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What Does Bitcoin Look Like?

Jamal Bouoiyour

CATT, University of Pau, France
E-mail: jamal.bouoiyour@univ-pau.fr

and

Refk Selmi*

ESC, University of Manouba, Tunisia
E-mail: s.refk@yahoo.fr

The paper seeks to address what Bitcoin looks like. Specifically, we attempt to identify the main determinants of Bitcoin price by means of rigorous evaluation through ARDL Bounds Testing method. Our findings reveal the extremely speculative behavior of Bitcoin, its partial usefulness in trade transactions without overlooking its dependence to the Shangai stock market and the hash rate. There is no sign of Bitcoin being a safe haven. Taking a step further, we re-investigate the focal link by accounting for the Chinese trading bankruptcy. The results appear fairly robust. Bitcoin is still perceived as speculative foolery and thus far from being a long-term promise.

Key Words: Bitcoin; Speculation; Trade transactions; Safe haven; Shangai stock market; Hash rate; ARDL Bounds Testing approach.
JEL Classification Numbers: E5, F39, F65.

1. INTRODUCTION

In 2009, a pseudonymous hacker calling himself Satoshi Nakamoto created "Bitcoin", the world's first completely virtual and decentralized currency. Since its creation, particular attention has been given to this emerging money. In the wake of growing interest in Bitcoin, researchers began dealing with this nascent currency by revolving around multiple questions: Is it a speculative bubble? Is it a short-term hedge? Is it a safe haven? Is it a long-run promise? Is it a future currency? The fact that these

* Corresponding author.

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questions get frequently asked deeply highlights the "complexity" of this phenomenon.

Unlike traditional fiat currencies (dollar, euro and yen), whose value is determined by law, Bitcoin is not convertible and not formally backed by a government or legal entity. Bitcoin operates like a free market system, since it does not rely on a central bank to issue it or a commercial bank to store it. Instead, investors perform their business transactions themselves without any intermediary. The peer-to-peer network eliminates the trade barriers and makes business easier. Every passing day, the increase in the number of companies which accept Bitcoin is making its perceived value real. Nevertheless, security concerns, the inelastic money supply coded via mathematic formula and unsustainable volatility have profoundly plagued this digital money.

Despite having a passionate following, this phenomenon is still difficult to be definitely tackled. Some studies suggest that Bitcoin is likely to be a speculative trap than a future currency since there is no guarantee of repayment at any time (Kristoufek 2013; Yermack 2014; Bouoiyour et al. 2015). It is not yet heavily accepted as a payment system across wide markets and does not have an underlying value derived neither from consumption nor production process such as the precious metals including gold (Ciain et al. 2014; Glaster et al. 2014). Being a digital currency, Bitcoin is highly sensitive to cyber-attacks that may play a destabilizing role in the Bitcoin system (Bouoiyour et al. 2015). All these studies have attempted to answer separately the aforementioned questions. There is only one study, to our best knowledge, that has tried to analyze more completely this phenomenon by assessing whether Bitcoin seems more driven by technical, financial or speculative factors. Kristoufek (2014) has employed a wavelet coherency approach to gauge the interconnection between Bitcoin and its drivers one by one (bivariate analysis) without considering additional variables that may have "pulling" role in explaining the Bitcoin price dynamic (multivariate analysis). Studying the bivariate relationship may not be robust when some relevant explanatory variables are not included. On the one hand, these methods may lead to confusing outcomes since the occurrence of noise cannot be heavily neglected, disrupting then the relationship investigated (Aguiar-Conraria and Soares, 2011; Ng and Chan, 2012). On the other hand, wavelet decomposition is generally applied to assess the signals and the periodicity that happen over time. Strictly speaking, when we consider only two variables, we generally fall on the problem of simple regression without control variable which is unable to capture proper results with regard to the focal linkage.

To reach new insights and to find better paths on what the focal new digital money looks like, we need further investigation while incorporating several fundamentals recorded in the existing literature. Accurately, via an ARDL Bounds Testing approach, innovation accounting method and VEC Granger causality test, we examine the short-run and the long-run links between Bitcoin price and its potential drivers including investors' attractiveness, exchange-trade volume, monetary Bitcoin velocity, estimated output volume, hash rate, gold price and Shangai stock market. By doing so, we draw 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 Bitcoin price, while the monetary velocity, the hash rate and the gold price have no influence. In the long-run, the substantial impacts speculation, 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 results appear fairly robust, since they change slightly when incorporating the dummy variable relative to the bankruptcy of Chinese trading company. The inclusion of 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-run and long-run relationships, this research confirms the heavy 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. Moreover, 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 meaningful and fruitful for investors and market regulators in the future.

2. BRIEF LITERATURE SURVEY

Bitcoin has engaged the attention of media and researchers, acknowledging its complexity. Economists share different views regarding this nascent virtual crypto-currency. The majority of researches on this phenomenon considered Bitcoin as speculative foolery rather than currency or payment system due to its swelling volatility (Buchholz et al. 2012; Kristoufek 2013; Ciaian et al. 2014; Bouoiyour et al. 2015). Some others called it "evil" since it is not controlled nor by central banks nor by governments. 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". As we aim at rigorously analyzing what does Bitcoin look like, we give a first insight by looking at main literature findings, evidencing how interacts Bitcoin price with its potential determinants.

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 the linkage between the considered variables at distinct frequencies involved. The obtained results reveal that the fundamentals such as exchange-trade ratio play substantial role in lower frequencies. The Chinese market index seems a main driver of Bitcoin price, while the contribution of gold price appears minor and sometimes unclear. He finds also that users' interest or the speculative behaviors of businesses play a powerful role on the dynamic of this new digital money. The interdependence between speculation and Bitcoin appears dominant at lower frequency bands. Specifically, the investors' attractiveness drives the price of Bitcoin up during the explosive prices period, while it drives it down under rapid decline period.

Gloser et al. (2014) try 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 intention to gather additional information about the Bitcoin development has a deeper effect on its exchange volume. Nevertheless, the nexus between digital money and users' interest seems insignificant when considering the volume within the Bitcoin system. These outcomes may be mainly attributed to the fact that users prefer usually to keep their Bitcoins in their exchange wallet to avoid speculation and possible cyber-attacks without any intention to use them in economic reasons (trade transactions, for example).

More recently, Bouoiyour et al. (2015) examine whether Bitcoin is a trade transaction tool or risky investment. They analyze the causal relationships between Bitcoin price and exchange-trade ratio on the one hand, and Bitcoin price and investors' attractiveness on the other hand unconditionally and conditioning upon relevant control variables including the Chinese market index and the hash rate. To this end, they use an improved frequency domain approach-based on unconditional and conditional data analysis. Some differences with respect to the frequencies involved were found, highlighting the difficulty to obtain clearer insights into this new crypto-currency. This study confirms the speculative behavior of Bitcoin without overlooking its usefulness in economic reasons as trade transactions. They deduce that because its higher sensitivity to media and its heavy association with speculation, Bitcoin remains an uncertain virtual asset. Therefore, if traders appreciate risky investments, serious disappointments may await the unwary users.

3. DATA AND METHODOLOGY

3.1. Data

The existing literature on Bitcoin price suggests potential factors that may affect significantly the dynamic of this virtual currency including investors' attractiveness, economic, macroeconomic and financial indicators and the technical drivers. For Bitcoin economy, we use two proxies which are the exchange-trade ratio and the monetary velocity determined respectively through the Bitcoin days destroyed for given transactions and the estimated output volume. The global macroeconomic and financial indicators that may impact the evolution of Bitcoin price include the gold price and the Shangai stock market index. Bitcoin technical drivers have been measured via the hash rate. Before beginning our analysis, it seems of utmost importance to give some details about the variables investigated:

- The Bitcoin price (BPI): The Bitcoin is new digital money that has recently attracted media 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 transactions. It has also some drawbacks including the lack of legal security, the extra volatility and the great speculation (Kristoufek 2014; Bouoiyour et al. 2015).

- The investors' attractiveness (TTR): As a proxy of investors' attractiveness to Bitcoin, we use daily Bitcoin views from Google as it able to properly depict the speculative character of users (Kristoufek 2013). This indicator is determined via the frequency of the online Google search queries related to the new digital money generally and Bitcoin particularly. Arguably, Piskorec et al. (2014) highlight the effectiveness of this proxy to accurately describe the behavior of investors.

- The exchange-trade ratio (ETR): The trade and exchange transactions expand the utility of holding the currency, leading to an increase in Bitcoin price. The exchange-trade ratio is measured as a ratio between volumes on the currency exchange market and trade (Bouoiyour et al. 2015).

- The monetary 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 currency has stayed relatively stable (Kristoufek 2014).

- The estimated output volume (EOV): It is similar to the total output volume with the addition of an algorithm which tries to remove change from the total value. This may reflect more accurately the true transaction volume. Basically, there is a negative relationship between the estimated output volume and Bitcoin price. Accordingly, Kristoufek (2014) shows that an increase in the estimated output volume leads to a drop in Bitcoin price in the long-run.

- 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 represents an indicator of the processing power of the Bitcoin network. For security goal, the latter must make intensive mathematical operations, prompting an increase in the hash rate. This may affect widely Bitcoin purchasers and increases substantially the demand of this new currency and in turn their prices. Generally speaking, the hash rate is associated positively to Bitcoin price (Kristoufek 2014).

- The gold price (GP): Bitcoin does not have an underlying value derived from consumption or production process such as gold. In that context, Ciaian et al. (2014) and Yermack (2014) provide evidence that there is any sign of Bitcoin being a safe haven.

- The Shangai market index (SI): The Shangai market is considered as the biggest player in Bitcoin economy and as a result may be perceived as a potential source of Bitcoin price volatility. Arguably, the announcement that Baidu (potential determinant of the Chinese online shopping) is accepting Bitcoin has affected considerably the price of the focal virtual currency. Recently, Bouoiyour et al. (2015), using an improved frequency domain approach-based on unconditional vs. conditional data analysis, find that Bitcoin is likely to be a speculative trap rather than business income, conditioning upon the performance of the Shangai market.

For empirical purpose, this study disentangles the existence of long-run cointegration between the aforementioned variables during the period spanning between 05/12/2010 and 14/06/2014 (equation 1). Taking a step further, we re-examine the link between this nascent money and its relevant determinants by accounting for the Chinese trading bankruptcy. We include a dummy variable that amounts 1 from 02/2013 and 0 otherwise (equation 2). All these data are extracted from Blockchain[1] and quandl[2]. To improve the precision power of results, we carry out a log-linear specification that incorporates TTR, ETR, MBV, EOV, HASH, GP and SI.

$$
\begin{aligned}
LBPI_t &= \alpha_0 + \alpha_1 LTTR_t + \alpha_2 LETR + \alpha_3 LMBV_t + \alpha_4 LEOV_t \\
&+ \alpha_5 LHASH_t + \alpha_6 LGP_t + \alpha_7 LSI_t + \epsilon_t \qquad (1)
\end{aligned}
$$

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

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

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. (2015) assume that an increased users' interest searching for information about Bitcoin leads to an increase in Bitcoin prices. Then, we expect $\alpha_1, \beta_1 > 0$. The exchange-trade ratio denotes the ratio between volumes on the currency exchange market and trade. Generally, the price of the currency is positively associated to the use of transactions as it expands the utility of holding the currency. So, it is expected that $\alpha_2, \beta_2 > 0$. The monetary velocity of this money is measured through the number of Bitcoin in a transaction multiplied 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 $\alpha_3, \beta_3 > 0$. An increase in the estimated output volume affects negatively Bitcoin price in the long term (Kristoufek, 2014). We expect therefore $\alpha_4, \beta_4 < 0$. The hash rate is associated positively to Bitcoin price. An increase in Bitcoin price generates the intention of market participants to invest and to mine. We expect that $\alpha_5, \beta_5 > 0$. Some studies indicate that that Bitcoin cannot be perceived as safe haven since they found that there is no significant correlation between it and gold price (Kristoufek 2014). In contrast, Palombizio and Morris (2012) show that gold price may be considered as the main source of demand and cost pressures and then seems a meaningful contributor of Bitcoin price dynamic. We expect $\alpha_6, \beta_6 > 0$. The Shangai market is one of the most substantial players on digital currencies (in particular, Bitcoin). We expect thus that $\alpha_7, \beta_7 > 0$. The Chinese trading bankruptcy may affect intensely Bitcoin price. Unsurprisingly, the Chinese market seems the Biggest Bitcoin market. So, we expect that $\beta_8 < 0$.

3.2. The ARDL Bounds Testing Method

To empirically investigate the long-run relationships and dynamic interactions among economic variables, we can use the bounds testing (or autoregressive distributed lag: ARDL) cointegration procedure introduced by Pesaran and Shin (1999). This procedure is pursued for at least four reasons. First, it allows us to estimate the cointegration relationship via OLS once the lag order of the model is well identified. Second, it enables to assess simultaneously the short-run and the long-run coefficients associated to the variables studied. Third, the bounds testing procedure does not require the pre-testing of the variables included in the model for unit roots unlike the Johansen cointegration for instance. It obviates the need to classify the time series into I(0) or I(1). Lastly, the test seems parsimonious in small sample data as is the case in the present research. Nevertheless, the procedure will crash in the presence of I(2) series.

The current study employs this method while attempting to rigorously address how Bitcoin looks like by examining the connection between Bitcoin price and the aforementioned relevant variables (Equation 1). To ensure the robustness of our results, we incorporate a dummy variable that denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise(Equation 2). The ARDL representation of equations (1) and (2) are formulated as follows:

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

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

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 is 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 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.

3.3. The innovative accounting approach and VEC Granger causality

The majority of empirical studies use the standard Granger causality test augmented with a lagged error correction term to analyze the causal links between economic variables. However, this method may be ineffective since it is unable to properly detect the possible shocks. Given this limitation and while trying to avoid pitfalls, we explore an innovative accounting approach by simulating variance decomposition and impulse response function. To do so, 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. Specifically, this technique enables to effectively depict how long independent variable reacts to its own shocks and shocks stemming in the dependent variables. Moreover and in an effort to identify whether there is a short-run causality between the variables investigated , 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 an LM test. The null hypothesis is accepted or rejected based on Wald chi-square test.

4. RESULTS AND DISCUSSION

4.1. ARDL results

To determine the most potential driver of Bitcoin price dynamic, we start by reporting the descriptive statistics (TABLE 1). We clearly show a substantial data variability, highlighting the 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 plausible. The Jarque-Bera test revealed high and significant values, leading to reject the assumption of normality for all the considered variables.

Before proceeding ARDL estimation, we determine the degree of integration of variables through Augmented 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. This implies that the ARDL procedure can be followed to test the cointegration hypothesis among the focal series.

As the lag order of the variables is an important step for the model specification within ARDL bounds testing framework, ., we determine the lag optimization based on lag-order selection among 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 1.

Summary of statistics

	LBPI	LTTR	LETR	LMBV	LEOV	LHASH	LGP	LSI
Mean	3.05291	1.574058	13.41844	15.01983	13.69757	10.83858	7.319273	7.744138
Median	2.50797	1.565531	13.32571	14.95729	13.68825	9.846016	7.357317	7.717494
Maximum	7.04838	4.804185	18.09288	18.97052	17.10051	18.45453	7.547765	8.022789
Minimum	−1.48069	−1.033161	4.057230	11.58991	10.64887	4.528026	7.084017	7.568131
Std. Dev.	2.07871	0.918618	2.235922	1.019057	1.033003	3.263868	0.120834	0.114295
Skewness	0.20358	0.201630	−0.668879	0.116808	0.009475	0.687444	−0.243169	0.761047
Kurtosis	2.28016	3.326236	4.017153	3.887130	3.684876	2.922190	1.703855	2.590701
Jarque-Bera	21.2311	8.362903	87.78542	26.12393	14.57141	58.86658	59.57174	77.22019
Probability	0.00002	0.015276	0.000000	0.000002	0.000685	0.000000	0.000000	0.000000

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).

The main results obtained through ARDL Bounds testing approach are reported in TABLE 4. We worthy show that: the investors' attractiveness plays a significant role in explaining Bitcoin price formation. Notably, 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, estimated output volume and gold price have no significant impact on Bitcoin price, while 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. Interestingly,

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	0.00672*	−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 criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

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).

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 considered time series.

Given its inability to account for possible shocks, discontinuities and sudden disturbances, we believe that it is important to apply the method of Gregory and Hansen (1996) to re-explore the interactions between the variables studied while accounting for nonlinearity. This technique is based on an unknown structural break stemming 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 even if we consider regime shifts or structural breaks (TABLE 6).

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 (FIG. 1) and the stability of ARDL parameters (FIG. 2).

From our results reported in TABLE 7, it is well shown that Bitcoin price interacts differently with its determinants depending to time periods (short or long terms). 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

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.

and the gold price have no influence on this digital money. These outcomes change remarkably in the long-run. The TTR, the EOV and the SI 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. Notably, 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.

TABLE 5.

The ARDL Bounds Testing Analysis

Estimated model	Optimal lag length	F-statistic	Prob.
FBPI (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	FBPI (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	

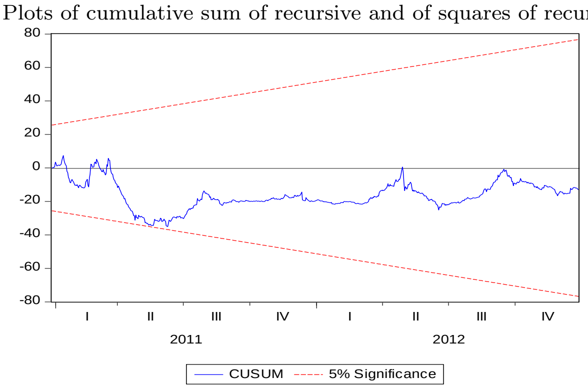
Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively.

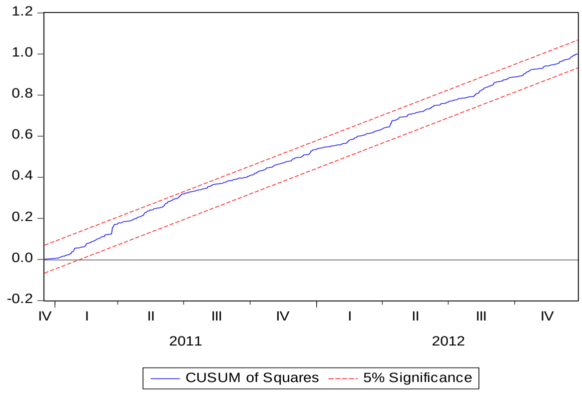
4.2. Innovative accounting approach results

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) seems the major driver of Bitcoin price (20.34%). The contribution of ETR appears minor (0.16%). Likewise, the monetary velocity, the estimated output volume and the hash rate do not have great effect on this new crypto-currency, with respective percentages equal to 0.035%, 0.037% and 0.003%. Gold price explains slightly BPI (0.095%), but we should not forget that the link between GP and BPI is insignificant in the aforementioned results. Additionally, the contribution of Chinese market index (SI) affects deeply the dynamic of BPI (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. By

FIG. 1. Plots of cumulative sum of recursive and of squares of recursive residuals





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

applying this technique, we can see the strength of the response of Bitcoin price to its own shock on the one hand and those of investors' attractiveness, exchange-trade volume, monetary velocity, estimated output volume, hash rate, gold price and Shangai market index on the other hand. FIG. 3 worthy indicates that the responses in Bitcoin price owing to forecast error stemming in TTR and SI seem positive over time, while the contributions of ETR, MBV, EOV, HASH and GP to Bitcoin price appear negligible.

Furthermore, we evaluate whether there is a causal relationship between the Bitcoin price dynamic and its aforementioned fundamentals. 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 $k = 1, \ldots, 12$. From the findings reported in TABLE 9, the serial correlation may be removed at the maximum lag length which is 3.

FIG. 2. Plots of cumulative sum of recursive coefficients

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

The non-causality test findings are reported in TABLE 10. It is well noticeable that we can reject the null hypothesis of no causality for the relationships running from $DLTTR$ to $DLBPI$, $DLETR$ to $DLBPI$ and $DLSI$ to $DLBPI$, while the reverse link is not supported for any case. This confirms the above outcomes obtained through the ARDL Bounds Testing method and the innovation accounting approach. For the rest of variables,

FIG. 3. Impulse Response Function

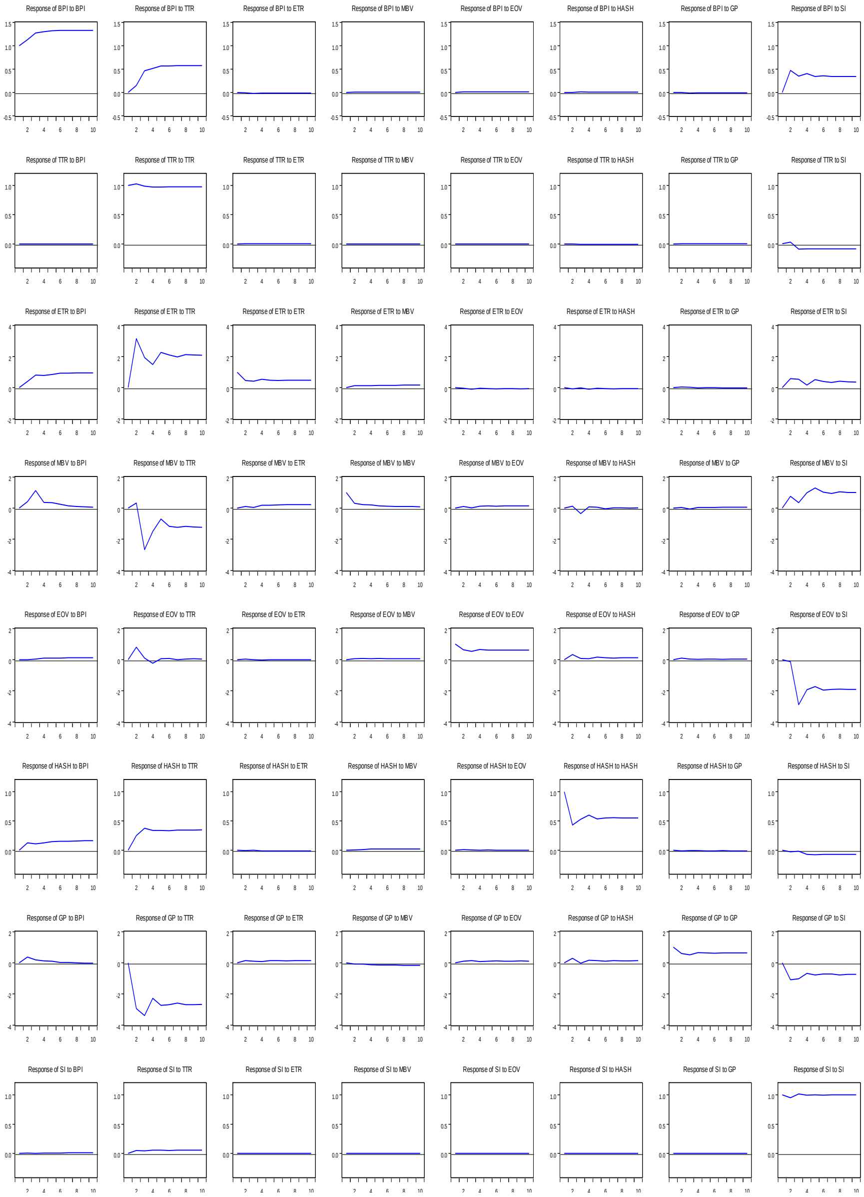


TABLE 7.

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	0.44
SE regression	0.7812
Breush-Godfrey serial correlation	0.3987 [0.1125]
Ramsey Reset test	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.

we accept the null hypothesis of non-causality (except for the linkage that runs from $DLBPI$ to $DLHASH$ and from $DLBPI$ to $DLMBV$). These results may be very useful for investors and market regulators.

5. ROBUSTNESS

The above findings clearly indicate that although of TTR, EOV and SI contribute greatly to the dynamic of BPI in the short-run; they appear without statistically significant effect in the long-run. While the monetary velocity, the hash rate and the gold price have no influence in the short

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

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

term. The impacts of MBV and GP on BPI seem insignificant either in the short or in the long-run, while the effect of the hash rate on BPI seems positive and significant in the long term. To check ensure the robustness of these results, we re-estimate the relationship between Bitcoin price and its determinants even if we incorporate a dummy variable relative to the bankruptcy of Chinese trading company while respecting the same steps. The accurate outcomes are reported in TABLE A-1, TABLE A-2, TABLE A-3, TABLE A-4, TABLE A-5, TABLE A-6, FIG A-1, FIG A-2 and FIG A-3 (APPENDIX). Comparing these results with the previous

TABLE 10.

VEC Granger Causality/Block Exogeneity Wald Tests

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

ones (i.e., without dummy variable), we put in evidence that the effects of TTR, ETR, MBV, EOV, $HASH$, GP and SI are solid and unambiguous, especially with respect to time-horizons (short-and long-run). Beyond the nuances of short and long terms, the present study confirms the speculative nature of Bitcoin without overlooking its "partial" usefulness in economic reasons (trade transactions) and its great dependence to the Chinese stock market and the processing power of Bitcoin network. Bitcoin is therefore perceived as speculative bubble, risky investment, short-term hedge and partially as business income. This new crypto-currency appears far from being a safe haven or a long-term promise.

Further explanatory variables have been added to reach conclusive outcomes (for example, oil price[3], Dow Jones index[4] and a dummy variable de-

[3]Palombizio and Morris (2012) find that oil price (OP) is a potential factor that may affect intensely inflation. If the price of oil experienced excessive ups and downs (i.e., sizeable volatility), the Bitcoin will depreciate.

[4]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 that America will not send the military to fight off the terrorist organizations have affected simultaneously Bitcoin and Dow Jones index. Due

noting the closing of road silk by FBI[5] (DV') equals to one from 23/10/2013 and 0 otherwise). Nevertheless, the obtained findings reveal that the effects of the additional time series are in the majority of cases insignificant and the estimates become clearly unstable (see FIG A-4, particularly). More details about these results are summarized in TABLE A-7, TABLE A-8, TABLE A-9, TABLE A-9, TABLE A-11, TABLE A-12, FIG A-5 and FIG A-6 (APPENDIX).

6. CONCLUSIONS AND SOME POLICY IMPLICATIONS

The present research attempts to reach clearer knowledge and better paths into a complex phenomenon: Bitcoin price. By attempting to address what does Bitcoin looks like, several extended questions emerge: Is it a speculative bubble? Is it a short-term hedge? Is it a safe haven? Is it a long-term promise? Is it a future currency? To effectively answer these questions, 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 unpleasant speculative behavior of Bitcoin. We also provide insightful evidence that Bitcoin may be served partially for trade transactions. However, there is any sign of being a safe haven. By accounting for the Chinese trading bankruptcy, the contribution of speculation and the Shangai stock market remain dominant, while the role of Bitcoin as business income dissipates in the long-run, highlighting the robustness of our results.

So, is Bitcoin a long-term promise? Given our obtained findings, it is difficult to reach clearer, solid and unambiguous evidence into Bitcoin phenomenon, since it is uncertain. This nascent digital money can remain as it can disappear, especially when considering that Bitcoin faces a structural economic problem regarding its limited amount recording 21 million units in 2140, implying that the money supply cannot continue to rise after this date. There are, up to now, 12 million Bitcoin in circulation. If this famous crypto-currency successfully displace fiat currencies (euro, dollar and yen), it will exert sizable deflationary pressures. Without definitely tackling the

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 the following link: http://coinbrief.net/bitcoin-price-news-analysis/

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

causes, the virtual currency seems highly correlated to the speculative behaviors of investors or people who hold it. This digital money is not issued by banking system and even less by any government, but by a computing algorithm. Unfortunately, the majority of users have not acknowledged about mathematical programs, and it is therefore unknown for them how far it can go. In sum, no one can predict the precise value and the specific form crypto-urrency will take since the technological development is heavily unpredictable. As technology becomes increasingly integrated into our everyday lives, crypto-currencies will obviously continue to grow and Bitcoin may probably be displaced by better digital currencies.

Intuitively, the sizeable volatility of Bitcoin and the difficulty of processing power network are likely to discourage investors. Additionally, the great attention to this crypto-currency in the Chinese media has drawn a huge number of Bitcoin believers in Chinese market. However, the ambiguous attitude of regulators towards Bitcoin in China, coupled with the typical Chinese investor's lack of experience will prompt an intensive speculation (Mei et al. 2009). This reinforces the evidence that this new virtual currency is likely to be short-term hedge and risky investment rather than long-term promise. There is a greater chance that Bitcoin collapses and disappears tomorrow rather than suddenly become internationally recognized.

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APPENDIX A

TABLE 1.

Lag-order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
FBPI (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; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise.

TABLE 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	0.48
SE regression	0.7241
Breush-Godfrey serial correlation	0.0133 [0.6214]
Ramsey Reset test	0.0217 [0.6528]

Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; [.]: p-value.

TABLE 3.

The ARDL Bounds Testing Analysis

Estimated model	Optimal lag length	F-statistic	Prob.
FBPI (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); DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise.

TABLE 4.

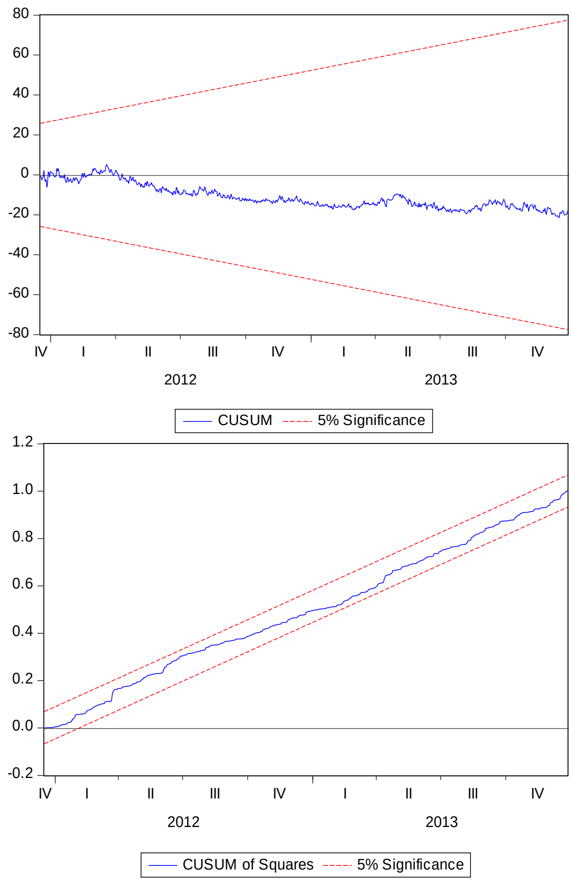
Gregory-Hansen Structural Break Cointegration Test

Estimated model	FBPI (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; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise.

FIG. 1. Plots of cumulative sum of recursive and of squares of recursive residuals

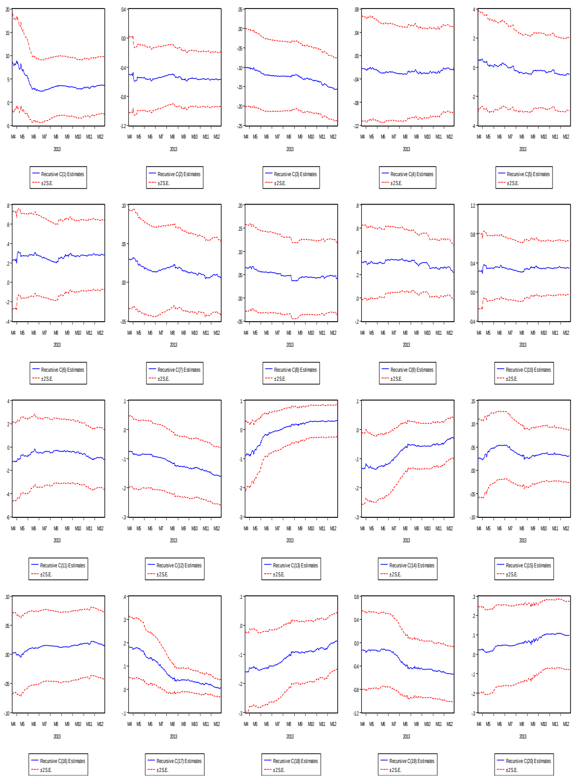
F_{BPI} (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LSI, DV)



Notes: The straight lines represent the critical bounds at 5% significance level; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise.

FIG. 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; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise.

TABLE 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	$-3.20\text{E-}06^{*}$ (-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 ; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; [.] : p-values.

TABLE 6.

Variance Decomposition of Bitcoin price

Period	S.E.	LBPI	LTTR	LETR	LMBV	LEOV	LHASH	LGP	LSI
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

FIG. 3. Impulse Response Function

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

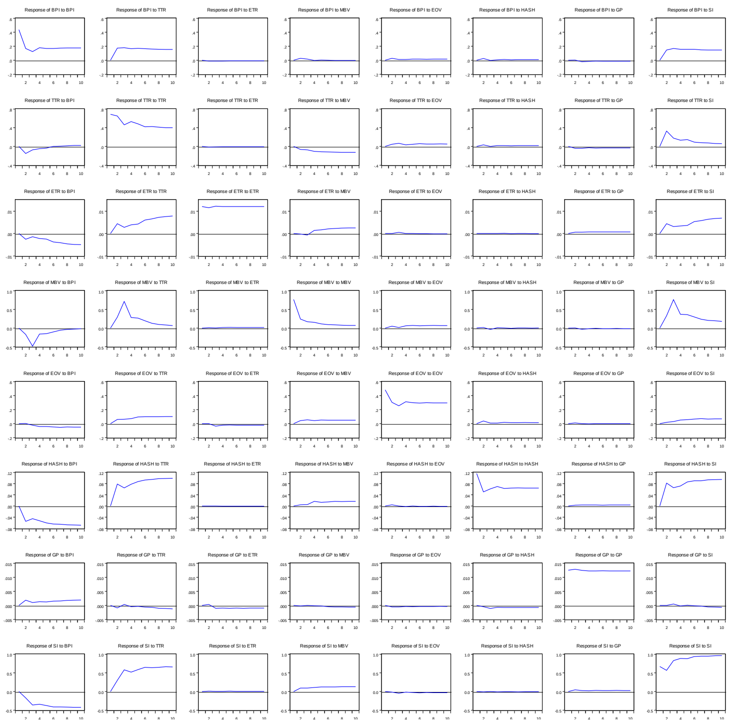


TABLE 7.

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: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': corresponds to the closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

TABLE 8.

The ARDL Bounds Testing Analysis (Equations with additional variables)

Dependent variable: $\Delta LBPI_t$			
	(1)	(2)	(3)
C	-2.4325^{*}	-1.7262^{*}	-1.4941^{*}
	(-1.7278)	(-2.5645)	(-2.1939)
$\Delta LBPI_{t-1}$	0.1185^{**}	0.0376^{*}	0.0288^{*}
	(3.0231)	(2.0056)	(1.6232)
$\Delta LBPI_{t-2}$	-	0.0394^{*}	-
		(2.2019)	
$\Delta LTTR_{t-1}$	0.1222^{**}	0.2062^{*}	0.0068^{*}
	(3.1537)	(1.7683)	(1.7044)
$\Delta LETR_{t-1}$	0.1153^{**}	0.0093^{*}	0.0087^{*}
	(3.0589)	(1.8553)	(1.7147)
$\Delta LMBV_{t-1}$	-0.1222	0.0010	0.0011
	(-0.2482)	(0.4548)	(0.6971)
$\Delta LEOV_{t-1}$	0.0030	0.0016	0.0021
	(0.3763)	(0.4187)	(0.5425)
$\Delta LHASH_{t-1}$	-0.0141	-0.0079	-0.0060
	(-0.5719)	(-0.6775)	(-0.5051)
ΔLGP_{t-1}	0.1559	-0.0614	-0.1064
	(0.5900)	(-0.4894)	(-0.8379)
ΔLOP_{t-1}	-0.1043	0.1004	0.0086
	(-0.5383)	(1.0901)	(0.9297)
$\Delta LDJI_{t-1}$	-0.1268	-0.1267	-0.0971
	(-0.3857)	(-0.8120)	(-0.6185)
ΔLSI_{t-1}	0.1468^{*}	0.1235^{*}	0.1104^{*}
	(2.000)	(1.9516)	(1.8452)
$LBPI_{t-1}$	0.0186^{*}	0.0141^{**}	-0.0079
	(1.6551)	(2.6353)	(-1.3922)
$LTTR_{t-1}$	-0.0162	0.0043	-0.0064
	(-1.5979)	(1.0714)	(-1.3244)
$LETR_{t-1}$	0.0158^{*}	0.0039^{*}	0.0059^{*}
	(2.2800)	(1.9519)	(1.8516)
$LMBV_{t-1}$	0.0032	-0.0027	-0.0037
	(0.5693)	(-0.9879)	(-1.3088)

TABLE 8—*Continued*

Dependent variable: $\Delta LBPI_t$			
	(1)	(2)	(3)
$LEOV_{t-1}$	0.0026	0.0051*	0.0039
	(0.4453)	(1.7506)	(1.3735)
$LHASH_{t-1}$	0.0056*	−0.0010	0.0081**
	(1.8862)	(−0.5489)	(2.6473)
LGP_{t-1}	−0.0534	−0.0011	−0.0143
	(−0.9023)	(−0.0405)	(−0.4907)
LOP_{t-1}	−0.0161	−0.0653	−0.0310
	(−0.2627)	(−0.2364)	(−0.9948)
$LDJI_{t-1}$	0.0355*	0.1008***	0.1002***
	(2.2728)	(3.8895)	(4.0147)
LSI_{t-1}	0.0762	0.0104	−0.0186
	(1.3060)	(0.3766)	(−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: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': corresponds to the closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

TABLE 9.

The ARDL Bounds Testing Analysis (Equations with additional variables)

Estimated model	Optimal lag length	F-statistic	Prob.
(1): FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)	3, 3,4, 1, 0, 0, 0, 0	4.5711*	0.0659
(2): FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)	3, 3,4, 1, 0, 0, 0, 0	4.4426*	0.0550
(3): FBPI (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: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': corresponds to the closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

TABLE 10.

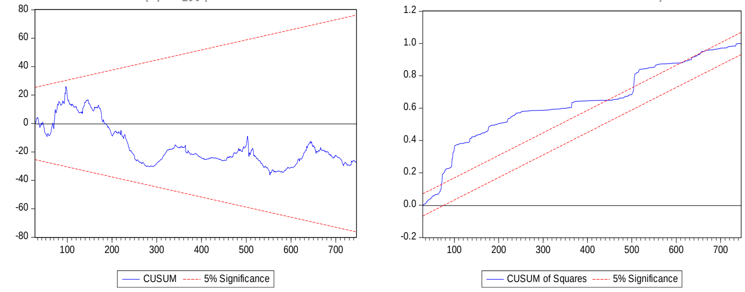
Gregory-Hansen Structural Break Cointegration Test (Equations with additional variables)

Estimated model	(1): FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)	(2): FBPI (LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV)	(3): FBPI (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	

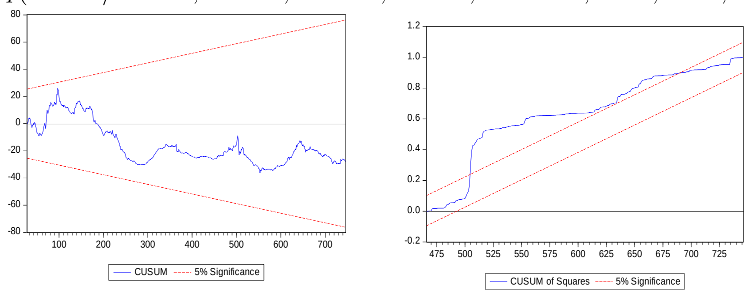
Notes: ***, ** and * imply significance at the 1%, 5% and 10% level, respectively; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': corresponds to the closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

FIG. 4. Plots of cumulative sum of recursive and of squares of recursive residuals (Equations with additional variables)

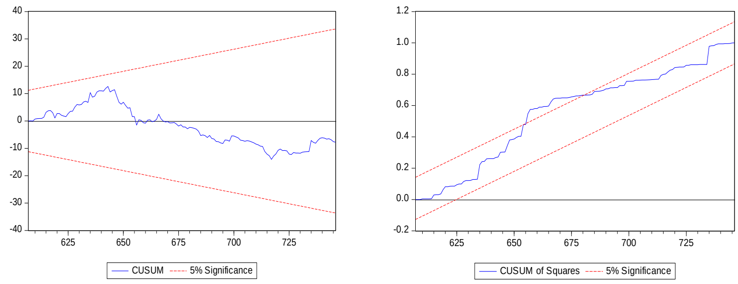
(1):
$F_{BPI}(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)$



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



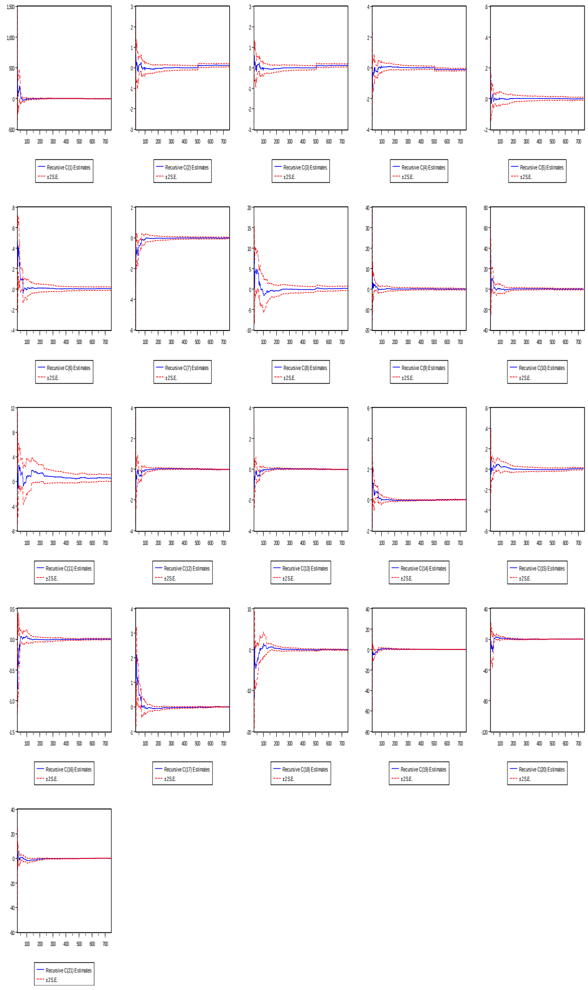
(3):
$F_{BPI}(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI, DV')$



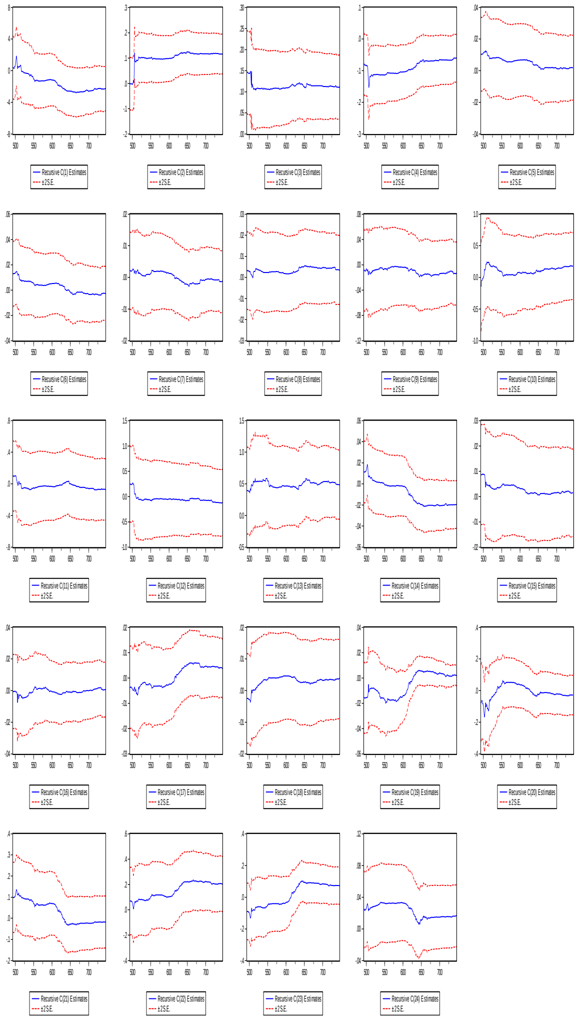
Notes: The straight lines represent the critical bounds at 5% significance level; DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': corresponds to the closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

FIG. 5. Plots of cumulative sum of recursive coefficients (Equations with additional variables)

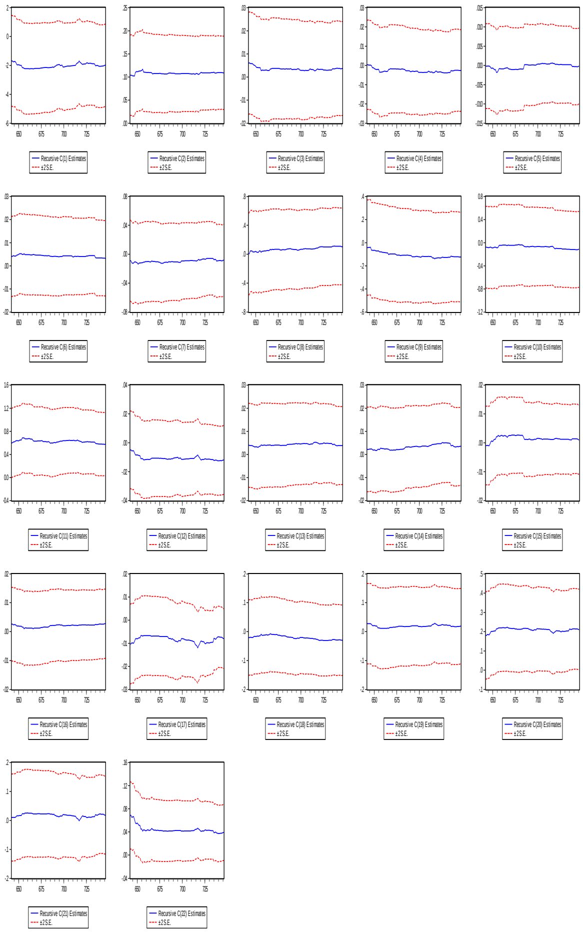
(1):
$F_{BPI}(LBPI/LTTR, LETR, LMBV, LEOV, LHASH, LGP, LOP, LDJI, LSI)$



(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.

TABLE 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^{***}	0.0281^{*}	0.0269^{**}
	(3.2270)	(2.1537)	(2.5852)
$\Delta LTTR_t$	0.4305^{*}	0.5702^{*}	0.4787^{***}
	(2.0214)	(2.1522)	(4.1026)
$\Delta LETR_t$	0.2157^{***}	0.0192^{***}	0.0172^{**}
	(8.4441)	(7.3397)	(2.6367)
$\Delta LMBV_t$	-2.2467	0.7897	0.4398^{*}
	(-0.1721)	(0.2109)	(1.7485)
$\Delta LEOV_t$	0.4158^{*}	-0.4434	0.0172
	(2.5803)	(-0.2068)	(0.3859)
$\Delta LHASH_t$	-0.0283	-0.0915	-0.0057
	(-0.3214)	(-0.7780)	(-0.3802)
ΔLGP_t	-3.4273	-0.0054	-0.0928
	(-1.5320)	(-0.3213)	(-0.6674)
ΔLOP_t	-2.4806	-0.7780	0.7488
	(-1.5448)	(-1.4343)	(1.4354)
$\Delta LDJI_t$	2.0697	0.8341	-0.0259
	(0.5522)	(0.6264)	(-1.3648)
ΔLSI_t	0.3256^{*}	0.4786^{**}	0.4784^{***}
	(1.6625)	(2.6372)	(4.6666)
ECT_t	-0.0023^{**}	-0.0020^{*}	-0.0026^{**}
	(-2.8790)	(-1.6791)	(-2.5190)
Long-run			
$LBPI_t$	0.1340^{***}	0.1265^{***}	0.1275^{**}
	(3.3768)	(3.2112)	(3.2394)
$LTTR_t$	-0.0131	0.0016	-0.0529
	(-1.3168)	(0.1611)	(-0.2708)
$LETR_t$	0.0088^{*}	0.0010^{*}	0.0029^{*}
	(1.8163)	(1.7842)	(1.8604)
$LMBV_t$	0.0001^{***}	0.0921	-0.0012
	(8.8192)	(0.9284)	(-0.2067)

TABLE 11—*Continued*

Dependent variable: $\Delta LBPI_t$			
	(1)	(2)	(3)
$LEOV_t$	0.0043	0.0655	-0.0070
	(0.5435)	(1.0307)	(-0.8598)
$LHASH_t$	0.0077^{*}	0.0029^{*}	0.0053^{*}
	(1.9745)	(1.8148)	(1.8371)
LGP_t	0.1518	0.1534	-0.1684
	(0.5697)	(0.5752)	(-0.6232)
LOP_t	-0.0518	-0.0515	0.0019
	(-0.2658)	(-0.2642)	(0.1915)
$LDJI_t$	0.1420^{***}	0.1852^{*}	0.2417^{***}
	(4.2680)	(2.4937)	(3.8358)
LSI_t	0.4400	0.4406	0.4457
	(1.5950)	(1.5948)	(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: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

TABLE 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	0.00000	0.00000	0.00000	0.00000	0.000000	0.00000	0.00000	0.000000
2	0.13351	69.6429	20.1029	0.0126	0.01414	0.04282	0.00242	0.00791	0.00015	0.02165	10.1522
3	0.17424	69.3178	20.0936	0.08429	0.06908	0.08224	0.00857	0.00469	0.08981	0.13229	10.11750
4	0.20822	69.2186	20.0780	0.08772	0.06310	0.09189	0.00613	0.00385	0.13053	0.19427	10.12585
5	0.2382	69.1321	20.0764	0.09382	0.06899	0.09809	0.00475	0.00446	0.15369	0.24247	10.12509
6	0.26511	69.0742	20.0754	0.09889	0.06991	0.10429	0.00426	0.00488	0.17124	0.27213	10.12463
7	0.28958	69.0401	20.0728	0.10204	0.07004	0.10790	0.00369	0.00522	0.18245	0.2922	10.1233
8	0.31214	69.0143	20.0715	0.10456	0.06969	0.11054	0.00331	0.00547	0.19044	0.30723	10.12275
9	0.33319	68.9942	20.07075	0.10661	0.06934	0.11262	0.00304	0.00565	0.19688	0.31870	10.12211
10	0.35298	68.9790	20.06981	0.10810	0.06882	0.11434	0.00282	0.00578	0.20197	0.32762	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	0.000000
2	0.133945	72.56927	20.13121	0.041758	8.8E-05	0.098224	0.02756	0.001589	0.000687	0.002292	17.127313
3	0.17576	72.0822	20.13425	0.14806	0.03469	0.24463	0.01796	0.08172	0.12257	0.03177	17.10206
4	0.20805	71.7392	20.10767	0.28919	0.03440	0.38193	0.02936	0.12379	0.14477	0.07531	17.07429
5	0.23777	71.1985	20.21750	0.32258	0.03296	0.64717	0.02293	0.12715	0.13963	0.21534	17.07614
6	0.26395	70.9037	20.29078	0.33606	0.04648	0.70942	0.01902	0.136528	0.17212	0.31687	17.06890
7	0.28824	70.7084	20.36059	0.33356	0.07918	0.73016	0.01595	0.137717	0.184304	0.375281	17.07481
8	0.31087	70.5771	20.40122	0.33026	0.12008	0.72251	0.01399	0.144631	0.194569	0.419226	17.07634
9	0.33261	70.4270	20.44057	0.34394	0.16216	0.72334	0.01347	0.146085	0.200372	0.461578	17.08140
10	0.35326	70.2972	20.48197	0.35034	0.20136	0.72406	0.01223	0.149376	0.210477	0.488857	17.08410
(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: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.

FIG. 6. Impulse Response Functions

(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: DV: denotes the bankruptcy of Chinese trading company equals to 1 from 02/2013 and 0 otherwise; DV': The closing of the Road Silk by FBI, which amounts 1 from 23/10/2013 and 0 otherwise.