of significance (Figure-2) and the stability of ARDL parameters (Figure-3).

Figure-2: Plots of cumulative sum of recursive and of squares of recursive residuals



Notes: The straight lines represent the critical bounds at 5% significance level.

Figure-3: Plots of cumulative sum of recursive coefficients



Notes: The straight lines represent the critical bounds at 5% significance level.

From our results reported in Table-7, we clearly notice that Bitcoin price interacts differently with its determinants depending to time periods. In the short-run, the users' interest, the exchange-trade ratio and the Shangai index affect positively and significantly the BPI. However, the monetary velocity, the estimated output volume, the hash rate, the gold price, the oil price and the Dow Jones index have no influence on this digital money. These outcomes change intensely in the long-run. The speculation and the Chinese stock market index which play the major role in the short term, have any effect on BPI in the long-run. The impact of ETR on BPI stills positive and significant, but becomes much less important. The impacts of *MBV, EOV, GP* and *OP* on *BPI* remain insignificant, whereas the hash rate and the *DJI* play a significant determinant role. Furthermore, the value of *ECT* is negative and statistically significant at 5 percent level, which is theoretically correct. It amounts (-0.0023), implying that the deviation in the short-run is corrected by 0.23% towards the long-run equilibrium path. The R-squared value indicates that 48% of Bitcoin price dynamic is explained by the explanatory variables under consideration.

4.2.Innovative accounting approach results

The results of the variance decomposition are reported in Table-8. We find that 68.97% percent of Bitcoin price is explained by its own innovative shocks. The investors' attractiveness (*TTR*) plays the major role in explaining the price dynamic of Bitcoin (20.06%). The contribution of *ETR* appears minor, amounting 0.10%. Similarly for Bitcoin monetary velocity, the estimated output volume and the hash rate with respective percentages equal to 0.06%, 0.11% and 0.002%. Gold price explains 0.005% of *BPI,* while *OP* contributes to *BPI* by 0.20%. Additionally, the contribution of Chinese market index (*SI*) in explaining the Bitcoin dynamic seems sharply intense compared to that of USA (*DJI*) with alternative percentages 10.12% and 0.32%.

To be more effective in our analysis, we add the results of the impulse response function. It traces the time path of the impacts of shocks of independent variable on the dependent variables in a VAR system. The impulse response function allows us to show how long independent variable reacts to shock stemming in the dependent variables. We can see also the magnitude of the response of Bitcoin price to its own shock, those of investors' attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price, oil price, Dow Jones and Shangai market indices. Figure-4 worthy indicates that the response in Bitcoin price owing to forecast error stemming in investors' attractiveness is positive over time but it dissipates gradually after six time horizons. The contributions of *ETR, MBV, EOV, HASH* and *GP* to Bitcoin price appear negligible. The response of Bitcoin price seems positive and stable due to the forecast errors stemming in oil price. Besides, the Bitcoin price reacts positively to the Dow Jones and Chinese market indices over all the considered period.

Table-7: Short-run and long-run Analysis

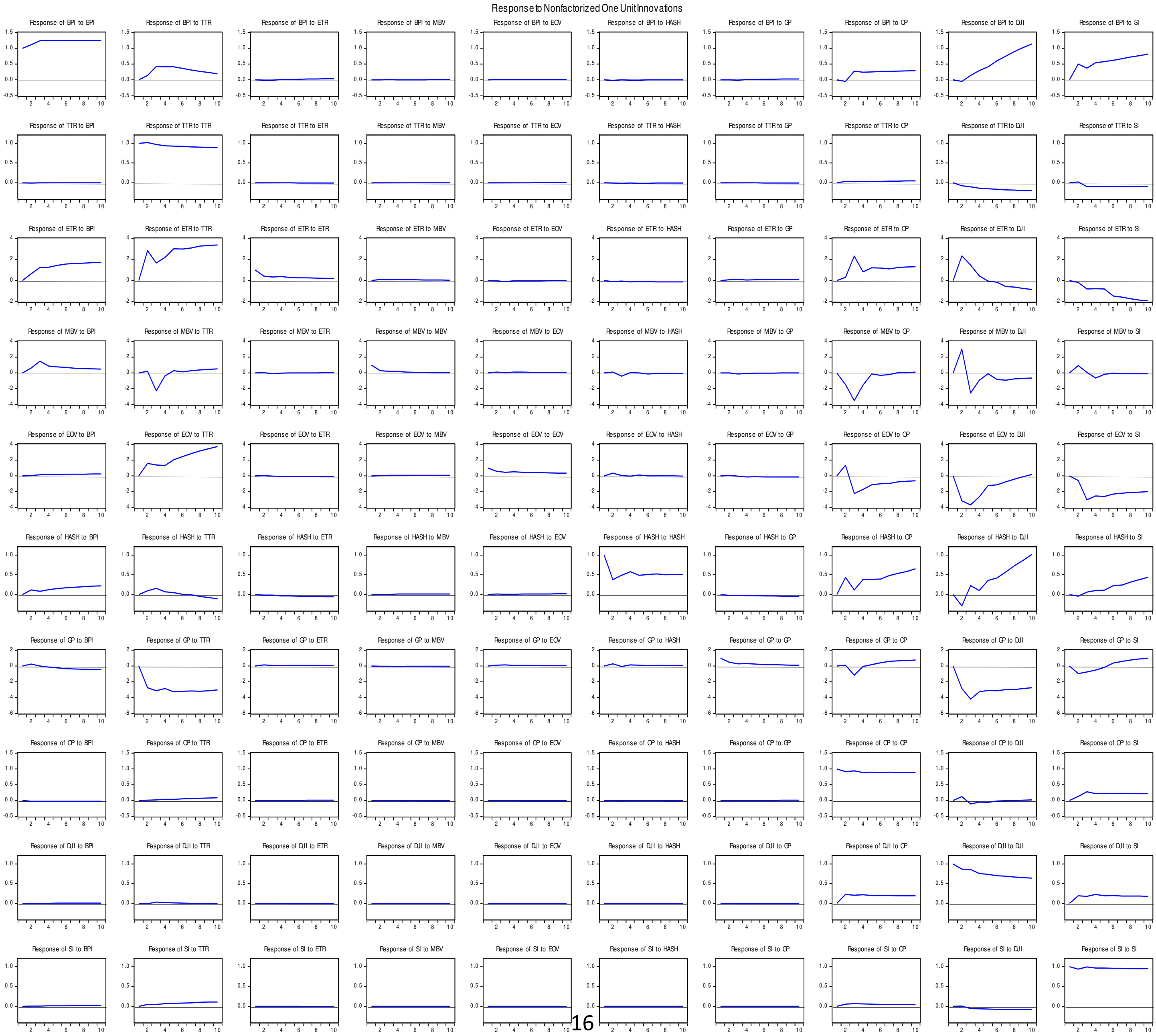
Dependent variable: $LBPI_t$	
Short-run	
$DLBPI_t$	0.1270*** (3.2270)
$DLTTR_t$	0.4305* (2.0214)
$DLETR_t$	0.2157*** (8.4441)
$DLMBV_t$	-2.2467 (-0.1721)
$DLEOV_t$	0.4158* (2.5803)
$DLHASH_t$	-0.0283 (-0.3214)
$DLGP_t$	-3.4273 (-1.5320)
$DLOP_t$	-2.4806 (-1.5448)
$DLDJI_t$	2.0697 (0.5522)
$DLSI_t$	0.3256* (1.6625)
ECT_t	-0.0023** (-2.8790)
Long-run	
$LBPI_t$	0.1340*** (3.3768)
$LTTR_t$	-0.0131 (-1.3168)
$LETR_t$	0.0088* (1.8163)
$LMBV_t$	0.0001*** (8.8192)
$LEOV_t$	0.0043 (0.5435)
$LHASH_t$	0.0077* (1.9745)
LGP_t	0.1518 (0.5697)
LOP_t	-0.0518 (-0.2658)
$LDJI_t$	0.1420*** (4.2680)
LSI_t	0.4400 (1.5950)
Diagnostic tests	
R-squared SE regression Breush-Godfrey serial correlation Ramsey Reset test	0.48 0.4597 [0.1386] 0.2392 [0.5674]

Notes : ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively Diagnostic tests results are based on F-statistic ; [.] : p-values.

Table-8: Variance Decomposition of Bitcoin price

S.E.	*LBPI*	*LTTR*	*LETR*	*LMBV*	*LEOV*	*LHASH*	*LGP*	*LOP*	*LDJI*	*LSI*
0.089236	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.133510	69.64294	20.10299	0.012666	0.014143	0.042821	0.002420	0.007915	0.000159	0.021659	10.15228
0.174247	69.31781	20.09368	0.084297	0.069088	0.082248	0.008574	0.004690	0.089813	0.132293	10.11750
0.208220	69.21861	20.07800	0.087726	0.063105	0.091891	0.006137	0.003851	0.130538	0.194279	10.12585
0.238292	69.13212	20.07648	0.093821	0.068997	0.098099	0.004751	0.004467	0.153696	0.242479	10.12509
0.265110	69.07429	20.07543	0.098891	0.069911	0.104294	0.004269	0.004888	0.171241	0.272138	10.12463
0.289584	69.04017	20.07283	0.102049	0.070048	0.107904	0.003690	0.005221	0.182453	0.292235	10.12339
0.312142	69.01439	20.07158	0.104564	0.069695	0.110543	0.003311	0.005473	0.190445	0.307239	10.12275
0.333190	68.99426	20.07075	0.106614	0.069345	0.112625	0.003047	0.005651	0.196888	0.318703	10.12211
0.352985	68.97904	20.06981	0.108108	0.068821	0.114341	0.002823	0.005788	0.201978	0.327628	10.12165

Figure-4: Impulse Response Function



Furthermore, we evaluate whether there is a causal relationship between the explanatory variables in question and the Bitcoin price dynamic. Before testing the non-causality hypothesis, we start by examining the residuals using the LM test for serial independence against the alternative of AR(k)/MA(k), for k = 1, ..., 12. From the findings reported in Table-9, the serial correlation may be removed at the maximum lag length which is 10. The non-causality test findings are reported in Table-10. It is clearly notable that we can reject the null hypothesis of no causality *DLTTR* to *DLBPI*, from *DLETR* to *DLBPI* and from *DLSI* to *DLBPI,* while the reverse link is not supported confirming therefore the above outcomes obtained through the ARDL Bounds Testing method and the innovation accounting approach (variance decomposition and impulse responses). For the rest of variables, we accept the null hypothesis of non-causality (except for the relationship that runs from *DLBPI* to *DLHASH* and the link running from *DLBPI* to *DLMBV*). These results may very useful for businesses, investors and regulators.

Table-9: VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h		
Lags	LM-Stat	Prob
1	38.55603	0.3547
2	31.55105	0.6801
3	28.60210	0.8051
4	28.89924	0.7937
5	46.62827	0.1105
6	17.97340	0.9948
7	36.78690	0.4323
8	45.86716	0.1255
9	36.89847	0.4272
10	47.23936	0.0995
11	25.64361	0.9000
12	27.21049	0.8541

Table-10: VEC Granger Causality/Block Exogeneity Wald Tests

Dependent variable*: DLBPI*			
Excluded	Chi-sq	df	Prob
DLTTR≠DLBPI	4.69526	2	0.0284
DLBPI≠DLTTR	1.08172	2	0.3532
DLETR≠DLBPI	4.75679	2	0.0927
DLBPI≠DLETR	1.28768	2	0.1172
DLMBV≠DLBPI	1.25430	2	0.5341
DLBPI≠DLMBV	13.2334	2	0.0013
DLEOV≠DLBPI	0.54221	2	0.7625
DLBPI≠DLEOV	0.39672	2	0.9528
DLHASH≠DLBPI	0.42937	2	0.8068
DLBPI≠DLHASH	6.17429	2	0.0456
DLGP≠DLBPI	2.81400	2	0.2449
DLBPI≠DLGP	0.60373	2	0.7394
DLOP≠DLBPI	2.88078	2	0.2368
DLBPI≠DLOP	1.07153	2	0.1480
DLDJI≠DLBPI	0.42550	2	0.8084
DLBPI≠DLDJI	1.02277	2	0.5997
DLSI≠DLBPI	3.35663	2	0.0867
DLBPI≠DLSI	1.21946	2	0.5435

5. Robustness

The above findings clearly indicate that the investors attractiveness, the exchange-trade ratio and the Chinese market index affect positively and significantly the Bitcoin price, while the monetary velocity, the estimated output volume, the hash rate, the gold price, the oil price and the Dow Jones index have no influence in the short term. However, the speculative nature of Bitcoin and the Chinese stock market index which play the major role in the short-run appear without statistically significant impact on Bitcoin price in the long-run. The influence of *ETR* on *BPI* becomes less strong, whereas the effects of *MBV, EOV, GP* and *OP* on *BPI* remain statistically insignificant in the majority of cases. The hash rate and the Dow Jones market index play significant roles on explaining the dynamic of this nascent virtual currency. To check properly and appropriately the robustness of these evidences, we re-estimate the relationships between Bitcoin price and its determinants by incorporating two dummy variables relative to the bankruptcy of Chinese trading company and the closing of Road Silk by FBI, using the same methods (i.e. an ARDL Bounds Testing method, an innovation accounting approach by simulating variance decomposition and impulse response function and VEC Granger causality test). Accurate details are reported in Table A-1, Table A-2, Table A-3, Table A-4, Table A-5, Figure A-1 and Figure A-2. Comparing these results with those of Equation without dummy variables, we put in evidence that the effects of *TTR, ETR, MBV, EOV, HASH, GP, OP, DJI* and *SI* are solid and unambiguous, especially in terms of time-horizons (i.e. short- and long-run assessments). Beyond the nuances of short and long terms, the present study confirms the speculative nature of Bitcoin without neglecting its usefulness in economic reasons and the importance of accounting for Chinese stock market and the processing power of Bitcoin network. At this stage, we can consider it only as a risky investment, short-term hedge and partially as business income. Nonetheless, this new crypto-currency seems far from being a safe haven and a long-term promise.

6. Concluding remarks and Policy implications

The present research attempts to reach clearer knowledge about the nascent crypto-currency (Bitcoin) by effectively answering the following questions: What Bitcoin looks like? Is it a safe haven or a “speculative bubble”? Is it a business income, a short-term hedge, a risky investment or a long-term promise?

To this end, we have regressed Bitcoin price on investors’ attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price, oil price, Dow Jones and Shangai market indices using an ARDL Bounds Testing method, an innovation accounting approach and VEC Granger causality test for daily data covering the period from December 2010 to June 2014. By doing so, we have checked the speculative nature of Bitcoin. We also provide insightful evidence that Bitcoin may be used for economic reasons but there is any sign of being a safe haven. By accounting for the Chinese trading bankruptcy and the closing of Road Silk, the contribution of the speculative behavior of investors and the performance of Chinese stock market remain dominant, while the role of Bitcoin as transactions tool dissipates in the long-run, highlighting the robustness of our results. Indeed, Bitcoin behaves heavily as a "speculative bubble", short-term hedge and risky investment and partially as business income. This new digital money is far from being a long-term promise, especially when considering that this virtual currency faces a great challenge (in particular a structural economic problem) regarding its limited amount recording 21 million units in 2140, implying that the money supply would not expand after this date. If this digital currency succeeds really to displace fiat currencies, it would exert great deflationary pressures.

This goes without saying that these findings should be treated with caution. Nobody is, up to now, able to estimate the true value of Bitcoin. The fact that the dynamic of the focal digital money is uncertain even more sustains speculation. Without tackling the main causes, the virtual currency seems highly correlated to the speculative behaviors of investors and people who hold this money. Bitcoin is not issued by banking system and even less by governments, but by a computing algorithm. Unfortunately, the majority of Bitcoin users have not heavily acknowledged about mathematical programs, and it is of course unknown for them how far it can go. The volatility of Bitcoin and the difficulty of processing power network are likely to discourage investors and users of this money. Intuitively, China represents the most active Bitcoin market in the world. The sizeable attention to this crypto-currency in the Chinese media has drawn a huge number of investors. However, the attitude of Chinese practitioners, advisers and regulators towards Bitcoin is ambiguous, yielding to much more speculation. This may reinforce the evidence thereby Bitcoin is short-term hedge, a poor long-term investment. We cannot confirm if this currency may be considered as long-term promise since the contribution of investors' interest appears dominant among the different estimations. This may support the conclusion of Bouoiyour et al. (2014) showing that it is very difficult to reach clearer insights and "one sided" evidence into Bitcoin Phenomenon.

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Appendices

Table A.1: Lag-order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
(1) : FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)						
0	782.4109	NA	0.006972	-2.128030	-2.058447	-2.101176
1	788.0603	11.11191	0.006883	-2.140856	-2.064947*	-2.111560*
2	791.0228	5.818642	0.006846	-2.146270*	-2.064035	-2.114533
3	792.0847	2.082820	0.006844*	-2.146441	-2.05738	-2.112262
(2) : FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)						
0	163.4746	NA	0.004414	-2.585117	-2.544254	-2.569759
1	164.5226	20.77749	0.004348	-2.600201*	-2.555252*	-2.583308
2	164.5759	1.055509	0.004351	-2.599458	-2.550422	-2.581029*
3	164.6161	0.795628	0.004355*	-2.598506	-2.545384	-2.578541

Notes: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Table A-2: The ARDL Bounds Testing Analysis

Dependent variable: *DLBPI*$_t$		
	(1)	(2)
C	-1.7262* (-2.5645)	-1.4941* (-2.1939)
$DLBPI_{t-1}$	0.0376* (2.0056)	0.0288* (1.6232)
$DLBPI_{t-2}$	0.0394* (2.2019)	-
$DLTTR_{t-1}$	0.2062* (1.7683)	0.0068* (1.7044)
$DLETR_{t-1}$	0.0093* (1.8553)	0.0087* (1.7147)
$DLMBV_{t-1}$	0.0010 (0.4548)	0.0011 (0.6971)
$DLEOV_{t-1}$	0.0016 (0.4187)	0.0021 (0.5425)
$DLHASH_{t-1}$	-0.0079 (-0.6775)	-0.0060 (-0.5051)
$DLGP_{t-1}$	-0.0614 (-0.4894)	-0.1064 (-0.8379)
$DLOP_{t-1}$	0.1004 (1.0901)	0.0086 (0.9297)
$DLDJI_{t-1}$	-0.1267 (-0.8120)	-0.0971 (-0.6185)
$DLSI_{t-1}$	0.1235* (1.9516)	0.1104* (1.8452)
$LBPI_{t-1}$	0.0141** (2.6353)	-0.0079 (-1.3922)
$LTTR_{t-1}$	0.0043 (1.0714)	-0.0064 (-1.3244)
$LETR_{t-1}$	0.0039* (1.9519)	0.0059* (1.8516)
$LMBV_{t-1}$	-0.0027 (-0.9879)	-0.0037 (-1.3088)
$LEOV_{t-1}$	0.0051* (1.7506)	0.0039 (1.3735)
$LHASH_{t-1}$	-0.0010 (-0.5489)	0.0081** (2.6473)
LGP_{t-1}	-0.0011 (-0.0405)	-0.0143 (-0.4907)
LOP_{t-1}	-0.0653 (-0.2364)	-0.0310 (-0.9948)
$LDJI_{t-1}$	0.1008*** (3.8895)	0.1002*** (4.0147)
LSI_{t-1}	0.0104 (0.3766)	-0.0186 (-0.5807)
DV1	-0.0163* (-1.7604)	---
DV2	---	-0.0278* (-2.4188)
R-squared SE regression Breush-Godfrey serial correlation Ramsey Reset test	0.44 0.7923 0.0069 [0.9338] 0.0316 [0.9689]	0.42 0.7795 0.0081 [0.4276] 0.0049 [0.6618]

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively; [.]: p-value; *DV1*: the Chinese trading bankruptcy which amounts 1 from 2/2013 and 0 otherwise; *DV2*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Table A-3: The ARDL Bounds Testing Analysis

Estimated model	Optimal lag length	F-statistic	Prob.
(1)	3, 3,4, 1, 0, 0, 0, 0	4.4426*	0.0550
(2)	3, 3,4, 1, 0, 0, 0, 0	4.4019*	0.0537
Significance level	Critical values: F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)*/ T=13 F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)*/ T=15		
	Lower bounds I(0)	Upper bounds I(1)	
1% 5% 10%	6.84 4.94 4.04	7.84 5.73 4.78	

Notes: ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively; Critical values were obtained from Pesaran et al. (2001).

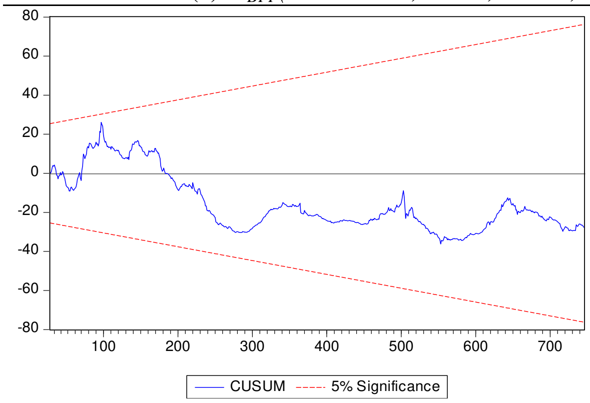
Table A-4: Gregory-Hansen Structural Break Cointegration Test

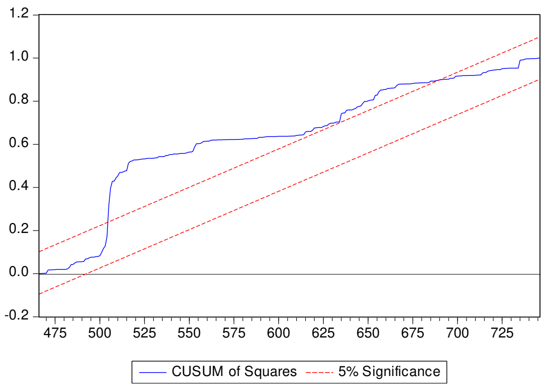
Estimated model	(1)	(2)
Structural break year	29/12/2013	23/10/2013
ADF-test	-4.9782**	-5.2139***
Prob.values	0.0015	0.0004
Significance level	Critical values of the ADF test	
1% 5% 10%	-5.8652 -4.9271 -4.8135	

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively.

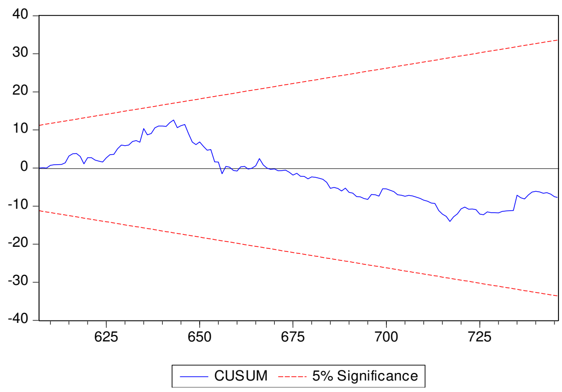
Figure A-1: Plots of cumulative sum of recursive and of squares of recursive residuals

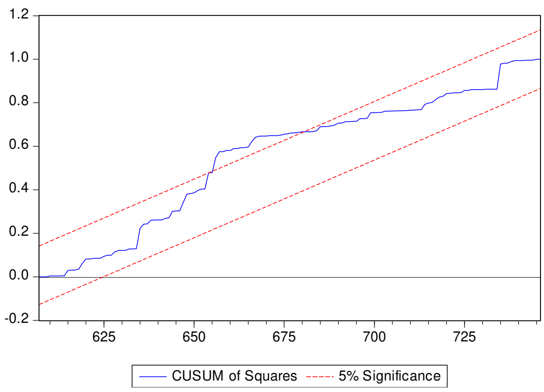
(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)*





(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)*

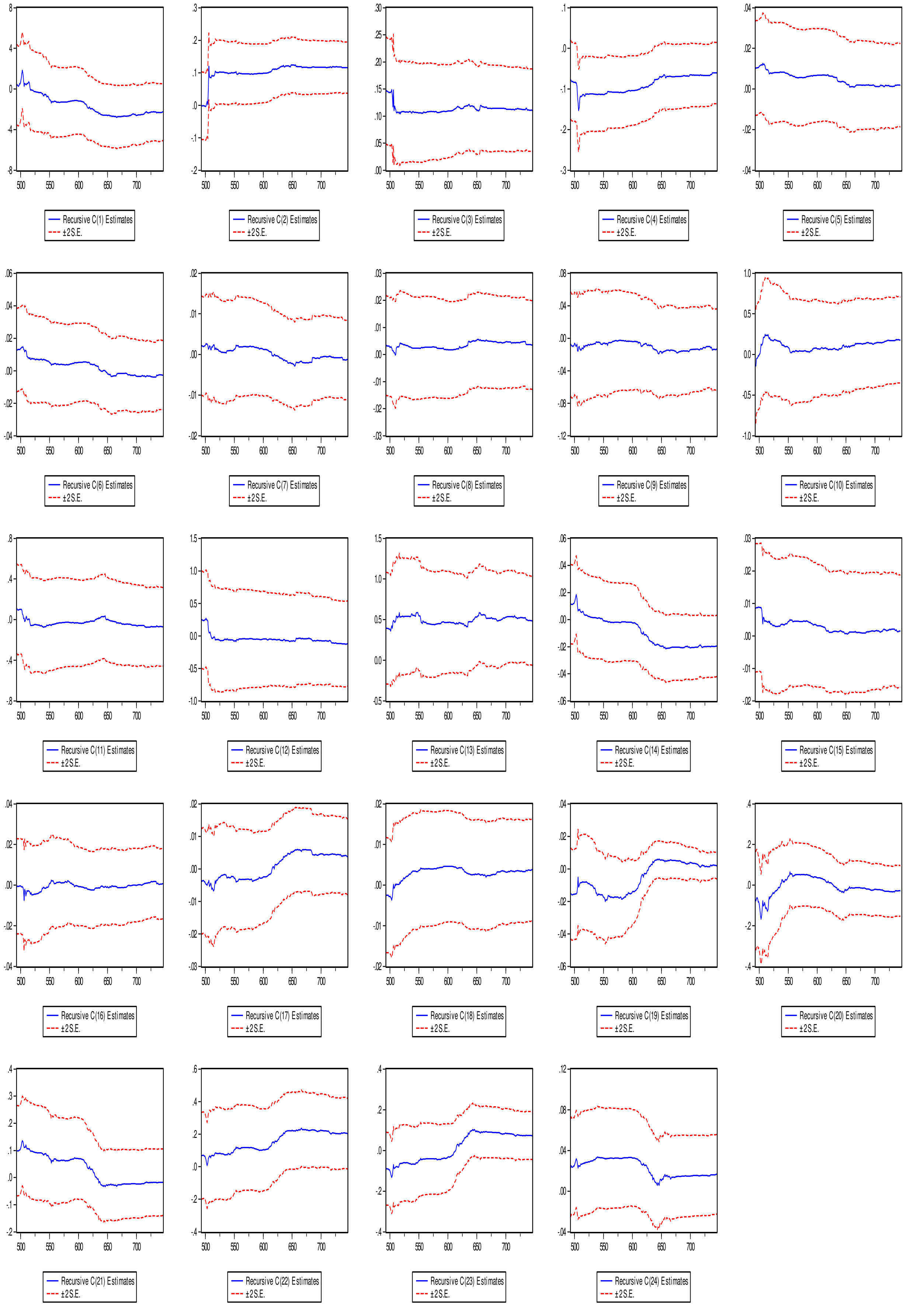




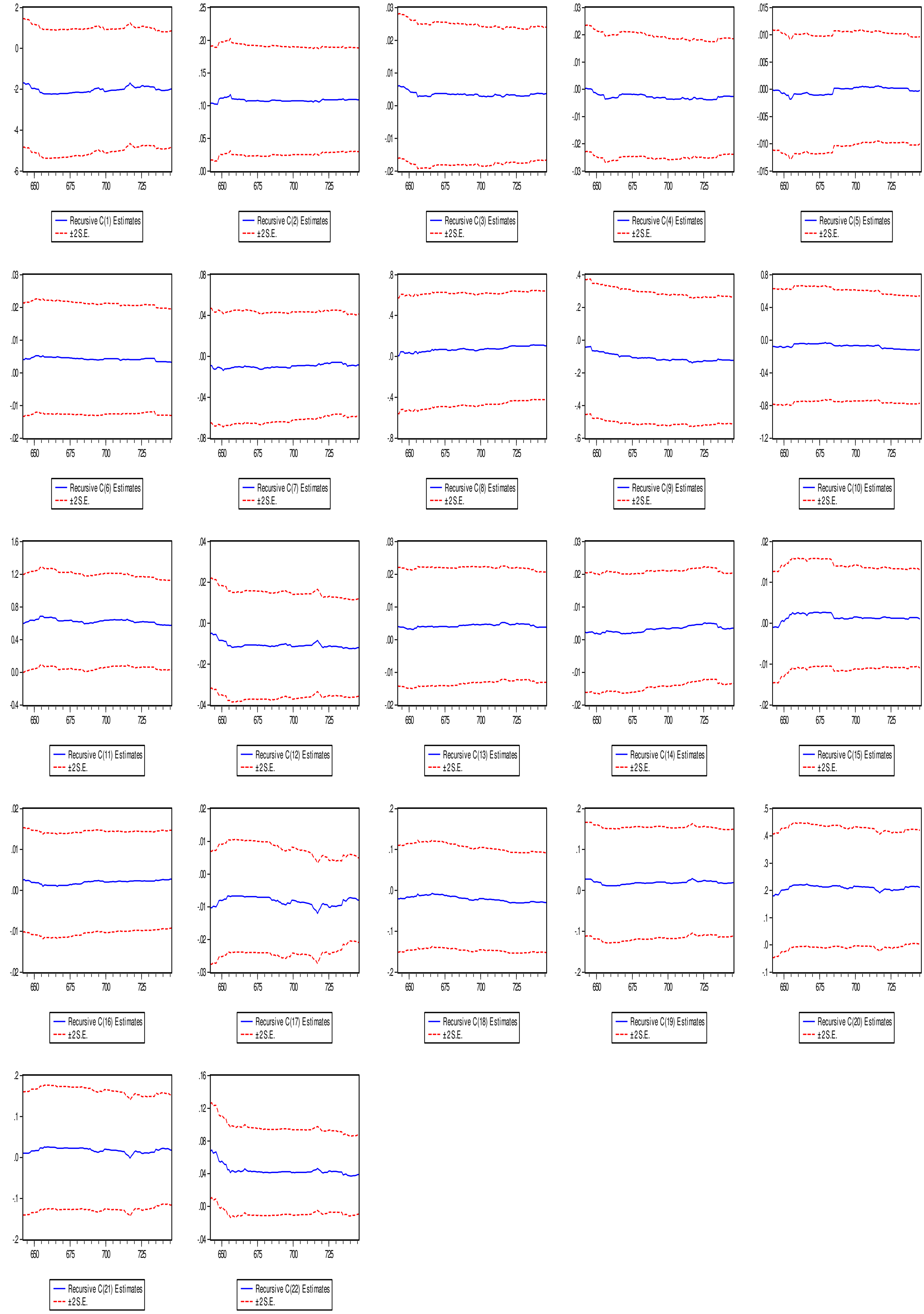
Notes: The straight lines represent the critical bounds at 5% significance level.

Figure A-2: Plots of cumulative sum of recursive coefficients

(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)*



(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)*



Notes: The straight lines represent the critical bounds at 5% significance level.

Table A-5: Short-run and long-run Analysis

Dependent variable: $LBPI_t$		
	(1)	(2)
Short-run		
$DLBPI_t$	0.0281* (2.1537)	0.0269** (2.5852)
$DLTTR_t$	0.5702* (2.1522)	0.4787*** (4.1026)
$DLETR_t$	0.0192*** (7.3397)	0.0172** (2.6367)
$DLMBV_t$	0.7897 (0.2109)	0.4398* (1.7485)
$DLEOV_t$	-0.4434 (-0.2068)	0.0172 (0.3859)
$DLHASH_t$	-0.0915 (-0.7780)	-0.0057 (-0.3802)
$DLGP_t$	-0.0054 (-0.3213)	-0.0928 (-0.6674)
$DLOP_t$	-0.7780 (-1.4343)	0.7488 (1.4354)
$DLDJI_t$	0.8341 (0.6264)	-0.0259 (-1.3648)
$DLSI_t$	0.4786** (2.6372)	0.4784*** (4.6666)
ECT_t	-0.0020* (-1.6791)	-0.0026** (-2.5190)
Long-run		
$LBPI_t$	0.1265*** (3.2112)	0.1275** (3.2394)
$LTTR_t$	0.0016 (0.1611)	-0.0529 (-0.2708)
$LETR_t$	0.0010* (1.7842)	0.0029* (1.8604)
$LMBV_t$	0.0921 (0.9284)	-0.0012 (-0.2067)
$LEOV_t$	0.0655 (1.0307)	-0.0070 (-0.8598)
$LHASH_t$	0.0029* (1.8148)	0.0053* (1.8371)
LGP_t	0.1534 (0.5752)	-0.1684 (-0.6232)
LOP_t	-0.0515 (-0.2642)	0.0019 (0.1915)
$LDJI_t$	0.1852* (2.4937)	0.2417*** (3.8358)
LSI_t	0.4406 (1.5948)	0.4457 (1.5960)
DV1	-0.0569* (-1.8245)	---
DV2	---	-0.0782** (-2.2516)
R-squared	0.49	0.46
SE regression	0.8934	0.8357
Breush-Godfrey serial correlation	0.0437 [0.6795]	0.0398 [0.5012]
Ramsey Reset test	0.0087 [0.9015]	0.0127 [0.8564]

Notes : ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively Diagnostic tests results are based on F-statistic ; [.] : p-values; *DV1*: the Chinese trading bankruptcy which amounts 1 from 2/2013 and 0 otherwise; *DV2*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Table A-6: Variance Decomposition of Bitcoin price

Period	S.E.	*BPI*	*TTR*	*ETR*	*MBV*	*EOV*	*HASH*	*GP*	*OP*	*DJI*	*SI*
(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)*											
1	0.088898	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000000
2	0.133945	72.56927	20.13121	0.041758	8.8E-05	0.098224	0.027560	0.001589	0.000687	0.002292	17.127313
3	0.175764	72.08224	20.13425	0.148067	0.034699	0.244634	0.017965	0.081727	0.122574	0.031775	17.102061
4	0.208055	71.73926	20.10767	0.289199	0.034402	0.381936	0.029360	0.123798	0.144773	0.075313	17.074290
5	0.237772	71.19855	20.217509	0.322583	0.032966	0.647179	0.022938	0.127155	0.139636	0.215343	17.076146
6	0.263958	70.90378	20.290786	0.336065	0.046484	0.709422	0.019024	0.136528	0.172126	0.316877	17.068907
7	0.288247	70.70841	20.360593	0.333563	0.079187	0.730169	0.015955	0.137717	0.184304	0.375281	17.074816
8	0.310877	70.57716	20.401228	0.330260	0.120080	0.722513	0.013992	0.144631	0.194569	0.419226	17.076343
9	0.332613	70.42705	2 0.440570	0.343948	0.162169	0.723344	0.013478	0.146085	0.200372	0.461578	17.081402
10	0.353263	70.29720	20.481974	0.350348	0.201365	0.724066	0.012238	0.149376	0.210477	0.488857	17.084102
(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)*											
1	0.087395	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.130853	74.35845	25.00083	0.169084	0.063336	0.249291	0.056673	5.73E-05	0.015324	0.003965	10.08298
3	0.170888	74.07583	25.08213	0.210320	0.151004	0.260412	0.067889	0.071403	0.009058	0.013847	10.05810
4	0.200639	73.91041	25.06713	0.208223	0.140833	0.232576	0.149281	0.114483	0.080100	0.046427	10.05053
5	0.228146	73.36040	25.05225	0.334346	0.171296	0.384731	0.198527	0.116988	0.070455	0.209062	10.10193
6	0.251440	72.85983	25.05138	0.483718	0.211823	0.461448	0.248267	0.096316	0.075465	0.401673	10.11008
7	0.272403	72.41273	25.07048	0.585694	0.414078	0.473728	0.263102	0.097604	0.065593	0.506023	10.11096
8	0.292613	71.84532	25.11079	0.536605	0.866225	0.467039	0.267483	0.109727	0.058930	0.607852	10.13001
9	0.312471	71.23209	25.16030	0.483560	1.349822	0.463842	0.254317	0.124232	0.055452	0.733107	10.14327
10	0.332569	70.60522	25.19070	0.429863	1.850939	0.469308	0.239178	0.156563	0.053518	0.849822	10.15488

Notes: *DV1*: the Chinese trading bankruptcy which amounts 1 from 2/2013 and 0 otherwise; *DV2*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Figure A-3: Impulse Response Function

(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV1)*

(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV2)*

Notes: *DV1*: the Chinese trading bankruptcy which amounts 1 from 2/2013 and 0 otherwise; *DV2*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.