What Bitcoin Looks Like?

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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 different variables (potential 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 behavior of Bitcoin. This virtual currency may be also used for economic reasons. However, there is any sign of being a safe haven. By considering the Chinese trading bankruptcy, the contribution of speculation (proxied by investors' attractiveness to Bitcoin) remains dominant, indicating the robustness of our results.

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

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 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 utmost 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 cannot be considered as convertible tangible asset (such as gold) or 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 for many reasons including the extra-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 essentially from its volatile and speculative behavior.

Despite its deeper popularity, there still very few works analyzing Bitcoin phenomenon. These researches seem insufficient to fully 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 investigating the link between Bitcoin and speculation (proxies by investors' attractiveness). In addition, Glaser et al. (2014) have attempted to evaluate if Bitcoin is an asset or a currency. Differently, Kristoufek (2014) has tried to investigate whether Bitcoin is more driven by technical, financial or speculative factors by applying coherency wavelet. This technique allows it to gauge the interconnection between each two variables without considering additional time series that may have "pulling role" on Bitcoin price dynamic. In other words, this analysis may be incomplete. More accurately, wavelet coherency cannot be considered usually as perfect technique On the one hand, it may lead to confuse outcomes since the occurrence of noise cannot be 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. Nevertheless, 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 effectively capture outcomes since it may distort the estimate. In that context, Aguiar-Conraria and Soares (2011) argue that the findings change substantially when we move from unconditional wavelet investigation (with only two variables) for conditional wavelet estimation (by adding supplementary explanatory variables). These findings were confirmed in the paper of Bouoiyour et al. (2014 a), which put in relation the exchange rate and oil price in Russia, using wavelet approach. This implies that the use of large-scale parameters of each two variables as the case of Kristoufek (2014)'s study may yield inconclusive results in terms of the relation 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 to elucidate users' information. For this purpose, the present paper attempts to address several questions: 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 effectively answer the above questions by carrying out convenient methods. More precisely, we regress Bitcoin price on investors' attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price and Shangai market index by applying an ARDL bounds Testing approach, innovation accounting method and VEC Granger causality test for daily data for the period 2010-2014.

By doing so, we show interesting findings: In the short-run, the investors attractiveness, the exchange-trade ratio, the estimated output volume and the Shangai index affect positively and significantly the Bitctoin price, while the monetary velocity, the hash rate and the gold price have no influence. In the long-run, the substantial impacts of speculative nature of Bitcoin, output volume and Chinese stock market index observed in the short term become statistically insignificant. The effect of exchange-trade ratio becomes less strong, while the effects of the monetary velocity and the gold price still insignificant. The hash rate explains significantly the dynamic of this new virtual currency. These findings are solid and unambiguous since they change slightly when incorporating the dummy variable relative to the bankruptcy of Chinese trading company. The inclusion of additional variables which have no great influence on Bitcoin price development (oil price, Dow Jones index and a dummy variable denoting the closing of Road Silk by FBI) has led to unstable estimates. 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 important role that play the Chinese stock market and the processing power of Bitcoin network in explaining this phenomenon. Intuitively, 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 some policy implications that may be fruitful for investors and regulators.

2. Brief literature survey

Bitcoin has engaged the attention of medias and researchers, acknowledging its complexity. 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.b) and Ciaian et al. (2014)). Others showed that with the absence of effective hedging instruments, this digital money can behave as a speculative bubble (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 a safe haven, a speculative bubble or a business income by analyzing the potential sources of Bitcoin price fluctuations including supply-demand fundamentals, speculative and technical drivers. Wavelet coherency has been carried out to assess properly the linkage between the considered variables at distinct frequencies. The obtained results reveal that the fundamentals such as exchange-trade ratio play substantial roles in the long-run (lower frequencies). The Chinese market 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 the 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 additional information about its development has a great effect on Bitcoin exchange volume. Nevertheless, the nexus between digital money and users' interest seems insignificant when considering the volume within the Bitcoin system. These observed outcomes may be heavily due 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 b) attempt to appropriately evaluate 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 in the 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 investigating what exactly Bitcoin looks like. Summing up, the focal studied links seem bidirectional and cyclical. These cycles can be short, medium or long depending to the directions of 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 find solid results 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 "pulling" roles on the explanation of the dynamic of this virtual currency including investors ' attractiveness, the global macroeconomic and financial indicators and the technical drivers. To measure the users' interest 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 through 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 via 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 and the Chinese or Shangai stock market index. Before beginning our analysis, it seems highly important to give some details about the variables under consideration:

- The Bitcoin price (*BPI*): 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 ones are the lack of legal security, the extra volatility and the great speculation (Kristoufek, 2014).
- The investors' attractiveness (*TTR*): To effectively determine the investors' attractiveness to Bitcoin, we can use daily Bitcoin views from Google[1] as it able to depict properly the speculative character of users (Kristoufek, 2013). Likewise, Bouoiyour et al. (2014 b) 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 and exchange transactions expand the utility of holding the currency that may lead to 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 transactions proxy (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 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 Bitcoin has provided new approaches concerning payments. Hence, some new words have emerged such as the "hash rate". It may be

[1] 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.

considered as an indicator or measure of the processing power of the Bitcoin network. For security goal, the latter 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 b).

- 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 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 important 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.b) advance 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 without and with considering a dummy variable denoting the bankruptcy of Chinese trading company (it amounts 1 from 02/2013 and 0 otherwise). All these data are extracted from Blockchain[2] and quandl[3]. To improve the precision power of results, we carry out a log-linear specification that incorporates *TTR, ETR, MBV, EOV, HASH, GP* and *SI.*

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

$$LBPI_t = \beta_0 + \beta_1 LTTR_t + \beta_2 LETR + \beta_3 LMBV_t + \beta_4 LEOV_t + \beta_5 LHASH_t + \beta_6 LGP_t + \beta_7 LSI_t + \beta_8 DV + \xi_t \quad (2)$$

Where ε, ξ 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 $a_1, \beta_1 > 0$. 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 $a_2, \beta_2 > 0$. 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 $a_3, \beta_3 > 0$. An increase in the estimated output volume affects negatively Bitcoin price in the long term (Kristoufek, 2014). We expect therefore $a_4, \beta_4 \prec 0$. The hash rate is associated positively to Bitcoin price. According to Bouoiyour et al. (2014.b), an increase in

[2] https://blockchain.info/
[3] http://www.quandl.com/

Bitcoin price generates the intention of market participants to invest and to mine, leading to a higher hash rate. We expect that $a_5, \beta_5 > 0$. Kristoufek (2014) reveals that Bitcoin is not heavily interacted with gold price. Palombizio and Morris (2012) argue that gold price may be considered as the main source of demand and cost pressures and then seems a contributor of inflation development and thus affect positively Bitcoin price. We expect $a_6, \beta_6 > 0$. The Chinese market index is considered as a substantial player in digital currencies and in particular Bitcoin. According to Kristoufek (2014) and Ciaian et al. (2014), the Bitcoin price is correlated with well Chinese performing economy. We expect thus that $a_7, \beta_7 > 0$. The Chinese trading bankruptcy may affect considerably Bitcoin price since Chinese market is one of the Biggest Bitcoin market. This event has led to a remarkable drop in the prices of Bitcoin (Bouoiyour et al. 2014). Indeed, it is well expected that $\beta_8 \prec 0$.

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 variables, 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 a dummy variable that denotes the bankruptcy of Chinese trading company on the other hand (Equation 2) to check the robustness of our results. The ARDL representation of equations (1) and (2) are formulated as follows:

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

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

Where D denotes the first difference operator; ε', ξ' 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, Breusch-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 and Shangai market index. This technique enables to test the strength of its impact on the concerned time series. The impulse response function captures the shock of the own series (the focal variable) with others variables 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. 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.

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* and *LGP*), providing that the asymmetrical distribution is preferable. The Jarque- Bera test revealed high and significant values, leading to reject the assumption of normality for all the considered variables.

Table-1: Summary of statistics

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

Before proceeding ARDL estimation, we determine the degree of integration of variables. To this end, we use Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results are reported in Table-2. We clearly notice that the variables are integrated either at level or at first difference. Given this finding, the ARDL bounds testing approach can be applied to test the cointegration hypothesis among the focal 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 3 (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***
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	795.3703	NA	0.006820	-2.149987	-2.048775	-2.110926
1	799.7037	8.463462	0.006758	-2.159183	-2.051645*	-2.117680
2	802.3041	5.071735*	0.006728	-2.163598	-2.049734	-2.119654*
3	803.4872	2.304132	0.006725*	-2.164103*	-2.043913	-2.117718
4	803.6028	0.224915	0.006741	-2.161663	-2.035148	-2.112837
5	803.6350	0.062545	0.006759	-2.158993	-2.026152	-2.107726
6	803.9671	0.643943	0.006772	-2.157151	-2.017984	-2.103442
7	804.0653	0.190309	0.006789	-2.154663	-2.009171	-2.098513
8	804.9309	1.673839	0.006791	-2.154292	-2.002474	-2.095701

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 investors' attractiveness plays a significant role in explaining Bitcoin price formation. Indeed, an increase by 10% in *TTR* expands the *BTP* by about 2.01%. The exchange-trade ratio affects positively and significantly the price of Bitcoin. An increase by 10% of *ETR* leads to an increase by 0.32% 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 0.03% in the prices of Bitcoin. Gold price has no influence on Bitcoin price, while Shangai market index contributes positively and significantly to *BPI* (i.e. an increase by 10% of *SI* leads to an increase by 1.18% in Bitcoin price).

Table-4: The ARDL Bounds Testing Analysis

Dependent variable: $DLBPI_t$	
C	0.6078 (1.0537)
$DLBPI_{t-1}$	0.11687** (2.96916)
$DLBPI_{t-2}$	0.11154** (2.95493)
$DLBPI_{t-3}$	-0.0618 (-1.6440)
$DLTTR_{t-1}$	0.20127*** (9.12259)
$DLETR_{t-1}$	0.0329* (1.6778)
$DLMBV_{t-1}$	0.00134 (0.2775)
$DLEOV_{t-1}$	0.0030 (0.37838)
$DLHASH_{t-1}$	0.01192 (0.4814)
$DLGP_{t-1}$	0.17445 (0.6631)
$DLSI_{t-1}$	0.1182* (1.9049)
$LBPI_{t-1}$	-0.01014 (-1.0310)
$LTTR_{t-1}$	0.0038 (0.4752)
$LETR_{t-1}$	0.0096* (1.8057)
$LMBV_{t-1}$	0.0038 (0.6587)
$LEOV_{t-1}$	0.0034 (0.5983)
$LHASH_{t-1}$	0.0035* (1.7380)
LGP_{t-1}	-0.1189 (-1.3637)
LSI_{t-1}	0.02128 (0.4324)
Diagnostic tests	
R-squared	0.4586
SE regression	0.8859
Breush-Godfrey serial correlation	0.0955 [0.9089]
Ramsey Reset test	0.03503 [0.8516]

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, LSI)*	3, 3,4, 1, 0, 0	4.702941*	0.0106
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).

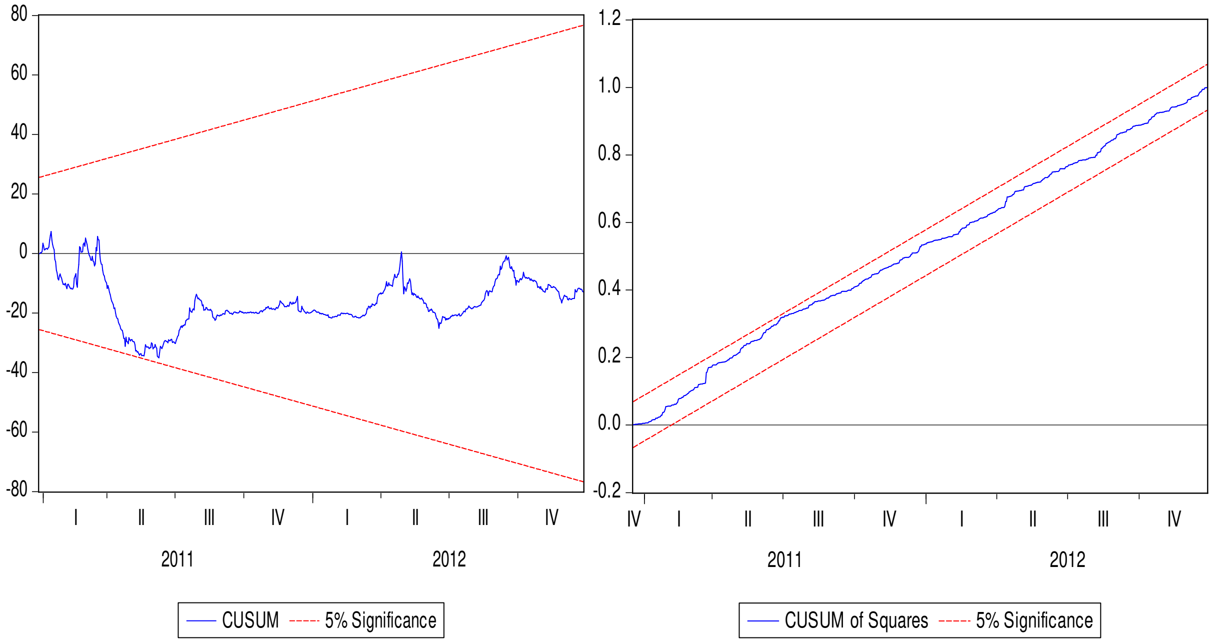
Table-6: Gregory-Hansen Structural Break Cointegration Test

Estimated model	F_{BPI}*(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI)*
Structural break year	27/10/2013
ADF-test	-4.9861**
Prob.values	0.0029
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.

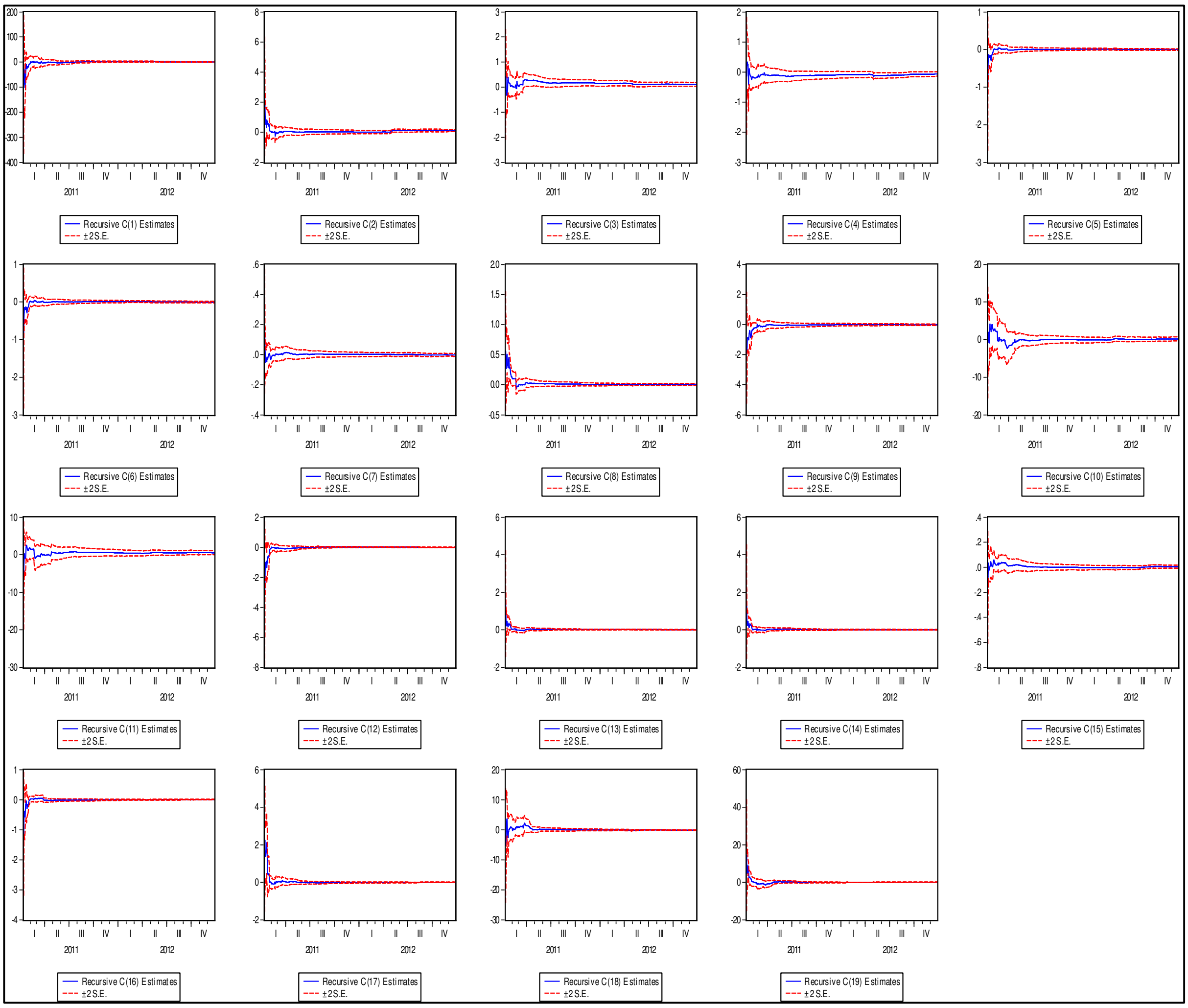
The diagnostic tests show that there is no evidence of serial correlation. The Ramsey reset test statistic reveals the performance of the short-run model (Table-4). The CUSUM and the CUSUM Squares test show the adequacy of the considered models at 5% level of significance (Figure-2) and the stability 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, it is well shown that Bitcoin price interacts differently with its determinants depending to time periods. In the short-run, the users' interest, the exchange-trade ratio, the estimated output volume and the Shangai index affect positively and significantly the *BPI*. However, the monetary velocity, the hash rate and the gold price have no influence on this digital money. These outcomes change intensely in the long-run. The speculation, the *EOV* 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* and *GP* on *BPI* remain insignificant, while the hash rate appears as significant player. Furthermore, the value of *ECT* is negative and statistically significant at 5 percent level, which is theoretically correct. It amounts (-7.97E-06), implying that the deviation in the short-run is corrected by 0.0007% towards the long-run equilibrium path. The R-squared value indicates that 44% of Bitcoin price dynamic is explained by the explanatory variables.

4.2.Innovative accounting approach results

The results of the variance decomposition are reported in Table-8. We find that 69.17% percent of Bitcoin price is explained by its own innovative shocks. The investors' attractiveness (*TTR*) plays the major role in explaining the price of the focal money (20.34%). The contribution of *ETR* appears minor (0.16%). Similarly for monetary velocity, the estimated output volume and the hash rate do not have great effect on the dynamic of this new currency, with respective percentages equal to 0.035%, 0.037% and 0.003%. Gold price explains 0.095% of *BPI* but we should not forget to mention that the link between *GP* and *BPI* appears insignificant in the above results. Additionally, the contribution of Chinese market index (*SI*) seems sharply considerable (10.14%).

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 velocity, estimated output volume, hash rate, gold price and Shangai market indices. Figure-4 worthy indicates that the responses in Bitcoin price owing to forecast error stemming in investors' attractiveness as well as the Chinese market index seem positive over time. The contributions of *ETR, MBV, EOV, HASH* and *GP* to Bitcoin price appear negligible.

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

Dependent variable: *$LBPI_t$*	
Short-run	
$DLBPI_t$	0.1252*** (3.1873)
$DLTTR_t$	0.5269** (2.8944)
$DLETR_t$	0.1287*** (7.0988)
$DLMBV_t$	2.7411 (0.2189)
$DLEOV_t$	0.0798*** (3.6287)
$DLHASH_t$	0.0594 (0.5379)
$DLGP_t$	-0.2415 (-0.9103)
$DLSI_t$	0.3802* (1.6444)
ECT_t	-7.97E-06** (-2.5130)
Long-run	
$LBPI_t$	0.1328*** (3.3635)
$LTTR_t$	0.1434 (0.5414)
$LETR_t$	0.0180* (1.7073)
$LMBV_t$	0.0043 (0.8892)
$LEOV_t$	0.0073 (0.8993)
$LHASH_t$	0.0072* (1.8478)
LGP_t	-0.0015 (-0.1556)
LSI_t	0.2157 (0.1062)
Diagnostic tests	
R-squared SE regression Breush-Godfrey serial correlation Ramsey Reset test	0.44 0.7812 0.3987 [0.1125] 0.2419 [0.6038]

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

Period	S.E.	*LBPI*	*LTTR*	*LETR*	*LMBV*	*LEOV*	*LHASH*	*LGP*	*LSI*
1	0.089209	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.133356	69.62125	20.02477	0.099387	0.021195	0.048033	0.000927	0.002721	10.18171
3	0.173881	69.36913	20.14811	0.154151	0.041684	0.040414	0.008345	0.074429	10.16373
4	0.207915	69.31502	20.21095	0.143917	0.034885	0.040420	0.005948	0.079367	10.16948
5	0.237979	69.26216	20.26038	0.154534	0.037175	0.038559	0.004840	0.083554	10.15879
6	0.264822	69.22643	20.29075	0.160299	0.037687	0.038561	0.004506	0.087948	10.15380
7	0.289336	69.20724	20.31188	0.161535	0.037241	0.038131	0.003989	0.091187	10.14878
8	0.311935	69.19196	20.32765	0.163871	0.036489	0.037956	0.003689	0.093026	10.14535
9	0.333019	69.18027	20.33966	0.165645	0.035905	0.037888	0.003476	0.094519	10.14264
10	0.352847	69.17171	20.34903	0.166578	0.035233	0.037921	0.003293	0.095698	10.14054

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 3. The non-causality test findings are reported in Table-10. It is 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. This confirms the above outcomes obtained through the ARDL Bounds Testing method and the innovation accounting approach. 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 be 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	165.7815	0.0000
2	162.7223	0.0000
3	172.6073	0.0000
4	74.87208	0.1661
5	108.8017	0.0004
6	52.65505	0.8435
7	86.67175	0.0312
8	59.58174	0.6333
9	73.80962	0.1882
10	67.46570	0.3595
11	69.17378	0.3071
12	88.51908	0.0229

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

Dependent variable*: DLBPI*			
Excluded	Chi-sq	df	Prob
DLTTR≠DLBPI	4.4897	2	0.0474
DLBPI≠DLTTR	0.7034	2	0.7035
DLETR≠DLBPI	2.9722	2	0.0226
DLBPI≠DLETR	4.2470	2	0.1196
DLMBV≠DLBPI	0.9299	2	0.6281
DLBPI≠DLMBV	13.698	2	0.0011
DLEOV≠DLBPI	1.1004	2	0.5768
DLBPI≠DLEOV	1.9394	2	0.3792
DLHASH≠DLBPI	0.3544	2	0.8376
DLBPI≠DLHASH	6.2336	2	0.0443
DLGP≠DLBPI	1.0579	2	0.3574
DLBPI≠DLGP	1.0588	2	0.3572
DLSI≠DLBPI	3.5051	2	0.0733
DLBPI≠DLSI	1.4394	2	0.4869

5. Robustness

The above findings clearly indicate that the investors' attractiveness, the exchange-trade ratio, the estimated output volume and the Shangai index affect positively and significantly the Bitcoin price, while the monetary velocity, the hash rate and the gold price have no influence in the short term. However, the speculative nature of *BPI*, the *EOV* 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, while the effects of *MBV* and *GP* on *BPI* remain insignificant in the majority of cases. The hash rate plays a significant role 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 a dummy variable relative to the bankruptcy of Chinese trading company, 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, Table A-6, Figure A-1, Figure A-2 and Figure A-3. Comparing these results with those of Equation without dummy variable, we put in evidence that the effects of *TTR, ETR, MBV, EOV, HASH, GP* 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 speculative bubble, 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.

To be more effective, we believe that the use of other combinations by adding other variables in Equations 3 and 4 may be fruitful (For example, we add oil price[4], Dow Jones index[5] and a dummy variable denoting the closing of road silk by FBI[6]) . Nevertheless, the obtained findings reveal that the effects of the additional time series are in the majority of cases insignificant and more importantly the estimates become remarkably unstable (see Figure A-4, particularly). More details about outcomes are reported in Table A-7, Table A-8, Table A-9, Table A-9, Table A-11, Table A-12, Figure A-5 and Figure A-6.

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[4] Palombizio and Morris (2012) find that oil price (*OP*) 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.

[5] The relationship between Bitcoin price and the Dow Jones index (*DJI*) appears complex, since the two variables seem sometimes correlated but not usually. For instance, 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. This seems 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 great 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. This implies that there is some relation between both variables. For details, you can refer to: http://coinbrief.net/bitcoin-price-news-analysis/

[6] The Road Silk is a roating-platform of drug on which transactions were through Bitcoin. Thus, its closing by FBI in 23/10/2013 (*DV'*) has affected substantially the dynamic of Bitcoin price.

6. Conclusions and some Policy implications

The present research attempts to reach clearer knowledge about a 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 or a risky investment? Is it a short-term hedge or a long-term promise?

To this end, we have regressed Bitcoin price on investors’ attractiveness, exchange-trade volume, monetary velocity, estimated output volume, hash rate, gold price and Shangai market index 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 clearly show the unpleasantly speculative behavior of Bitcoin. We also provide insightful evidence that *BPI* may be used for economic reasons. However, there is any sign of being a safe haven. By accounting for the Chinese trading bankruptcy, the contribution of speculation 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. Intuitively, by using other combinations of variables by adding supplementary time series (oil price, Dow Jones index and a dummy variable denoting the closing of road silk by FBI), the estimates become remarkably unstable. It is important to mention here that these last variables have no statistically significant influence in the majority of cases in Bitcoin price dynamic.

In a nutshell, Bitcoin behaves heavily as a “speculative bubble”, short-term hedge and risky investment and partially as business income. There is any evidence to be a safe haven. 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 its dynamic is uncertain even more sustains great speculation. Without tackling the main causes, the virtual currency seems highly correlated to the speculative behaviors of investors and people who hold this money. This digital money is not issued by banking system and even less by governments, but by a computing algorithm. Unfortunately, the majority of users have not heavily acknowledged about mathematical programs, and it is of course unknown for them how far it can go.

Importantly, the volatility of Bitcoin and the difficulty of processing power network are likely to discourage investors and users of this money. Additionally, the sizeable attention to this crypto-currency in the Chinese media has drawn a huge number of investors in China’s market. However, the attitude of practitioners, advisers and regulators towards Bitcoin in this country is ambiguous, reinforcing the possible detrimental effects of speculation. This may sustain the evidence thereby this nascent virtual currency is short-term hedge and a risky investment. We cannot confirm at this stage if Bitcoin 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 b) showing that it is very difficult to reach clearer insights and solid and conclusive outcomes into phenomenon.

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Appendices

Table A.1: Lag-order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
F_{BPI} (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)						
0	781.6729	NA	0.007309	-2.080742	-1.974351*	-2.039709*
1	782.5517	1.714736	0.007312	-2.080413	-1.967763	-2.036966
2	782.9059	0.690066	0.007325	-2.078656	-1.959747	-2.032795
3	785.3696	4.793244*	0.007295*	-2.082638*	-1.957472	-2.034364
4	785.3825	0.025151	0.007315	-2.079952	-1.948528	-2.029264
5	785.4114	0.056055	0.007334	-2.077310	-1.939627	-2.024208
6	785.4309	0.037764	0.007354	-2.074642	-1.930700	-2.019126
7	785.4515	0.039790	0.007374	-2.071977	-1.921777	-2.014047
8	785.6675	0.417417	0.007390	-2.069844	-1.913385	-2.009500

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: $DLBPI_t$	
C	3.4815 (1.1373)
$DLBPI_{t-1}$	0.5641** (3.0184)
$DLBPI_{t-2}$	0.1557*** (3.8357)
$DLTTR_{t-1}$	0.4846* (1.8352)
$DLETR_{t-1}$	0.0825* (1.6934)
$DLMBV_{t-1}$	0.0049 (0.2057)
$DLEOV_{t-1}$	0.0428 (1.9022)
$DLHASH_{t-1}$	0.0075 (0.4132)
$DLGP_{t-1}$	0.3248 (0.1847)
$DLSI_{t-1}$	0.3516* (2.2567)
$LBPI_{t-1}$	0.1602*** (3.2488)
$LTTR_{t-1}$	0.0336 (1.1308)
$LETR_{t-1}$	0.0314 (0.8947)
$LMBV_{t-1}$	0.0344 (1.2216)
$LEOV_{t-1}$	0.0137 (0.4755)
$LHASH_{t-1}$	0.0092* (1.8607)
LGP_{t-1}	-0.0555 (-1.1431)
LSI_{t-1}	-1.0622 (-0.8250)
DV	-0.0957 (-1.8796)
R-squared SE regression Breush-Godfrey serial correlation Ramsey Reset test	0.48 0.7241 0.0133 [0.6214] 0.0217 [0.6528]

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

Table A-3: The ARDL Bounds Testing Analysis

Estimated model	Optimal lag length	F-statistic	Prob.
F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)*	3, 3,4, 1, 0, 0	4.2852*	0.0381
Significance level	Critical values		
	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).

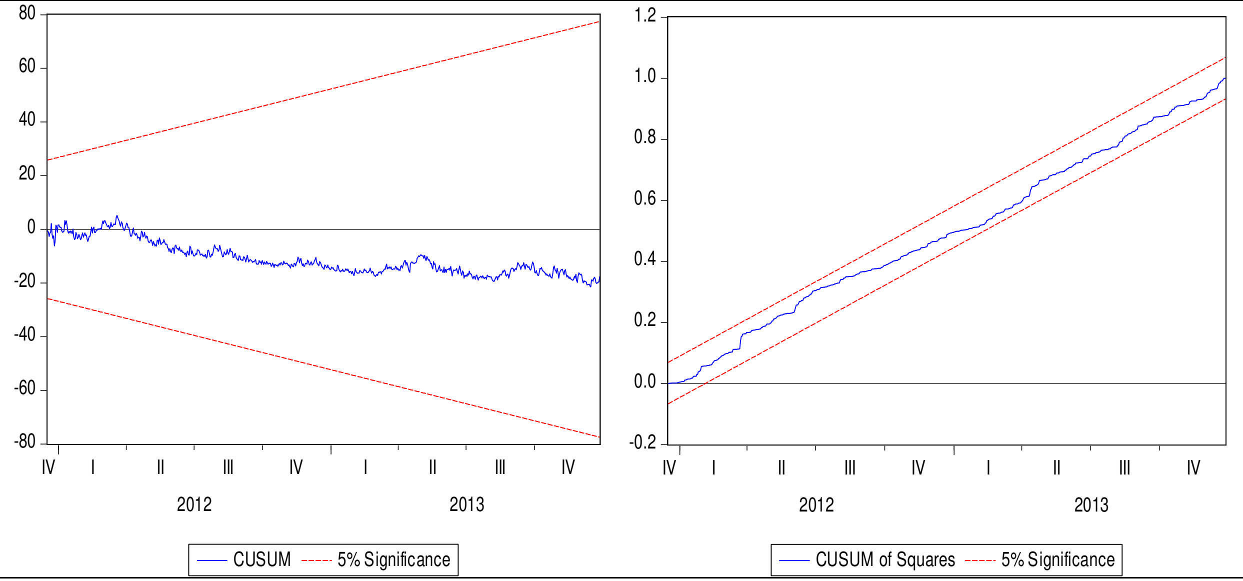
Table A-4: Gregory-Hansen Structural Break Cointegration Test

Estimated model	F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)*
Structural break year	18/12/2013
ADF-test	-4.8743***
Prob.values	0.0000
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.

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

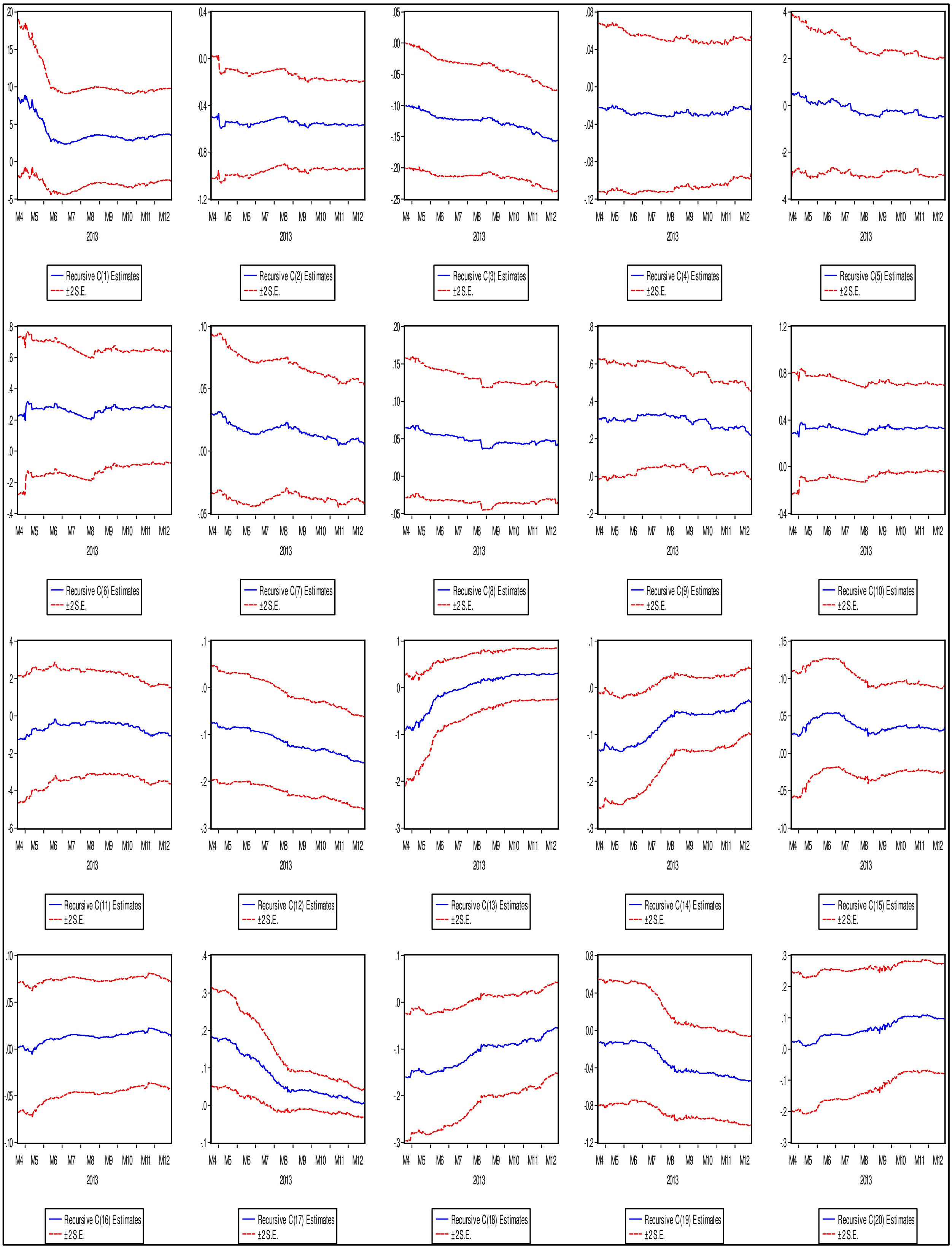
F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)*



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

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

F_{BPI} (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LGP, LSI, DV)



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

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

Dependent variable: $LBPI_t$	
Short-run	
$DLBPI_t$	0.3722*** (7.6306)
$DLTTR_t$	0.3107** (3.2019)
$DLETR_t$	0.0954*** (5.4125)
$DLMBV_t$	-5.1072 (-1.3082)
$DLEOV_t$	0.1583*** (3.7943)
$DLHASH_t$	0.3040 (0.1569)
$DLGP_t$	-0.0238 (-0.9867)
$DLSI_t$	0.2272** (2.9769)
ECT_t	-3.20E-06* (-1.7186)
Long-run	
$LBPI_t$	0.2309*** (4.7347)
$LTTR_t$	0.0279 (1.2933)
$LETR_t$	0.0222* (1.9182)
$LMBV_t$	0.0287 (0.9623)
$LEOV_t$	-0.0030 (-0.0778)
$LHASH_t$	0.0076* (1.9784)
LGP_t	0.2140 (0.8852)
LSI_t	0.3295 (0.2478)
DV	-0.0812* (-1.7697)
R-squared	0.36
SE regression	0.5376
Breush-Godfrey serial correlation	0.0862 [0.5034]
Ramsey Reset test	0.0129 [0.3185]

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

Table A-6: Variance Decomposition of Bitcoin price

Period	S.E.	*BPI*	*TTR*	*ETR*	*MBV*	*EOV*	*HASH*	*GP*	*SI*
1	0.437211	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.531016	69.16401	20.07857	0.046293	0.192572	0.172621	0.216206	7.05E-05	10.12964
3	0.587408	68.89641	20.06423	0.074224	0.207786	0.157107	0.180322	0.175893	10.24402
4	0.653719	68.88240	20.05204	0.094030	0.169006	0.140286	0.155463	0.211353	10.29542
5	0.713412	68.85767	20.04848	0.091867	0.142428	0.156410	0.158901	0.212927	10.33130
6	0.765985	68.85128	20.04238	0.094067	0.123555	0.162226	0.144646	0.224575	10.35726
7	0.815668	68.84969	20.03788	0.097420	0.109980	0.162901	0.135923	0.233969	10.37223
8	0.862787	68.84846	20.03494	0.099140	0.098834	0.165991	0.130940	0.239833	10.38186
9	0.907295	68.84839	20.03210	0.100438	0.090140	0.169011	0.125686	0.244983	10.38925
10	0.949679	68.84880	20.02980	0.101707	0.083155	0.170850	0.121426	0.249415	10.39483

Figure A-3: Impulse Response Function

F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)*

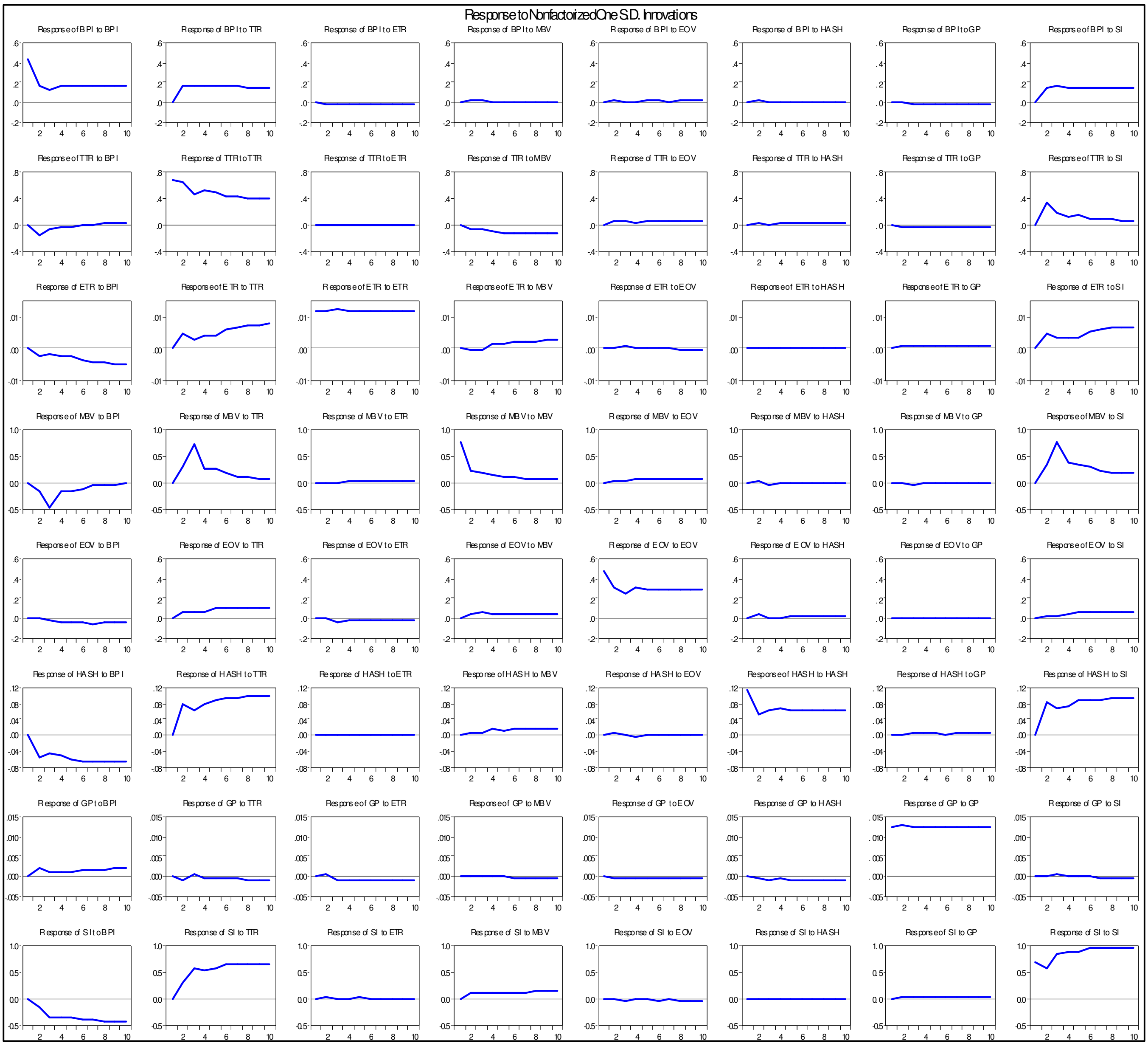


Table-A.7: Lag-order selection (Equations with additional variables)

Lag	LogL	LR	FPE	AIC	SC	HQ
(1) *: FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*						
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
(2) *: FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)*						
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
(3) *: FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV')*						
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. *DV'*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Table A-8: The ARDL Bounds Testing Analysis (Equations with additional variables)

Dependent variable: $\Delta LBPI_t$			
	(1)	(2)	(3)
C	-2.4325* (-1.7278)	-1.7262* (-2.5645)	-1.4941* (-2.1939)
$\Delta LBPI_{t-1}$	0.1185** (3.0231)	0.0376* (2.0056)	0.0288* (1.6232)
$\Delta LBPI_{t-2}$	---	0.0394* (2.2019)	---
$\Delta LTTR_{t-1}$	0.1222** (3.1537)	0.2062* (1.7683)	0.0068* (1.7044)
$\Delta LETR_{t-1}$	0.1153** (3.0589)	0.0093* (1.8553)	0.0087* (1.7147)
$\Delta LMBV_{t-1}$	-0.1222 (-0.2482)	0.0010 (0.4548)	0.0011 (0.6971)
$\Delta LEOV_{t-1}$	0.0030 (0.3763)	0.0016 (0.4187)	0.0021 (0.5425)
$\Delta LHASH_{t-1}$	-0.0141 (-0.5719)	-0.0079 (-0.6775)	-0.0060 (-0.5051)
ΔLGP_{t-1}	0.1559 (0.5900)	-0.0614 (-0.4894)	-0.1064 (-0.8379)
ΔLOP_{t-1}	-0.1043 (-0.5383)	0.1004 (1.0901)	0.0086 (0.9297)
$\Delta LDJI_{t-1}$	-0.1268 (-0.3857)	-0.1267 (-0.8120)	-0.0971 (-0.6185)
ΔLSI_{t-1}	0.1468* (2.000)	0.1235* (1.9516)	0.1104* (1.8452)
$LBPI_{t-1}$	0.0186* (1.6551)	0.0141** (2.6353)	-0.0079 (-1.3922)
$LTTR_{t-1}$	-0.0162 (-1.5979)	0.0043 (1.0714)	-0.0064 (-1.3244)
$LETR_{t-1}$	0.0158* (2.2800)	0.0039* (1.9519)	0.0059* (1.8516)
$LMBV_{t-1}$	0.0032 (0.5693)	-0.0027 (-0.9879)	-0.0037 (-1.3088)
$LEOV_{t-1}$	0.0026 (0.4453)	0.0051* (1.7506)	0.0039 (1.3735)
$LHASH_{t-1}$	0.0056* (1.8862)	-0.0010 (-0.5489)	0.0081** (2.6473)
LGP_{t-1}	-0.0534 (-0.9023)	-0.0011 (-0.0405)	-0.0143 (-0.4907)
LOP_{t-1}	-0.0161 (-0.2627)	-0.0653 (-0.2364)	-0.0310 (-0.9948)
$LDJI_{t-1}$	0.0355* (2.2728)	0.1008*** (3.8895)	0.1002*** (4.0147)
LSI_{t-1}	0.0762 (1.3060)	0.0104 (0.3766)	-0.0186 (-0.5807)
DV	---	-0.0163* (-1.7604)	---
DV'	---	---	-0.0278* (-2.4188)
R-squared	0.54	0.44	0.42
SE regression	0.8881	0.7923	0.7795
Breush-Godfrey serial correlation	0.6231 [0.4097]	0.0069 [0.9338]	0.0081 [0.4276]
Ramsey Reset test	0.2664 [0.6058]	0.0316 [0.9689]	0.0049 [0.6618]

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

Table A-9: The ARDL Bounds Testing Analysis (Equations with additional variables)

Estimated model	Optimal lag length	F-statistic	Prob.
(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*	3, 3,4, 1, 0, 0, 0, 0	4.5711*	0.0659
(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)*	3, 3,4, 1, 0, 0, 0, 0	4.4426*	0.0550
(3): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV')*	3, 3,4, 1, 0, 0, 0, 0	4.4019*	0.0537
Significance level	Critical values		
	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); *DV':* The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

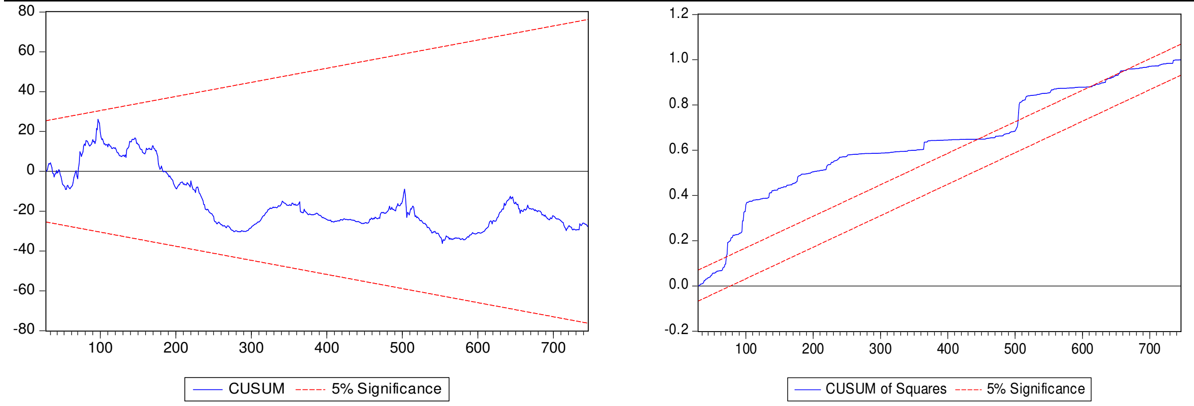
Table A-10: Gregory-Hansen Structural Break Cointegration Test (Equations with additional variables)

Estimated model	(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*	(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)*	(3): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)*
Structural break year	23/10/2013	26/2/2013	23/10/2013
ADF-test	-5.9234***	-4.9782**	-5.2139***
Prob.values	0.0015	0.0015	0.0004
Significance level	Critical values of the ADF test		
1%	-5.8652		
5%	-4.9271		
10%	-4.8135		

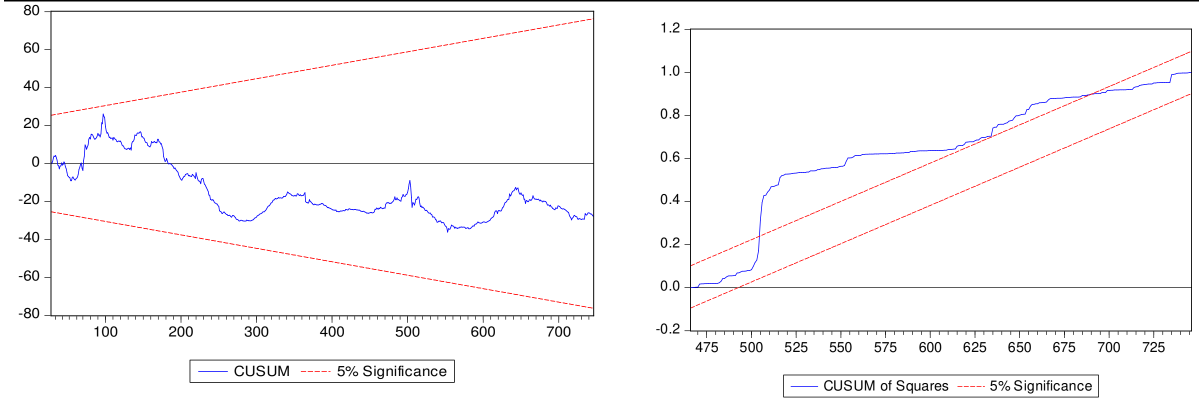
Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively; *DV':* The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Figure A-4: Plots of cumulative sum of recursive and of squares of recursive residuals (Equations with additional variables)

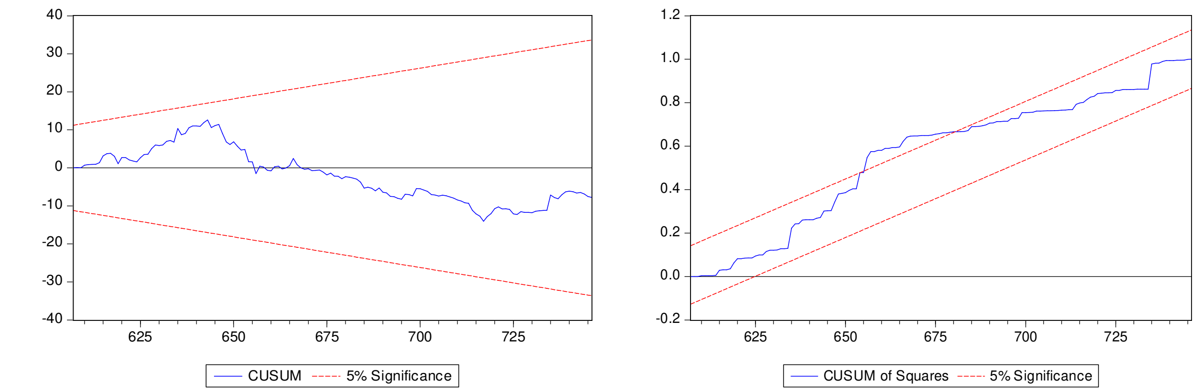
(1): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*



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



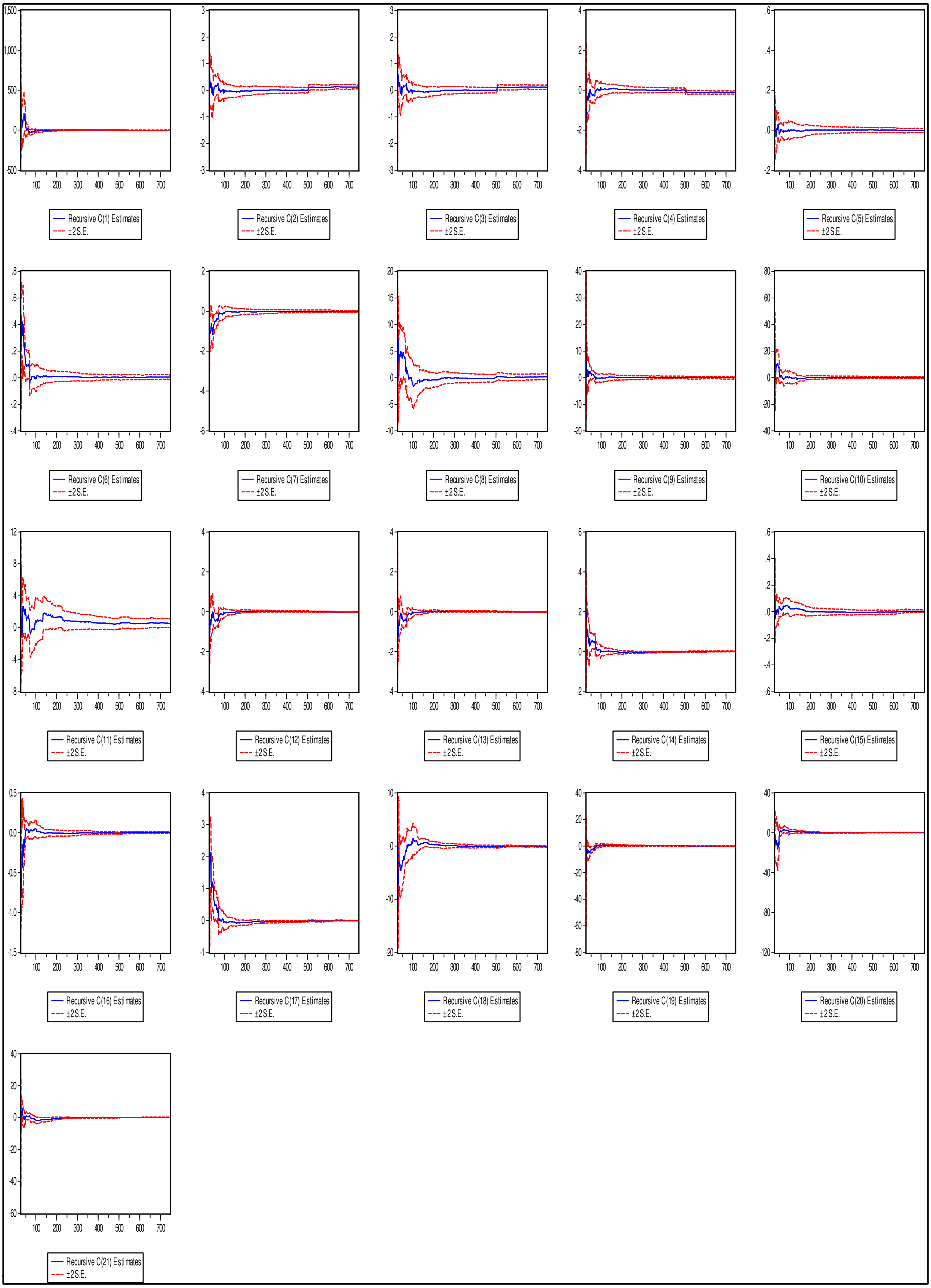
(3): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV')*



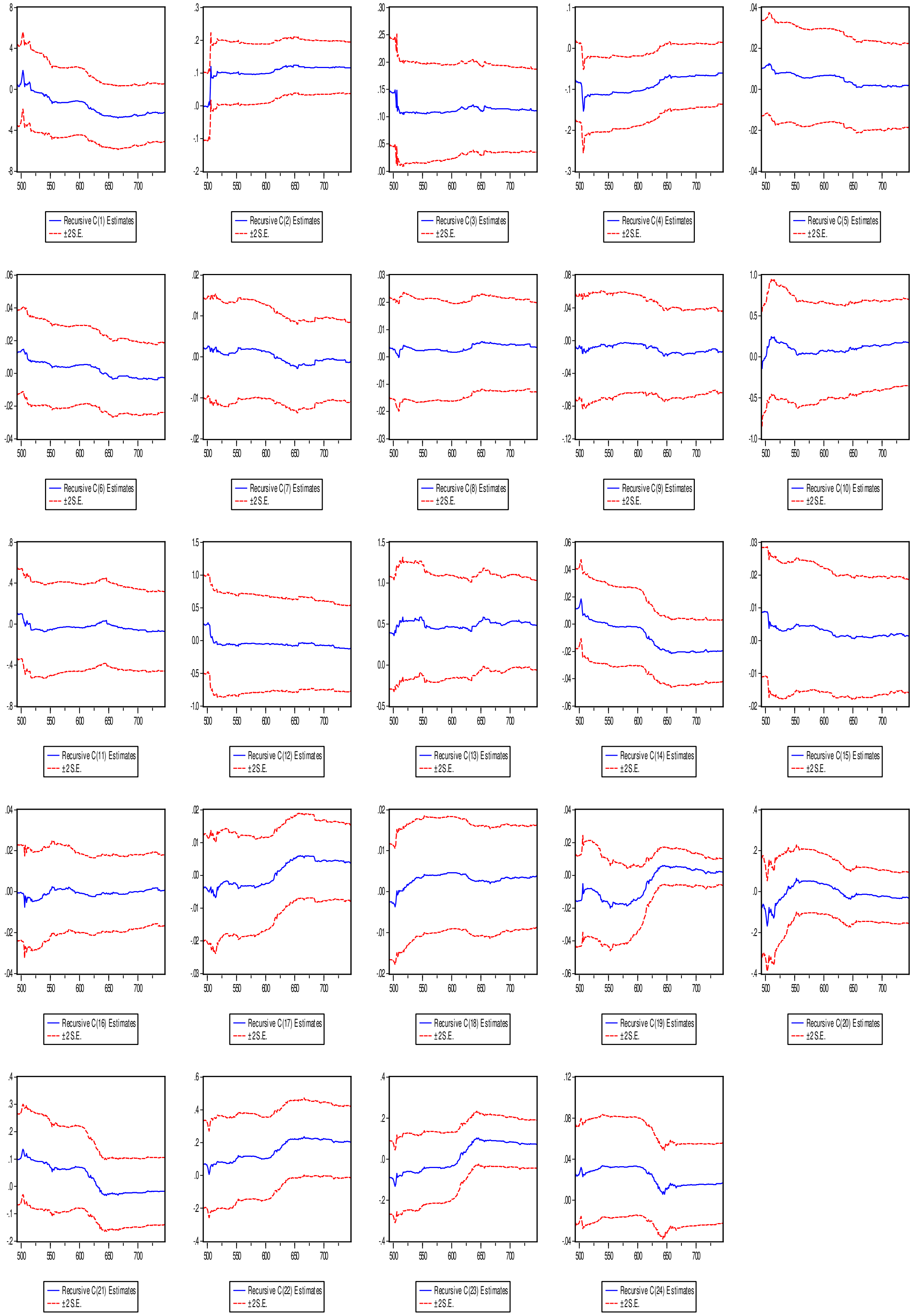
Notes: The straight lines represent the critical bounds at 5% significance level; *DV':* The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Figure A-5: Plots of cumulative sum of recursive coefficients (Equations with additional variables)

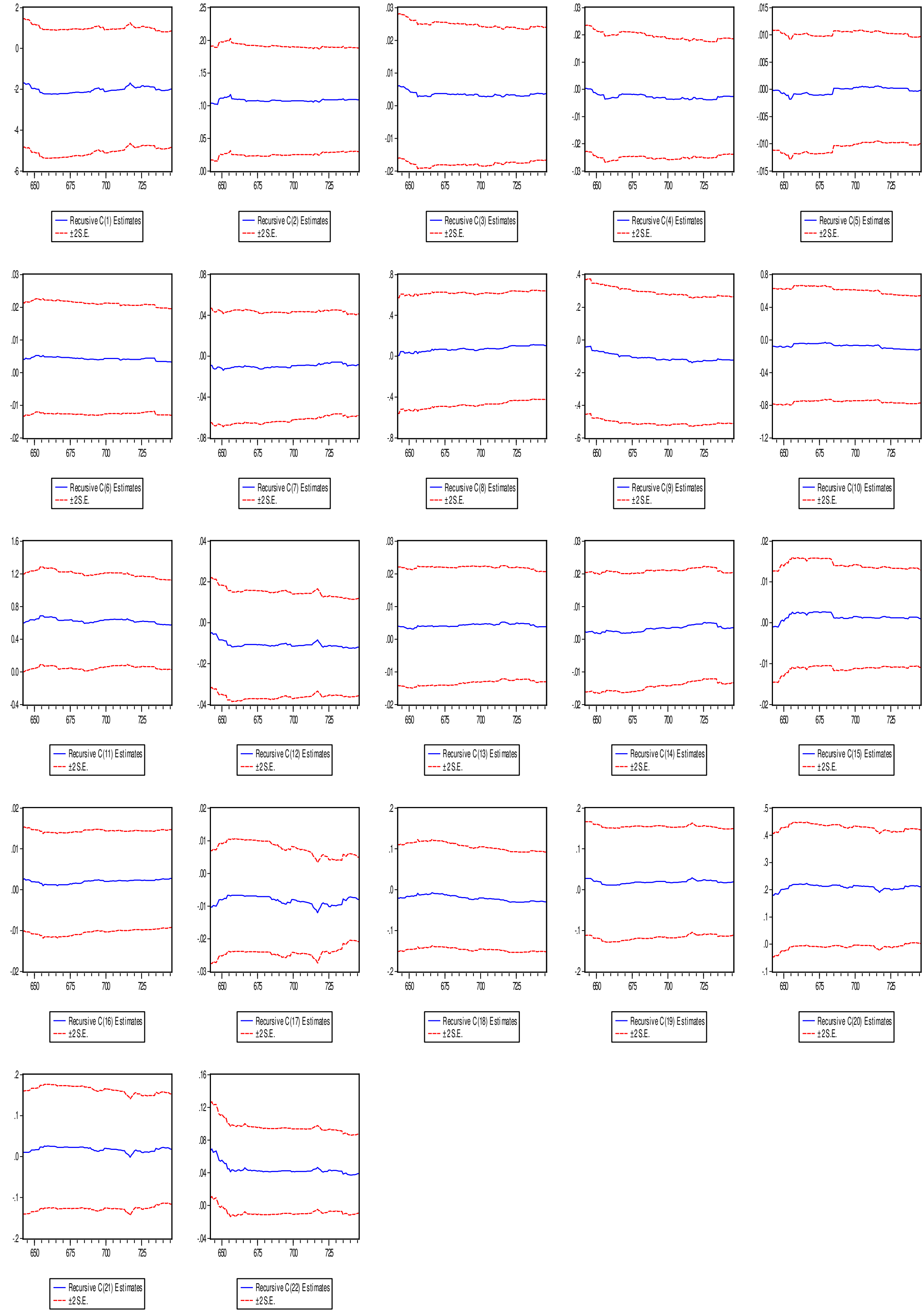
(1): *FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI*)



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



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



Notes: The straight lines represent the critical bounds at 5% significance level; *DV'*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Table A-11: Short-run and long-run Analysis (Equations with additional variables)

Dependent variable: $LBPI_t$			
	(1)	(2)	(3)
Short-run			
$\Delta LBPI_t$	0.1270*** (3.2270)	0.0281* (2.1537)	0.0269** (2.5852)
$\Delta LTTR_t$	0.4305* (2.0214)	0.5702* (2.1522)	0.4787*** (4.1026)
$\Delta LETR_t$	0.2157*** (8.4441)	0.0192*** (7.3397)	0.0172** (2.6367)
$\Delta LMBV_t$	-2.2467 (-0.1721)	0.7897 (0.2109)	0.4398* (1.7485)
$\Delta LEOV_t$	0.4158* (2.5803)	-0.4434 (-0.2068)	0.0172 (0.3859)
$\Delta LHASH_t$	-0.0283 (-0.3214)	-0.0915 (-0.7780)	-0.0057 (-0.3802)
ΔLGP_t	-3.4273 (-1.5320)	-0.0054 (-0.3213)	-0.0928 (-0.6674)
ΔLOP_t	-2.4806 (-1.5448)	-0.7780 (-1.4343)	0.7488 (1.4354)
$\Delta LDJI_t$	2.0697 (0.5522)	0.8341 (0.6264)	-0.0259 (-1.3648)
ΔLSI_t	0.3256* (1.6625)	0.4786** (2.6372)	0.4784*** (4.6666)
ECT_t	-0.0023** (-2.8790)	-0.0020* (-1.6791)	-0.0026** (-2.5190)
Long-run			
$LBPI_t$	0.1340*** (3.3768)	0.1265*** (3.2112)	0.1275** (3.2394)
$LTTR_t$	-0.0131 (-1.3168)	0.0016 (0.1611)	-0.0529 (-0.2708)
$LETR_t$	0.0088* (1.8163)	0.0010* (1.7842)	0.0029* (1.8604)
$LMBV_t$	0.0001*** (8.8192)	0.0921 (0.9284)	-0.0012 (-0.2067)
$LEOV_t$	0.0043 (0.5435)	0.0655 (1.0307)	-0.0070 (-0.8598)
$LHASH_t$	0.0077* (1.9745)	0.0029* (1.8148)	0.0053* (1.8371)
LGP_t	0.1518 (0.5697)	0.1534 (0.5752)	-0.1684 (-0.6232)
LOP_t	-0.0518 (-0.2658)	-0.0515 (-0.2642)	0.0019 (0.1915)
$LDJI_t$	0.1420*** (4.2680)	0.1852* (2.4937)	0.2417*** (3.8358)
LSI_t	0.4400 (1.5950)	0.4406 (1.5948)	0.4457 (1.5960)
DV	---	-0.0569* (-1.8245)	---
DV'	---	---	-0.0782** (-2.2516)
R-squared	0.48	0.49	0.46
SE regression	0.8561	0.8934	0.8357
Breush-Godfrey serial correlation	0.4597 [0.1386]	0.0437 [0.6795]	0.0398 [0.5012]
Ramsey Reset test	0.2392 [0.5674]	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; *DV'*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

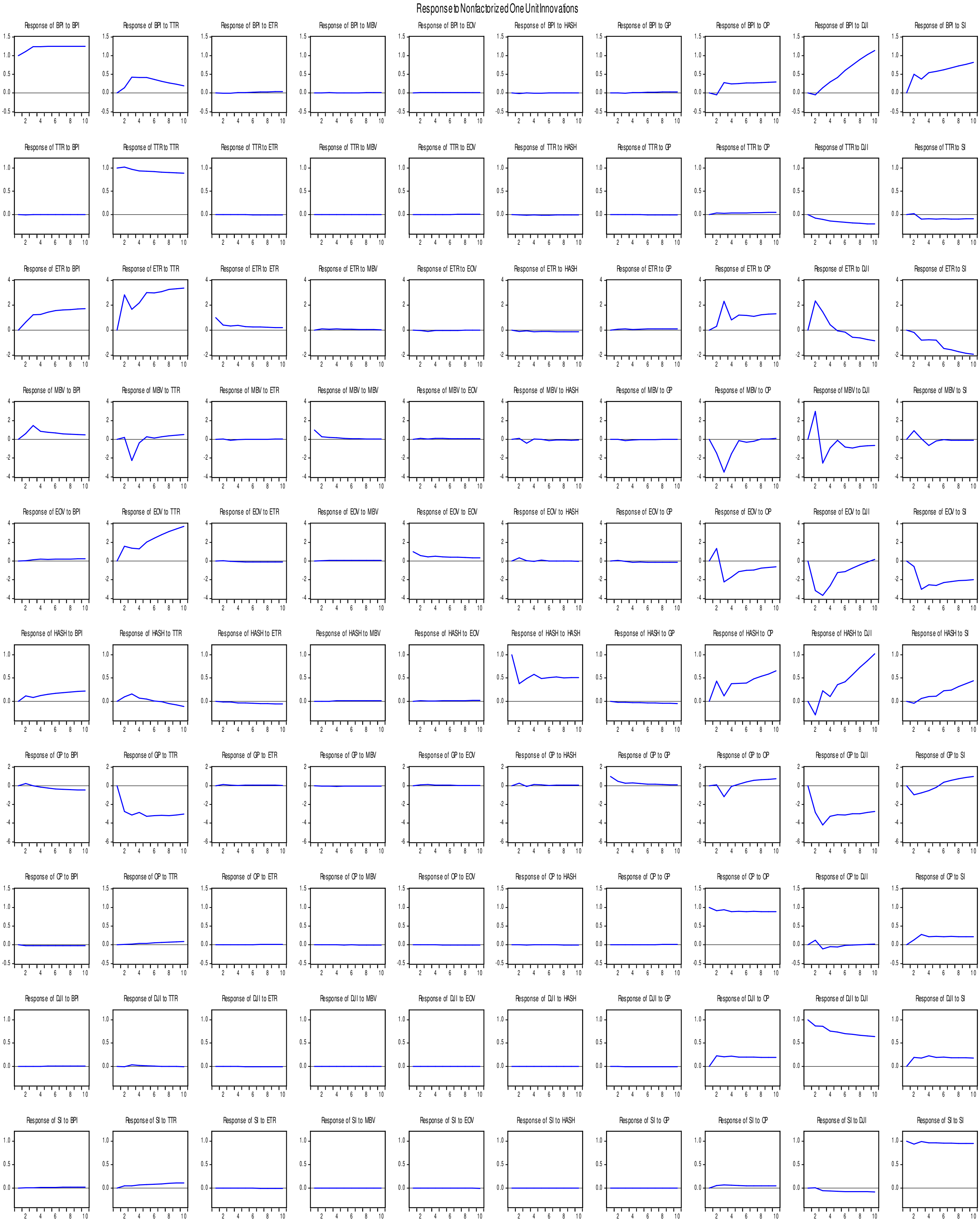
Table A-12: Variance Decomposition of Bitcoin price (Equations with additional variables)

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)*											
1	0.089236	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.133510	69.64294	20.10299	0.012666	0.014143	0.042821	0.002420	0.007915	0.000159	0.021659	10.15228
3	0.174247	69.31781	20.09368	0.084297	0.069088	0.082248	0.008574	0.004690	0.089813	0.132293	10.11750
4	0.208220	69.21861	20.07800	0.087726	0.063105	0.091891	0.006137	0.003851	0.130538	0.194279	10.12585
5	0.238292	69.13212	20.07648	0.093821	0.068997	0.098099	0.004751	0.004467	0.153696	0.242479	10.12509
6	0.265110	69.07429	20.07543	0.098891	0.069911	0.104294	0.004269	0.004888	0.171241	0.272138	10.12463
7	0.289584	69.04017	20.07283	0.102049	0.070048	0.107904	0.003690	0.005221	0.182453	0.292235	10.12339
8	0.312142	69.01439	20.07158	0.104564	0.069695	0.110543	0.003311	0.005473	0.190445	0.307239	10.12275
9	0.333190	68.99426	20.07075	0.106614	0.069345	0.112625	0.003047	0.005651	0.196888	0.318703	10.12211
10	0.352985	68.97904	20.06981	0.108108	0.068821	0.114341	0.002823	0.005788	0.201978	0.327628	10.12165
(2): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)*											
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
(3): F_{BPI} *(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV')*											
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

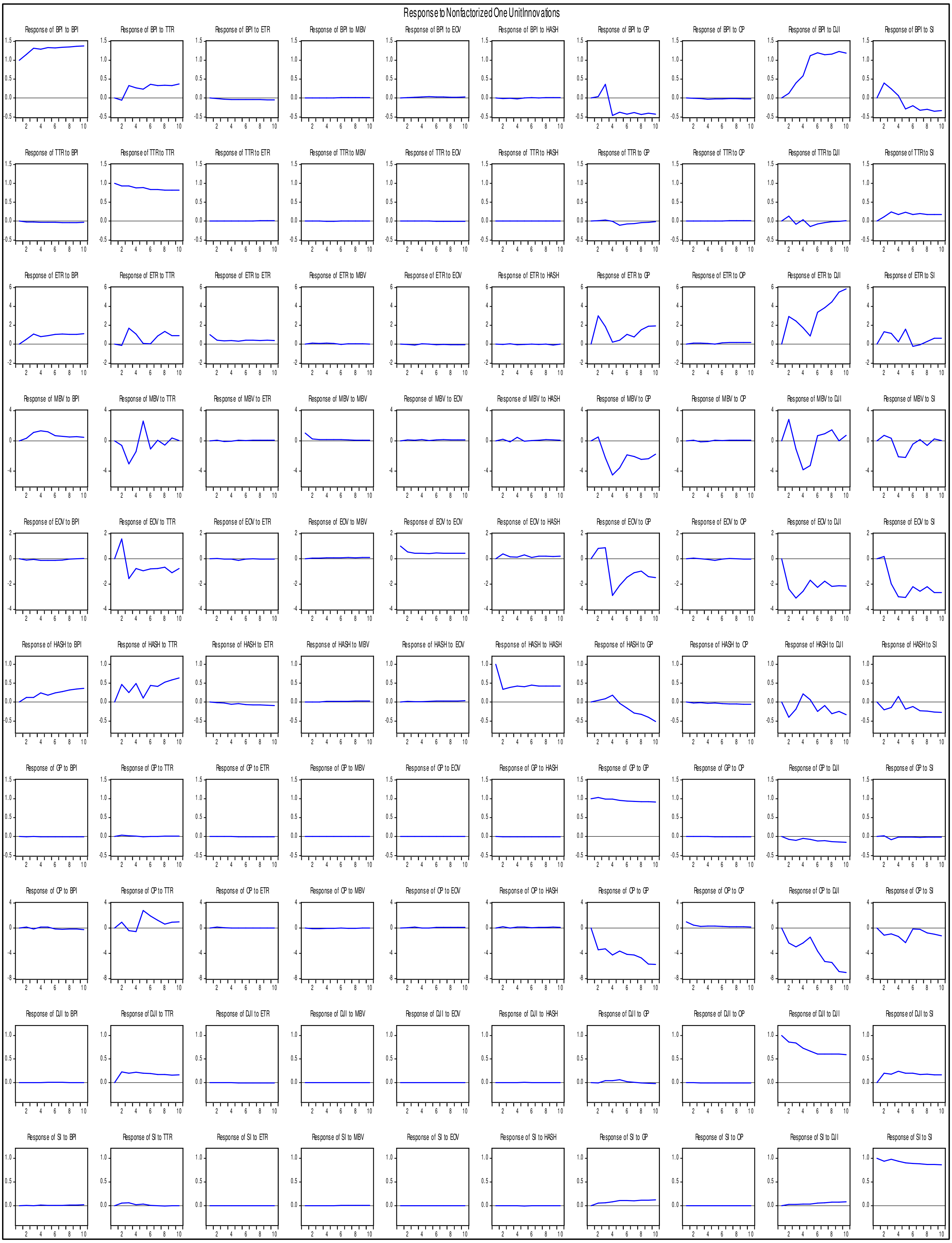
Notes: *DV'*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

Figure A-6: Impulse Response Function

(1): *FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)*



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



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

Notes: *DV'*: The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.