The effects of markets, uncertainty and search intensity on bitcoin returns

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Abstract

We review the literature and examine the effects of shocks on bitcoin returns. We assess the effects of factors such as stock market returns, exchange rates, gold and oil returns, FED's and ECB's rates and internet trends on bitcoin returns. Alternative VAR and FAVAR models are employed and generalized as well as local impulse response functions are produced. Our results reveal (i) a significant interaction between bitcoin and traditional stock markets, (ii) a weaker interaction with FX markets and the macroeconomy and (iii) an anemic importance of popularity measures. Lastly, we reveal the increased impact of Asian markets on bitcoin compared to other geographically-defined markets, which however appears to have waned in the last two years after the Chinese regulatory interventions and the sudden contraction of CNY's share in bitcoin trading volume.

Keywords: bitcoin, cryptocurrency, exchange rate, returns, FAVAR, factor analysis

JEL classification codes: G12, G15

1. Introduction

Bitcoin is a digital currency that has been gaining more attention by both investors and researchers since its introduction by Nakamoto (2008). It has three important advantages: (i) direct transactions that do not imply a need for bank intermediation, (ii) low transaction fees and (iii) anonymity. The consumer base and transaction frequency in the digital currencies market have expanded considerably (Dyhrberg, 2016b). At the same time, the number of businesses and organisations that accept bitcoin as a means of payment is growing rapidly (Polasik et al., 2015). Its ability to serve as a medium of exchange alongside standard fiat currencies and other payment technologies has gradually been acknowledged (Kristoufek, 2015; Polasik et al., 2015).

Apart from its increasing use in transactions, bitcoin has also some favourable characteristics as an asset. It has been argued to possess hedging capabilities against the FTSE Index and the US dollar and the advantages of both commodities and currencies (Dyhrberg, 2016a,b). It can function as a diversifier and in some cases as a hedge or safe heaven against commodities and Asian stocks (Bouri et al., 2017c). There has been also evidence suggesting that its inclusion in a well-diversified portfolio can improve risk-return combinations (Brière et al., 2015; Bouri et al., 2017a), while it could also have a place in a central bank's external assets portfolio (Moore and Stephen, 2016). Last but not least, its speculative features have widely been discussed in the literature (e.g. MacDonell, 2014; Huhtinen, 2014; Baek and Elbeck, 2015; Yermack, 2015; Bouoiyour et al., 2015; Cheah and Fry, 2015; Ciaian et al., 2016a,b). Its argued bubble behaviour may have served speculators well.[1] Indicative of its advantages as an asset is its inclusion in the investment options of Britain's largest online trading platform. After clients' requests, Hargreaves Lansdown has started offering its

[1] See www.marketwatch.com/bitcoins-rally-seems-closely-tied-to-something-you-may-do-every-day-2017-08-15 for bitcoin's recent and earlier bubble behavior.

customers access to a Swedish fund tracking the bitcoin price.[2]

This study investigates the effects of shocks in stock market indices, exchange rates, gold and oil, central bank rates, internet trends and policy uncertainty on bitcoin returns employing alternative VAR and (the more flexible) Factor-Augmented VAR (FAVAR) models. This is done by producing generalized and local impulse response functions. Furthermore, we use factor and principal component (PC) analysis to gauge the magnitude of the effects that European, US and China-Japan markets have on bitcoin returns. To the best of our knowledge, this study is the first to (i) provide an overview of the existing literature and (ii) systematically differentiate among the effects of geographically defined markets on bitcoin. Our results suggest a significant interaction between bitcoin and traditional stock markets, a weaker with FX markets and the macroeconomy and an anemic importance of popularity measures. Lastly, we reveal the increased impact of Asian markets on bitcoin compared to other geographically-defined markets, which however appears to have waned in the last two years after the Chinese regulatory interventions, which has been accompanied by a sudden contraction of CNY's share in bitcoin trading volume and a rapid expansion of USD's share.

The rest of the paper is organized as follows: section 2 reviews the literature, section 3 presents the data, while section 4 the methodology. The results are discussed in sections 5 and 6; the last section concludes.

2. Literature review

Although research on bitcoin has expanded, there are limited reviews of the literature available. Polasik et al. (2015) group bitcoin research on four main areas. The first one examines technological and security issues, the second one public and legal issues, the third one political, sociological and ethical implications of

[2]See http://www.telegraph.co.uk/investing/funds/britains-largest-broker-offers-bitcoin-investment.

bitcoin and other cryptocurrencies. The last one, in which our contribution lies, focuses on economic and financial issues from both theoretical and empirical perspective.[3] The existing empirical literature (e.g. Kristoufek, 2013; Bouoiyour and Selmi, 2015; Ciaian et al., 2016a,b) has identified four main categories of drivers affecting the price of bitcoin: (1) market forces of supply and demand for bitcoin, (2) investment attractiveness of bitcoin, (3) global macroeconomic and financial developments and (4) bitcoin-technology-related factors. We mainly examine factors in the second and third category.

The expanding literature on bitcoin reflects the increased interest on the topic. Huhtinen (2014) finds an increase in the supply (i.e. total number of bitcoins mined) to cause a decrease in the price of bitcoin suggesting an inflationary effect of the increasing supply. Kristoufek (2013) supports the latter but only in the long term; in the short run the relationship is not significant and no conclusion can be drawn regarding the sign or the direction of causality. Similarly, Li and Wang (2016) find a significant effect only in the long-run, while Gronwald (2015) argues that the fluctuations in bitcoin price should be ascribed only to factors affecting demand, as there is no uncertainty on the supply-side. Kristoufek (2015) finds that in the long run bitcoin appreciates, as the demand for use in trade increases. An increase in price boosts exchange transactions in the short run suggesting that bitcoin's long-run behaviour can be explained by the quantity theory of money. In the short run, it is susceptible to bubbles and busts. Polasik et al. (2015) find evidence that demand driven by the users' transactional needs leads to price increases, but supply is not statistically significant in affecting bitcoin returns, as it is determined through a known mathematical algorithm and, therefore, is more predictable. The findings of Bartos (2015) and Ciaian et al. (2016a,b) suggest that supply and —more profoundly— demand have a significant impact on the bitcoin price.

[3]Fantazzini et al. (2016) review the econometric and mathematical tools that have been used in the bitcoin modelling.

In relation to technological factors, the hash rate (i.e. the computational power of bitcoin miners) is commonly employed as an indicator. Bouoiyour and Selmi (2015) employ an ARDL framework and find that the effect of the hash rate on bitcoin price is positive and significant, but relatively weak. Their innovative accounting approach suggests that the contribution of the hash rate on bitcoin price is trivial and only some evidence of a significant positive impact is found in the long run. Kristoufek (2015) finds a positive relation between the hash rate and bitcoin price in the long-run, which, nevertheless, has been vanishing over time.

Macroeconomic and financial developments have been more frequently addressed and the results have been mixed. Ennis (2013) provides evidence of independence of bitcoin returns in relation to equity and bond markets, but suggests that the cryptocurrency could serve as hedge for the US and Europe sovereign debt markets and for the euro, but not the dollar. Li and Wang (2017) conclude that bitcoin responds to short-term changes in the US inflation, interest rate and money supply. Bouoiyour and Selmi (2015) reveal the dependence of bitcoin on the Shanghai market index, which is more pronounced in the short-run, suggesting a positive effect of the index on bitcoin. Bouoiyour and Selmi (2017) find that bitcoin can act as a weak safe haven in the short-run and as a hedge in the medium- and the long-run against the U.S. stock market. Dyhrberg (2016a,b) concludes that bitcoin reacts positively to increases in the federal funds rate, the FTSE Index and the USD/EUR exchange rate, while the response to USD/GBP exchange rate increases is negative. In the short run, Wang et al. (2016) find WTI crude oil price to have little impact, whereas the Dow Jones industrial average index a relatively larger one on bitcoin price. In the long run, they both have a negative impact on bitcoin price. Out of all the financial variables examined by MacDonell (2014) only CBOE Volatility Index has a significant effect. Using implied volatility indices (VIXs) of 14 developed and developing equity markets, Bouri et al. (2017b) find that bitcoin reacts positively to global uncertainty. Other studies question the effects of macroeconomic and financial variables on bitcoin.[4] Polasik et al. (2015) conclude that bitcoin is not much connected with traditional currency markets and the macroeconomy emphasizing that its returns are highly driven by popularity and attractiveness.

Popularity, commonly proxied by Google and Wikipedia trends, seems to have a more pronounced effect in the existing empirical literature. Within a LASSO framework, Panagiotidis et al. (2018) examine the significance of twenty-one potential drivers of bitcoin returns, which we also consider in this paper, and find search intensity (Google trend) to be one of the most important ones.[5] Kristoufek (2013) finds a strong bidirectional relationship between bitcoin price and both Google and Wikipedia search queries. This is confirmed for the most part in the wavelet coherence analysis of Kristoufek (2015). Employing ARDL models, Li and Wang (2017) also conclude that Google trends have a positive effect on bitcoin price both in the long and short run, where the effect is experienced with a 3-day lag, while the number of Twitter mentions only has a negative impact in the short run with a 5-day lag. They attribute the weaker and more delayed effect of Twitter mentions on their passive character and inability to significantly increase public attention. They conclude that Google trends are a better lead index for the bitcoin market. Bouoiyour and Selmi (2015) find Google trends to have a positive effect and emerge as the most important factor that drives bitcoin price. However, this positive effect is not supported by Vockathaler (2015) and Bartos (2015), while the positive effect of Wikipedia searches is confirmed by Ciaian et al. (2016a,b). Lastly, Bukovina and Marticek (2016) find sentiment to possess a minimal explanatory power for bitcoin volatility, which, nevertheless,

[4]For example, Sàfka (2014) argues that the relationship between bitcoin and the real economy is inconsistent and at most part of time insignificant. Bartos (2015) underlines that macro-financial developments have no major effect on bitcoin price. Baek and Elbeck (2015) find no influence of fundamental economic factors on bitcoin and Ciaian et al. (2016a,b) do not find evidence that macro-financial developments have an effect on bitcoin in the long run.

[5]Cretarola and Talamanca (2017) develop a theoretical bivariate continuous time model for bitcoin price dynamics where bitcoin is influenced by sentiment and confidence.

significantly increases during times of excessive volatility, while their results also show that positive sentiment is more influential for bitcoin excessive volatility. Table 1 in the appendix summarizes the existing empirical economic literature on bitcoin. To the best of our knowledge, this is the most complete presentation of the literature.

3. Data

The data employed are daily (7-day week) —as bitcoin (Coindesk Bitcoin Price Index) is traded 24–7–365. First we estimate the models in a sample covering the period from 18 July 2010 to 30 September 2016 and then we update the sample to include the period from 18 July 2010 to 31 August 2018 and re-estimate the models. The first would capture the period of rise in the price of bitcoin whereas the second the adjustment that took place subsequently. The later would allow us to compare the results from the two periods. Table 2 summarises the data, their notations and the sources for all the variables employed. Google trends data were retrieved using the R package *'gtrendsR'* and for Wikipedia trend the package *'wikipediatrend'* was used. The data for Wikipedia trend were available till the 21st of January 2016. The most recent data were filled from tools.wmflabs.org.[6] Kristoufek (2013) emphasizes the difference between interest due to positive versus negative events and finds significant asymmetries in the effects of Google and Wikipedia trends depending on whether the price of bitcoin is above or below trend (Kristoufek, 2013, 2015). We follow his intuition and

[6]Due to discrepancies in the data and different scaling between the two sources, a simple linear regression was estimated for the time period for which data from both sources was available (Pearson correlation coefficient for the common period was 0.94) and Wikipedia trend values from 21 January and on were estimated using the values from https://tools.wmflabs.org/pageviews. The explosion of the trend during 7-11th March 2015 may be associated with the Wall Street Journal's article reporting that a Silicon Valley bitcoin startup called '21' had quietly raised $116 million in venture capital with the participation of prominent names in venture capital (see /https://blogs.wsj.com/digits/2015/03/10/secretive-bitcoin-startup-21-reveals-record-funds-hints-at-mass-consumer-play/).

decompose all internet trend variables used in the analysis as follows:

$$\text{Above-trend internet feedback}_t = \text{Internet trend}_t \times D \tag{1}$$

$$\text{Below-trend internet feedback}_t = \text{Internet trend}_t \times (1 - D) \tag{2}$$

where D a dummy variable taking the value 1, when the internet trend variable is above its 7-day simple moving average and 0, when below. Google trends measure the number of searches for the term “bitcoin”; the raw data are converted to a $0 - 100$ scale and provided in this scale by Google. Similarly, Wikipedia trends measure the number of times the Wikipedia article on bitcoin has been assessed each day.

Values for variables that are not in daily frequency or are in a 5-day week frequency have been interpolated (e.g. ECB deposit facility rate has been filled with the last cited value, until a new rate is imposed, while linear interpolation was used for the policy uncertainty indices). Logarithmic first differences are used for the BPI index, stock market indices, exchange rates, Brent oil and gold; the rest of the variables are either in their levels or in logarithms.[7] Following Forbes and Rigobon (2002), we account for differences in opening hours of the stock markets by using 2-day rolling averages for all stock-market-specific variables and bitcoin returns.[8] Figure 1 plots the data.

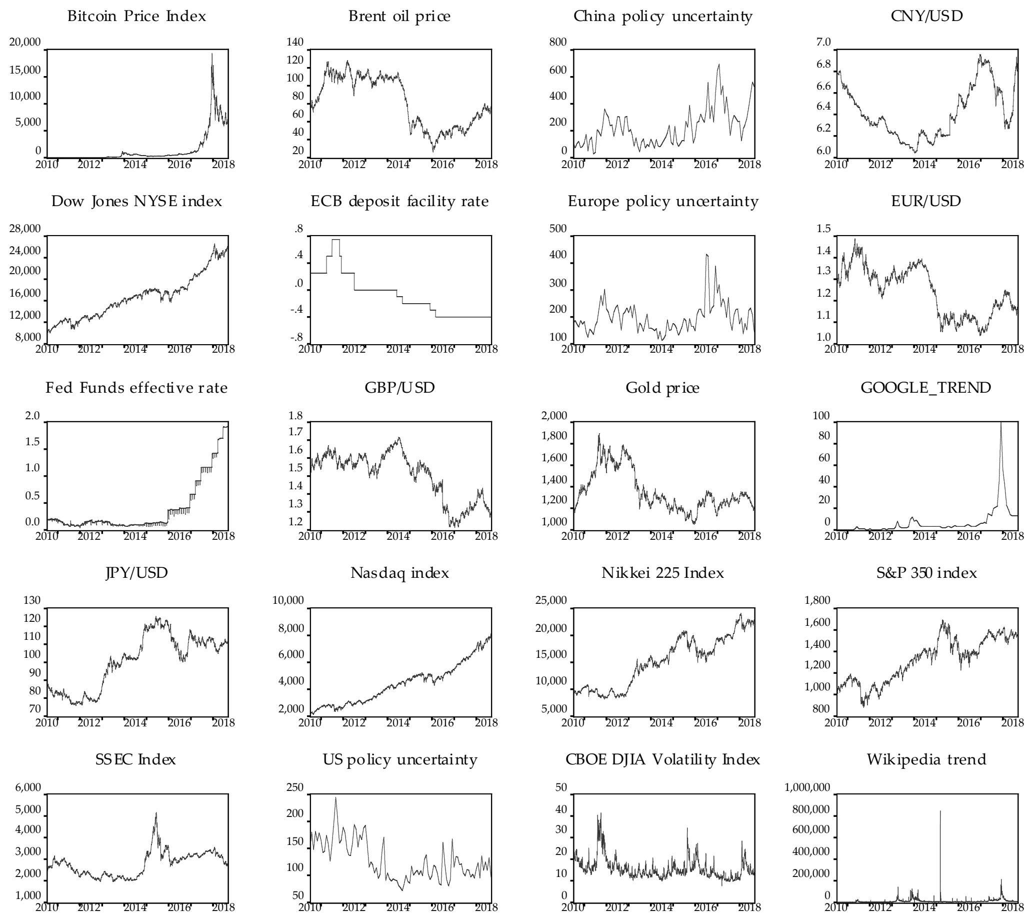
[7]Policy uncertainty indices, VXD and Wikipedia trend are in logarithms. All variables were found to be I(0) using unit root tests with and without breaks. Results are available upon request.

[8]Their results remain robust, when using daily or weekly returns. However, this may not be always the case. Becker et al. (1992) suggest that the significant correlation they trace between Japanese and lagged US stock index returns can be associated with the use of non-synchronous data. Non-synchronous trading and the importance of accounting for it have also been stressed in other studies (e.g. Miller, 2012; Výrost et al., 2015; Grigoryeva et al., 2017; Peresetsky and Yakubov, 2017).

Table 2: Variables employed, (7-day week) sample: 18 July 2010 to 31 August 2018 (number of observations: 2,967)

Variable	Related region	Source	Code
Coindesk Bitcoin Price Index (BPI)	-	coindesk.com	-
Brent oil price (in USD per barrel)	-	Quandl	FRED/DCOILBRENTEU
Gold price (in USD per troy ounce)	-	Quandl	WGC/GOLD_DAILY_USD
Fed Funds effective rate	US	Quandl	FED/RIFSPFF_N_D
ECB deposit facility rate	Europe	Quandl	BUNDESBANK/BBK01_SU0200
EUR/USD exchange rate	Europe	ECB stats	-
GBP/USD exchange rate	Europe	Quandl	FRED/DEXUSUK
CNY/USD exchange rate	China	FRED St. Louis	FRED/DEXCHUS
JPY/USD exchange rate	Japan	Quandl	FRED/DEXJPUS
Dow Jones NYSE index	US	Quandl	BCB/7809
Nasdaq index	US	Quandl	BCB/7810
Nikkei225 index	Japan	Quandl	NIKKEI/INDEX
S&P350 index	Europe	us.spindices.com	-
Shanghai Composite Index (SSEC)	China	Quandl	SGE/CHNMKT
CBOE DJIA Volatility Index (VXD)	US	Quandl	CBOE/VXD
US policy uncertainty index	US	policyuncertainty.com	-
Europe policy uncertainty index	Europe	policyuncertainty.com	-
China policy uncertainty index	China	policyuncertainty.com	-
Google trend for the term 'bitcoin'	-	R package 'gtrendsR'	-
Wikipedia trend for the article on bitcoin	-	R package 'wikipediatrend' tools.wmflabs.org/pageviews	- -

Figure 1: Levels of the variables



Note: see Table 2 for the variables employed.

4. Methodology

We employ Vector Autoregressive (VAR) models that allow us to gauge the interaction between the employed variables and bitcoin. A p-th order VAR of k endogenous variables in its standard form can be written as:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + e_t \tag{3}$$

where A_0 a $k \times 1$ vector of intercepts, A_i is a $k \times k$ matrix of coefficients, Y_t a $k \times 1$ vector of the variables at time t and e_t a $k \times 1$ vector generalization of white noise:

$$E(e_t) = 0 \quad \text{and} \quad E(e_t e_\tau') = \begin{cases} \Omega & \text{for } t = \tau \\ 0 & \text{otherwise.} \end{cases}$$

with Ω a $k \times k$ symmetric positive definite matrix.

We consider the following four alternative VAR models. The first is the standard VAR, the second is the Factor-Augmented Vector Autoregressive (FAVAR) model proposed by Bernanke et al. (2005), estimated by a two-step principal component approach, the third follows the Bai and Ng (2002) criteria to reduce the number of factors we employ in the VAR and the last model assesses the robustness of the results using principal components analysis as the first step before estimating the VAR. The number of the variables that can potentially influence bitcoin is not limited. We will consider more than one approaches to reduce the number of variables that can interact with bitcoin. Granger causality, factor analysis and principal component analysis are employed to examine as many variables as possible in the VAR specification (directly and indirectly).

In the first approach, given all the potential variables (the 20 variables listed in Table 2 except the first one) that can affect bitcoin, we start with the largest possible VAR(4)[9] that contains all the variables. We then remove variables one by one beginning from the one with the higher p-value in the no Granger causality null hypothesis test (the Schwarz criterion-SIC is reassessed after removing each variable).[10] This process leads to a VAR with 11 variables (that includes positive and negative internet feedback) and for which no Granger causality is rejected at the 10% significance level. We introduce shocks to the 10 variables (excluding bitcoin) and test how bitcoin reacts under both generalised impulse responses (GIRFs) and local projections (LPs) (Jordà, 2005, 2009).[11]

Given that this approach can suffer from mispecification, one can argue in favour of taking into account all variables by employing factor analysis. Thus, we also estimate a FAVAR with 7 lags (lag order based on SIC), where all variables are included and are reduced to 2 factors. In this way, all variables are considered and the accuracy of the estimates is improved. The model is estimated with a two-step principal component approach as in Bernanke, Boivin and Eliasz (2005). All potential variables (the 19 variables presented in Table 2) are included in the FAVAR and the IRFs of bitcoin returns to each one of them are computed.

Next, we assess whether specific regions affect bitcoin more and employ the factor analysis of Stock and Watson (2002). Including again all the variables under examination geographic-region-specific factors are created, as well as an internet trend factor combining Google and Wikipedia trends. Then, a VAR(6) (lag order based on SC) including the geographic-region-specific factors, the internet trend factor and gold and Brent oil returns is estimated, followed by generalized impulse responses and by local projections. In order to assess the robustness of the results, we estimate another VAR(3) (lag order based on SC)

[9] This is the maximum lag order for which there is no problem of a near singular matrix. All commonly used criteria suggest that 4 lags should be used.

[10] That is, we remove the variable with highest p-value in the test, reassess SIC, change lag order, where necessary, run the model again, remove the next variable and so forth, until no variable has a p-value over 10%.

[11] The results for all the estimated VAR and FAVAR models are available upon request.

using principal component analysis.[12]

Generalized impulse response analysis for the unrestricted VAR models was introduced by Pesaran and Shin (1998), where orthogonalization of shocks is unnecessary and results are invariant to the ordering of the variables. They demonstrate that major differences can exist between orthogonalized and generalized IRFs showing that for a non-diagonal error variance matrix the two coincide only for impulse responses of the shocks to the first equation in the VAR.

Local projections (LPs) were developed by Jordà (2005, 2009) as an alternative approach to estimation of IRFs that does not require specification and estimation of the true underlying multivariate dynamic system. Instead of using one set of VAR coefficients, this method estimates new coefficients for each forecast horizon to produce the IRFs. In this way, misspecification errors are not aggregated as the forecast horizon expands — as is the case with standard IRFs from a VAR.

Table 3 summarizes the alternative methodological approaches employed in this paper. The last two are more flexible in the sense that can accommodate more factors.

[12]Four PCs per region are estimated, so that the results are comparable with those of the factor analysis. Figure 10 in the appendix presents the proportion of total variance explained for each number of PCs. There is no sign in favour of opting for less than 4 PCs in the cases of Europe and China-Japan. For the US only when moving from 3 to 4 PCs the proportion explained experiences a relatively smaller increase.

Table 3: Summary of the employed methodologies

	Model	Details
(1)	Granger causality tests → selected variables in VAR, GIRFs and LPs	Variables for which no Granger causality is rejected at the 10% level included in the VAR, Jordà (2005, 2009) generalized impulse responses by local projections (LPs) estimated with marginal 90% confidence bands
(2)	Factor-Augmented VAR, IRFs	Two-step principal component approach for estimation, 2 factors, 7 lags used, 1000 bootstrap replications, central bank rates set as slow-moving variables, 90% confidence intervals for IRFs
(3)	Factor analysis → VAR using computed factors, GIRFs and LPs	Variables standardized (zero mean and unit variance) → Factor analysis carried out for each region's group of variables separately (regions divided in the US, Europe and China-Japan) and one factor for the two internet trends, (gold and Brent oil returns are used as are) using the method of asymptotic principle components, number of factors based on Bai and Ng (2002) criteria, IRFs as in the first method
(4)	Principal components → VAR using computed principal components, GIRFs and LPs	Principal components estimated using correlation matrix and ordinary measures, IRFs as in the first method

5. Results

In this section we present the results for the period 17 June 2010 to 30 September 2016. This corresponds to the period where the price of bitcoin was on the rise.

5.1. First model: standard VAR approach

In the first model, we keep only the variables which have a significant effect on bitcoin returns (based on the Granger causality tests, see Table 4). The resulting VAR consists of eleven variables (including the BPI return). Figure 2 plots the GIRFs and LPs produced by the first method.[13]

Contrary to Kristoufek (2013, 2015) and Ciaian et al. (2016a,b) shocks to Wikipedia trend do not seem to affect bitcoin (both when the latter is above and below trend). Kristoufek (2013, 2015) finds that during episodes of explosive prices, interest drives prices further up, and during rapid declines, it pushes them further down. However, the results of the first model do not support these findings serving as evidence that bitcoin is now less driven by investor's interest and is less susceptible to bubbles. When bitcoin is above trend (see Equation 1), only Google trend shocks appear to have a significant impact. This significant positive impact is in agreement with the results of Panagiotidis et al. (2018).

In line with Dyhrberg (2016a,b), who finds similarities in the behaviour of gold and bitcoin, shocks to gold appear to have a positive effect on BPI return, which, however is reversed later as the horizon increases. A depreciation of the Yen relative to the USD can lead to a positive and persistent response of bitcoin turning negative in the ninth day after the shock. Positive responses to Dow Jones and Nasdaq shocks may reveal some degree of interconnection with traditional financial markets corroborating recent studies (e.g. Dyhrberg, 2016a,b; Wang et al., 2016) in contrast to earlier ones finding little or no relationship (e.g.

[13]Granger causality tests results are presented in Table 4. All VAR and FAVAR results are available upon request.

Table 4: VAR(7) Granger Causality Wald Tests

Sample: 7/27/2010 to 9/30/2016, Obs: 2,258			
Excluded	Chi-sq	df	Probability
JPY/USD 2-day return	36.25897	7	0
2-day log CBOE VXD	15.45391	7	0.0306
Nasdaq 2-day return	14.52716	7	0.0426
Dow Jones NYSE 2-day return	19.20873	7	0.0076
Log China policy uncertainty	27.02677	7	0.0003
Log US policy uncertainty	14.68776	7	0.0402
Positive Google feedback	33.86439	7	0.0000
Positive Wikipedia feedback	12.83197	7	0.0763
Negative Wikipedia feedback	14.22556	7	0.0473
Gold 2-day return	32.20149	7	0
All	172.1599	56	0

Note: lag length order based on SIC. The null hypothesis of no Granger causality is examined. The *p*-values are coming from re-estimating VAR models deleting one variable at a time.

Ennis, 2013). This connection is also supported by the negative response to a shock to CBOE VXD suggesting that increased volatility in traditional markets negatively affects bitcoin. MacDonell (2014) finds similar results for CBOE VXD and suggests that this finding may imply that investors turn to bitcoin, whose high volatility offers opportunities for speculation, when volatility in traditional markets is low.

Lastly, increased policy uncertainty in China seems to have a pronounced negative impact on bitcoin returns based on both the GIRFs and LPs; this negative effect is also captured in the analysis by Panagiotidis et al. (2018). Bouoiyour and Selmi (2015) have traced the impact of the Chinese market through bitcoin's dependence to the Shangai stock market. Our results also reveal the role of Chinese policy uncertainty, not previously examined in the existing literature.

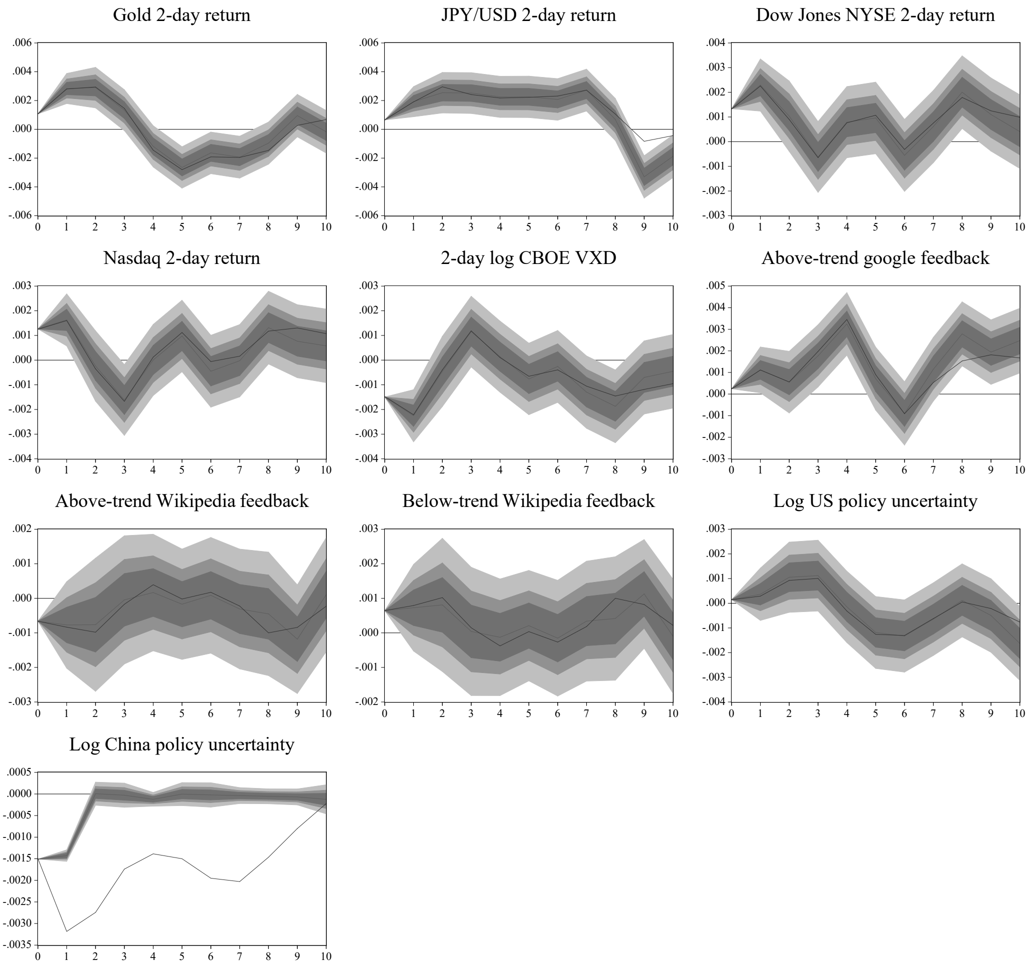
5.2. Second model: FAVAR approach

Figure 3 shows the IRFs computed using the FAVAR model.[14] The results for Google trend remain qualitatively the same, as Google trend shocks have a statistically significant impact on bitcoin only when it is above trend. Nevertheless, in this model bitcoin seems to respond to Wikipedia trend shocks as well, but the effect is positive both when bitcoin is below and above trend, which does not support the earlier findings of Kristoufek (2013, 2015).

The positive response to gold shocks is confirmed in the second method[15], as is the connection of bitcoin with traditional markets. In this model, bitcoin reacts positively to shocks on Dow Jones, Nasdaq, the Shanghai Composite Index (SSEC), S&P350 and possibly Nikkei225. However, it now also reacts positively to uncertainty shocks in traditional markets, as proxied by the VXD. Such a response could be explained as investors would be tempted by the relative lower

[14]The estimated FAVAR model is available upon request.
[15]The response to gold shocks is robust to all four models. Gold has been identified as one of the most important factors for bitcoin by (Panagiotidis et al., 2018).

Figure 2: Model 1, VAR(7) GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 50%, 70% and 90% confidence intervals in red. For more on Model 1 see Table 3.

volatility of bitcoin (increased volatility in traditional markets and constantly high volatility of bitcoin would make the differential lower). In the FAVAR, bitcoin does not respond to shocks to any of the four exchange rates, while the standard VAR only traces a response to JPY/USD shocks indicating lack of interaction with the traditional currency markets, as Polasik et al. (2015) also concludes. Nonetheless, the results contradict those of Dyhrberg (2016a,b), who finds USD/EUR and USD/GBP exchange rates to affect bitcoin.

Bitcoin reacts positively to an oil shock, while in Models 3 and 4, only a minimal positive response may be traced. Given that the null of no Granger causality is not rejected in the first model, this weak evidence of a positive response is in agreement with the results of the VECM employed by Wang et al. (2016). Bouri et al. (2017c) also find a weak relationship suggesting that bitcoin can only act as a diversifier for oil.

An increase in the federal funds rate appears to have a positive impact on bitcoin. Dyhrberg (2016b), who also traces this effect, suggests that a raise in the federal funds rates and the subsequent appreciation of the US dollar will cause online purchases to rise. This will result in increased demand for bitcoin, given its role in the international online trade. This explanation focuses on the bitcoin as a medium of exchange, while it assumes that US consumers use bitcoin in their transactions more than the average foreign consumer, who will reduce their international online purchases when their national currency depreciates.[16] From the investment side, interest rate increases confine access to borrowed funds for businesses, raising their cost of debt and suppressing profits, thus, making investors willing to turn from equities to bitcoin.

On the other side, a shock to the ECB rate poses a delayed, but persistent negative impact on bitcoin. This can be explained in Dyhrberg's (2016b) manner, providing that eurozone consumers use bitcoin in transactions less than the ones

[16] Regional data cannot be available due to the anonymity of transactions using bitcoin.

in the US and other non-EU countries.[17] In fact, the delayed and persistent response to an ECB rate shock is consistent with the exchange side explanation, given the time frame between an interest rate increase and the lasting effect on exchange rates and international prices, while the immediate and short response to a federal funds rate shock with the investment side one, as investors' can make a quick and one-off adjustment to the new expectations formed due to the interest rate rise.

Bitcoin's response to policy uncertainty shocks is positive for all three regions (US, Europe and China). This could be explained in a similar manner as the response to VXD; as policy uncertainty affects traditional markets, bitcoin's volatility will not be seen as deterring a factor to invest in bitcoin. These novel results highlight the nature of bitcoin as an alternative asset[18] not (or weakly) affected by the macroeconomy as previously argued (e.g. Bartos, 2015; Baek and Elbeck, 2015; Polasik et al., 2015; Elendner et al., 2016; Ciaian et al., 2016a,b) . However, the result for China comes in disagreement with the effect captured in the standard VAR.

The summary of the results from the second model are as follows. First, in contrast to the first one, it captures some Wikipedia trend effects, while it also strengthens the results of the first model in regards to the reduced tendency of internet trends to aggravate bitcoin's behavior in the manner suggested by Kristoufek (2013, 2015) and Cretarola and Talamanca (2017). Second, it corroborates the results for gold and oil of the standard VAR, while it provides further evidence on the degree in which bitcoin is connected with traditional

[17]Bitcoin trading volume by currency could serve as evidence corroborating the view that EU-consumers use bitcoin in transactions less than others; see for example https://data.bitcoinity.org.

[18]Skully (2007) defines alternative assets, by identifying the original asset to which the alternative refers and then finding a major difference —in his analysis, the difference is in liquidity. In this context, given the high liquidity of bitcoin, its major differences with traditional assets and currencies lie on the lack of regulation, ultimate anonymity and decreased co-dependence with the macroeconomy and traditional financial markets. For an analysis of bitcoin as an alternative investment vehicle, see Hong (2016).

stock markets and on the weak interaction with currency markets. Third, it has offered evidence regarding the effects that the Federal funds and the ECB rates can have on bitcoin through international online trade and equity markets. Lastly, the positive responses to policy uncertainty shocks it has traced serve as evidence of the weak relationship with the macroeconomy, not captured in the first model. This result contradicts those by Demir et al. (2018), who find that bitcoin returns are generally negatively associated with increases in policy uncertainty in Europe; nevertheless, they trace a positive and significant at the higher quantiles.

The results are summarized in Table 5. The sign of the first IRF for bitcoin to shocks in the examined variables (at the 10% level of significance) is presented based on the first two models. It is evident that gold (positive response), Dow Jones (positive response), Nasdaq (positive response) and above trend Google feedback (positive response) emerge as affecting bitcoin under both specifications (unrestricted VAR and FAVAR). Dastgir et al. (2018) also find a relationship between Google trend and bitcoin returns; they uncover a bi-directional relationship which mainly exists in the tails of the distribution.

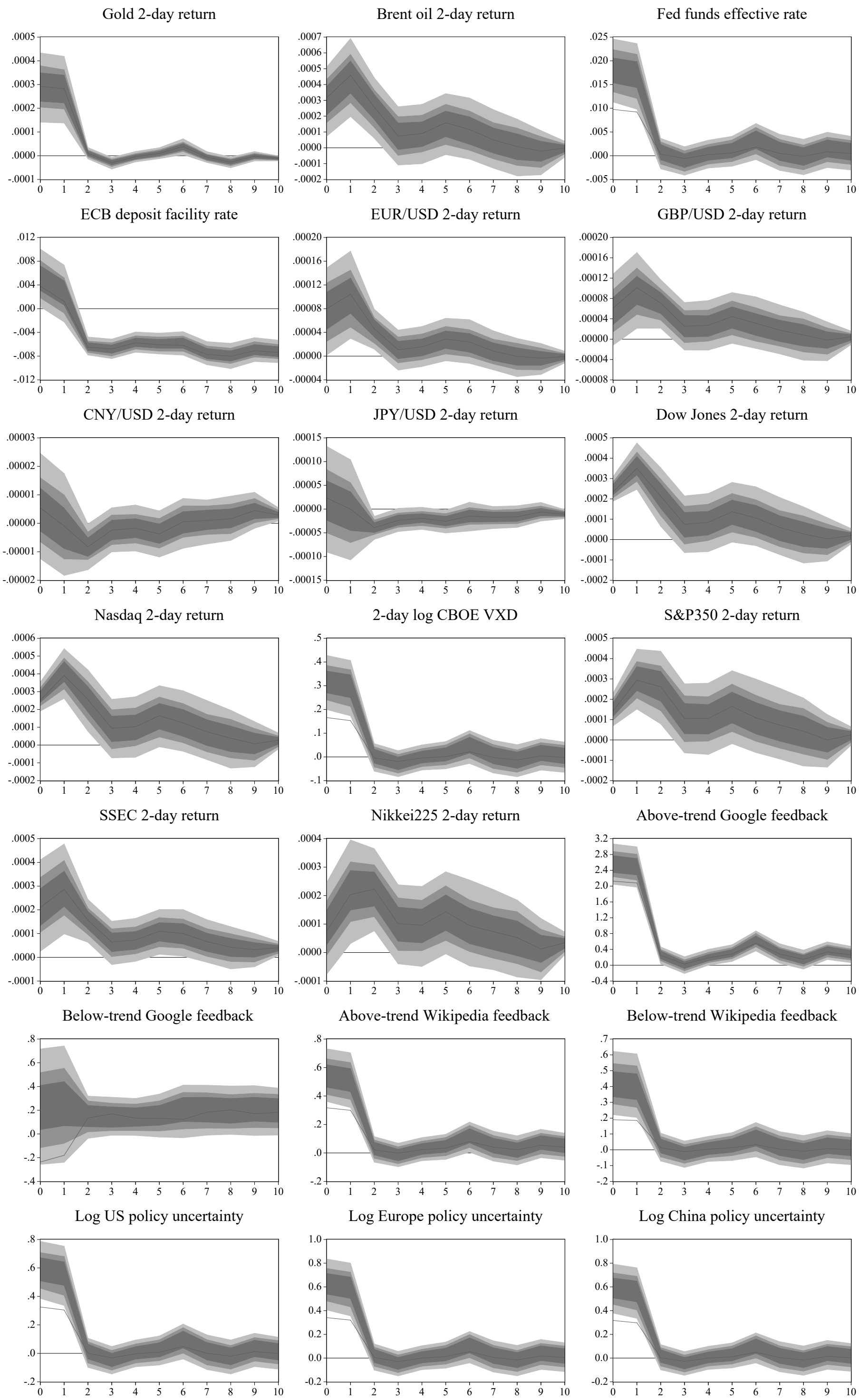
5.3. Third and fourth model: VARs with factor analysis and principal component analysis

This section aims to reduce the number of variables in the VAR using factor analysis and principal component analysis assessing whether specific regions affect bitcoin more.[19] Table 6 summarizes the results with regard to the regional markets.[20] It shows the number of factors/principal components that bitcoin has

[19]These two models are the most flexible ones, as they can handle more factors and in this sense offer more. Although the four models are not directly comparable (for example, Groen and Kapetanios (2013) show that in FAVAR modelling standard information criteria, such as SIC, are not consistent estimators of the true dimension of the relevant factor space), the adjusted R^2 for the bitcoin equation in the four cases are: (1) 0.5093, (2) 0.45965, (3) 0.49598 and (4) 0.40235.

[20]Table 8 in the appendix presents the Bai and Ng (2002) criteria for the number of factors.

Figure 3: Model 2, Bernanke et al. (2005) FAVAR IRFs of BPI 2-day return to



Note: IRFs with 50%, 70% and 90% confidence intervals in red. For more on Model 2 see Table 3.

Table 5: Effects on bitcoin from shocks to variables

Variable	Models (1)	Models (2)
Brent oil price (in USD per barrel)	NG	+
Gold price (in USD per troy ounce)	+	+
Fed Funds effective rate	NG	+
ECB deposit facility rate	NG	INS
EUR/USD exchange rate	NG	INS
GBP/USD exchange rate	NG	INS
CNY/USD exchange rate	NG	INS
JPY/USD exchange rate	+	INS
Dow Jones NYSE index	+	+
Nasdaq index	+	+
Nikkei225 index	NG	INS
S&P350 index	NG	+
Shanghai Composite Index (SSEC)	NG	+
CBOE DJIA Volatility Index (VXD)	-	+
US policy uncertainty index	INS	+
Europe policy uncertainty index	NG	+
China policy uncertainty index	-	+
Above-trend Google feedback	+	+
Below-trend Google feedback	NG	INS
Above-trend Wikipedia feedback	INS	+
Below-trend Wikipedia feedback	INS	+

Notes: NG stands for no Granger causality (for the variables not included in the first model), while INS,+ and - for insignificant, positive and negative impulse responses, respectively (sign of the first response). Models (1) and (2) refer to the ones described in Table 3.

a significant positive/negative local impulse response to shocks to (at the 10% level of significance) based on the last two models. China-Japan region has 3 significant factors/principal components in the two models[21], the USA 2, while Europe significantly reacts to 2 factors in Model 3 and only to one PC in Model 4. Table 7 presents the variance decomposition of bitcoin returns for models 3 and 4.[22] It shows that after 10 days the share of China is more than double and around quintuple of Europe and the US, respectively in the factor, while in the VAR with the PCs the share of China is around double of the others. Shocks to internet trend factors have no significant effect on bitcoin, while in principal components analysis, above (below)-trend internet feedback shocks have only a delayed positive (negative) effect on bitcoin.

These last two models offer valuable additional evidence.[23] First, they corroborate the positive responses to gold and oil shocks captured previously and the diminished effect of internet trends on bitcoin relative to earlier studies, as well as their weakened role in bitcoin's bubble behavior. More importantly, the geographical-region-specific factor analysis implemented provides new evidence not traced in the FAVAR, nor in the standard VAR. The results of the last two models can serve as evidence of the increased impact of the Asian markets —represented by China and Japan— on bitcoin compared to the US and the European markets. This comes in agreement with the fact that the largest share of bitcoin tracing volume has recently been denominated in Chinese Yuan.[24] Combined with the evidence of the effect of Chinese policy uncertainty and the frequent—and often unpredictable—interventions of Asian regulatory authori-

[21]In Model 3 bitcoin has a significant positive response to 3 factors. In Model 4 it has a significant positive response to 2 PCs and a negative one to one PC.

[22]See Table 3 for details about the differences between the models.

[23]The findings of the last two models are in agreement and they are in some sense adding to the findings of the first two that are more in line with the previous literature. Even though we have not formally tested the 4 models against each other, we claim that the last two models offer more as they are more flexible and can handle more factors.

[24]For example, see https://data.bitcoinity.org.

ties on cryptocurrencies and bitcoin,[25] this result stresses the role of the Asian markets in bitcoin developments.

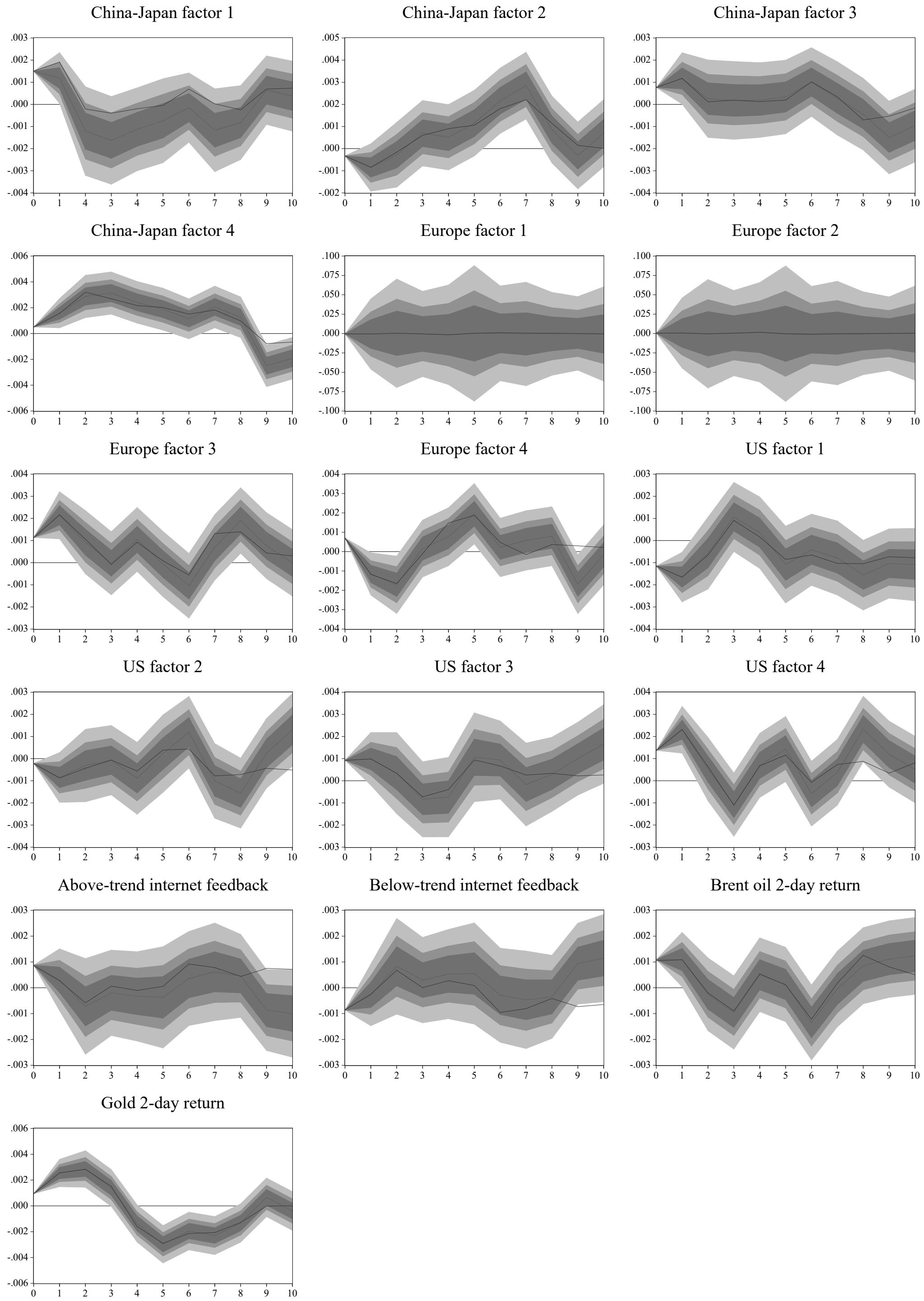
Table 6: Regional market effects on bitcoin

	Models					
	(3)			(4)		
Markets	# of +	# of -	# of INS	# of +	# of -	# of INS
China-Japan	3	0	1	2	1	1
US	1	1	2	2	0	2
Europe	1	1	2	1	0	3

Notes: the three columns under each model show the number of factors/principal components, which bitcoin has a positive, negative or insignificant local impulse response to. Models (3) and (4) are presented in Table 3 and the number of significant responses is derived from Figures 4 and 5.

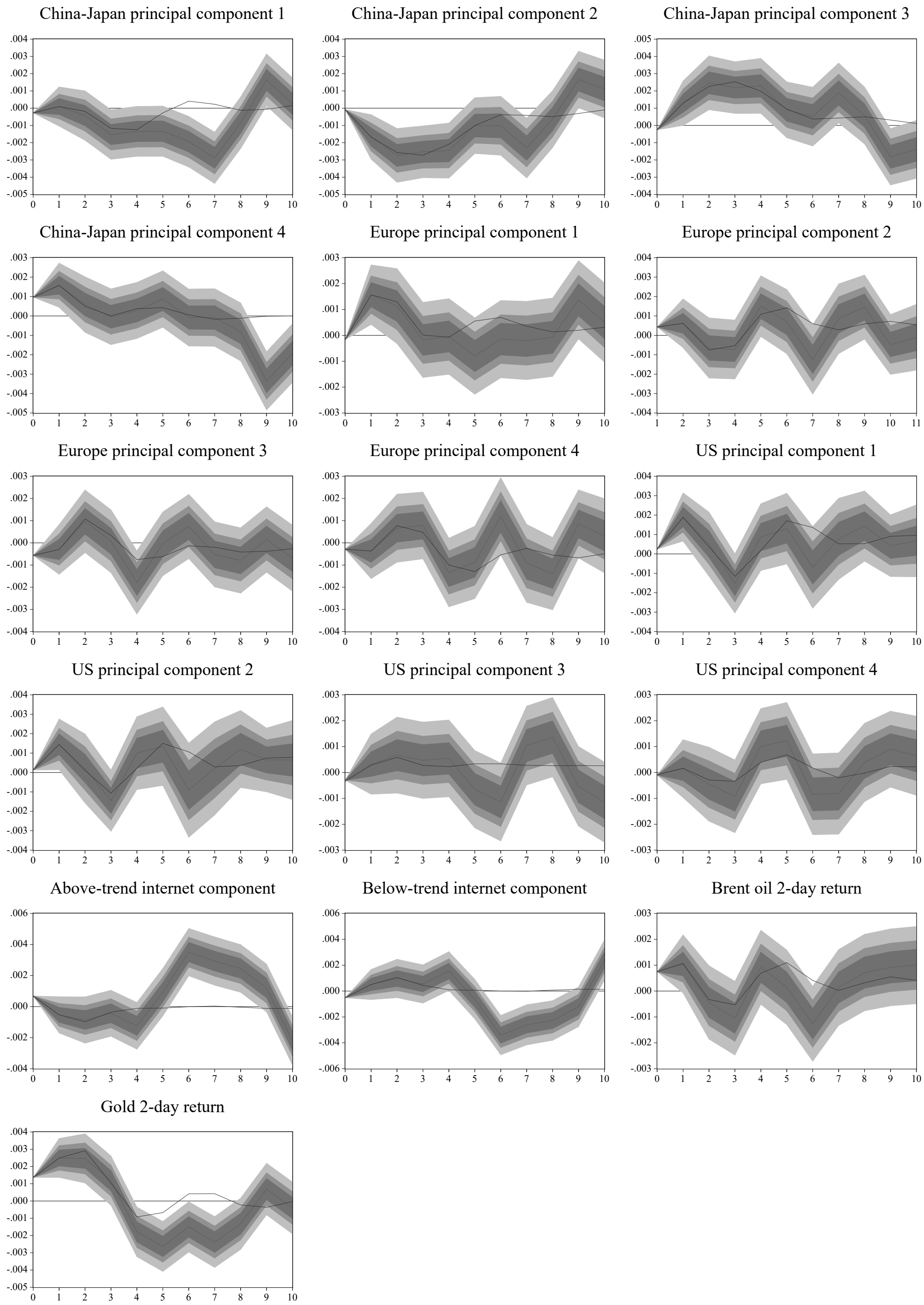
[25] For example, see the following on regulatory interventions in China, Japan and Singapore: https://www.coindesk.com, https://www.forbes.com, https://www.forbes.com, https://www.forbes.com, https://www.coindesk.com, https://www.reuters.com, https://www.ft.com, https://www.theguardian.com, https://www.bloomberg.com, https://www.telegraph.co.uk, https://www.bbc.com.

Figure 4: Model 3, VAR(6) after factor analysis GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 50%, 70% and 90% confidence intervals in red. For more on Model 3 see Table 3.

Figure 5: Model 4, VAR(3) with principal components GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 50%, 70% and 90% confidence intervals in red. For more on Model 4 see Table 3.

Table 7: Variance decomposition of BPI 2-day return for models (3) and (4)

Models	Period	BPI	China-Japan	Europe	US	Internet	Brent oil	Gold
(3)	1	100	0	0	0	0	0	0
	2	99.44	0.19	0.22	0.03	0.01	0.01	0.09
	3	97.88	1.03	0.41	0.10	0.13	0.03	0.43
	4	96.88	1.61	0.42	0.29	0.17	0.06	0.56
	5	95.70	2.02	0.79	0.34	0.42	0.07	0.66
	6	94.39	2.40	0.98	0.54	0.59	0.07	1.02
	7	93.42	2.83	1.04	0.64	0.62	0.14	1.30
	8	92.31	3.38	1.24	0.70	0.66	0.14	1.58
	9	91.82	3.55	1.42	0.72	0.68	0.19	1.62
	10	91.62	3.63	1.45	0.76	0.72	0.22	1.62
(4)	1	100	0	0	0	0	0	0
	2	99.21	0.24	0.27	0.17	0.06	0.00	0.05
	3	98.02	0.71	0.52	0.26	0.13	0.02	0.35
	4	97.38	1.17	0.51	0.38	0.14	0.02	0.39
	5	96.84	1.46	0.63	0.43	0.14	0.04	0.45
	6	96.56	1.50	0.76	0.50	0.14	0.05	0.50
	7	96.38	1.52	0.81	0.61	0.14	0.05	0.50
	8	96.30	1.53	0.82	0.65	0.14	0.05	0.51
	9	96.24	1.55	0.84	0.67	0.14	0.05	0.51
	10	96.15	1.55	0.87	0.70	0.15	0.06	0.52

Note: China, Europe and US refer to aggregated effects of their factors/principal components in models (3) and (4), which correspond to Figures 4 and 5 respectively.

6. Updated sample results

In this section we update the sample to include the period 17 June 2010 to 31 August 2018 and re-estimate the models following the same methodology as before. The sample includes the period where the adjustment in the price of bitcoin took place.

6.1. First model: standard VAR approach

In the first model, we again keep only the variables which have a significant effect on bitcoin returns (based on the Granger causality tests, see Table 8). The resulting VAR consists of nine variables (including the BPI return). Figure 6 plots the GIRFs and LPs produced by the first method.

The results in the updated sample are in accordance with those in the first sample. All variables that have survived in the VAR(5) (see 8) are also included in the VAR(7) estimated on the first sample (see Table 4) with the exception of Negative Google feedback, instead of which the VAR(7) includes Positive Google Feedback. Furthermore, the estimated IRFs are very similar for the two samples; Tables 5 and 9 show that the signs of the IRFs for the first period always agree in the models for the two samples for the cases where the IRFs are significant—the only differences are for JPY/USD, China policy uncertainty and above-trend Google feedback, which induce a significant response of bitcoin returns in the first sample, but not in the updated one.

6.2. Second model: FAVAR approach

Figure 7 shows the IRFs computed using the FAVAR model.[26] The results are summarized in Table 9.

The results of the FAVAR in the updated sample agree with those in the first sample. Comparing Tables 5 and 9 we again observe that the signs of the IRFs

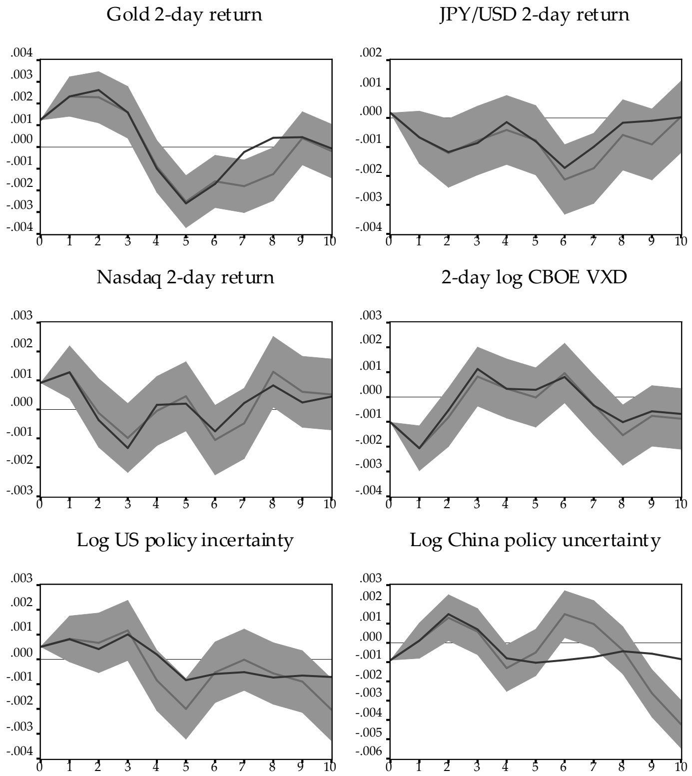
[26]The estimated FAVAR model is available upon request.

Table 8: VAR(5) Granger Causality Wald Tests

Sample: 7/25/2010 to 8/31/2018, Obs: 2,960			
Excluded	Chi-sq	df	Probability
Dow Jones NYSE 2-day return	12.4395	5	0.0292
Gold 2-day return	31.1436	5	0
Negative Google feedback	19.3092	5	0.0017
JPY/USD 2-day return	16.8656	5	0.0048
Log China policy uncertainty	12.1255	5	0.0331
Log US policy uncertainty	25.2258	5	0.0001
2-day log CBOE VXD	15.0933	5	0.01
Nasdaq 2-day return	11.1607	5	0.0483
All	126.712	40	0

Note: lag length order based on SIC. The null hypothesis of no Granger causality is examined. The p-values are coming from re-estimating VAR models deleting one variable at a time.

Figure 6: Model 1, VAR(5) GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 90% confidence intervals in red. For more on Model 1 see Table 3.

for the first period always agree in the models for the two samples for the cases where the IRFs are significant—the only differences are for SSEC, which bitcoin returns react positively and significantly to based on the first sample, but not in the updated one, and for ECB deposit facility rate, EUR/USD and below-trend Google feedback, which induce a significant response to bitcoin returns in the updated sample, but not in the first one.

6.3. Third and fourth model: VARs with factor analysis and principal component analysis

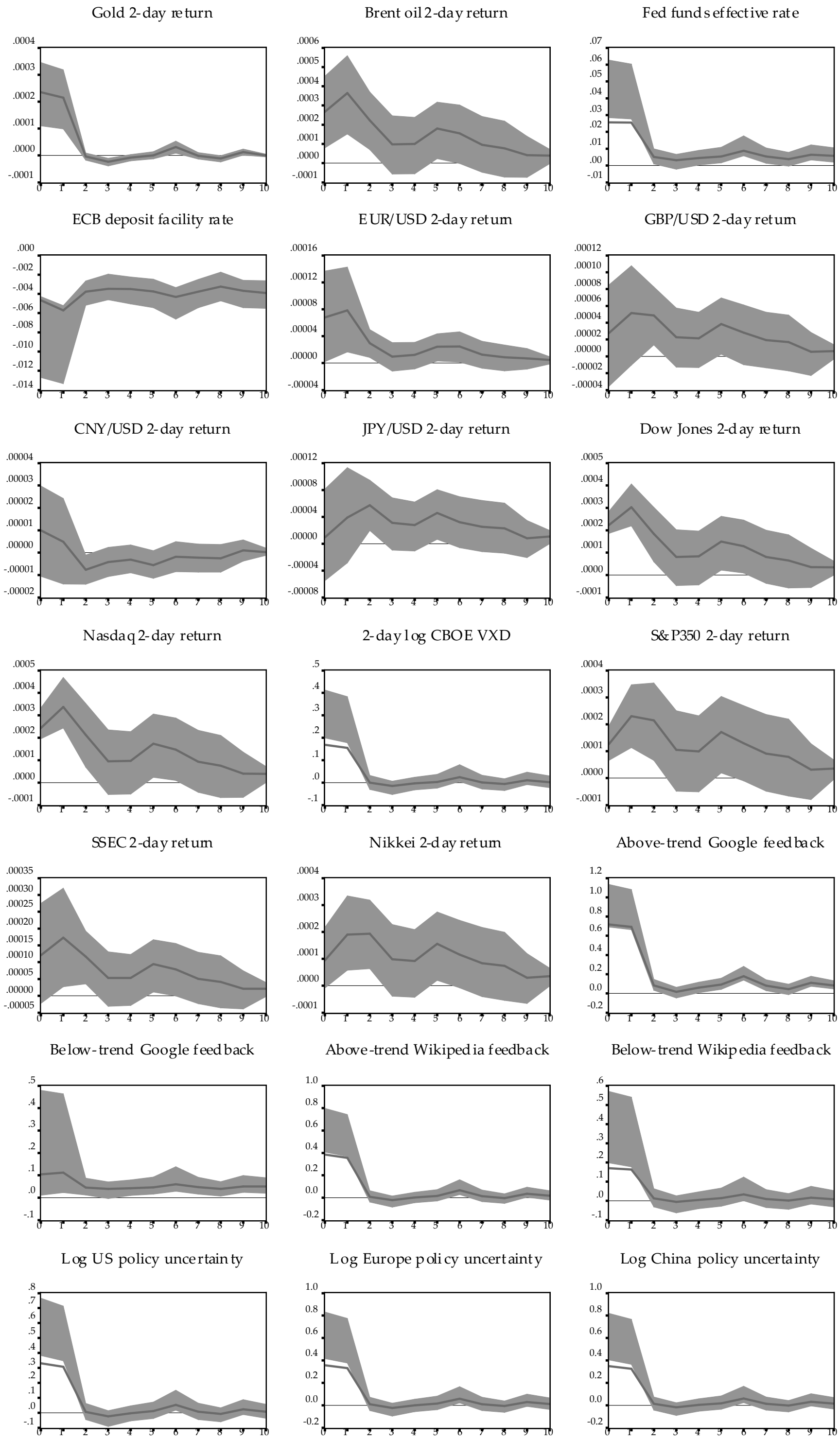
Table 10 summarizes the results with regard to the regional markets. In this case, the results deviate when compared to those of the first sample. Table 10 shows that China and Japan appear to have a reduced impact based on the updated sample when the results are compared to those of the first sample (see Table 10). The significance of the European market appears relatively unchanged, while that of the US increased.

This comes in accordance with the development and expansion of the bitcoin market, as in its first phase it was dominated by China and, more broadly, Asia. The hike of bitcoin during 2016 has often been attributed to the Chinese market; however, in late 2016-early 2017, Chinese regulatory authorities took strong measures to control the market.[27] This was accompanied by a sudden contraction of CNY's share in bitcoin trading volume and a rapid expansion of USD's share, which took place during the very first months of 2017; the shares in January 2017 were 96.3% and 2%, respectively, a month later 24.4% and 40.9% and by November 2017 the picture had changed completely with corresponding shares 0.1% and 70.1%.[28] Given that our first sample covers the

[27] See for example https://www.businessinsider.com, https://www.ft.com and footnote 25.

[28] See https://data.bitcoinity.org/markets/volume/. Recently there have also been favorable developments for bitcoin in the US; for instance, Goldman and Intercontinental Exchange (ICE), parent company of the New York Stock Exchange, has been working on an online trading platform that would allow large investors to buy and hold bitcoin (see https://www.nytimes.com/) and Goldman Sachs has made preparations to trade contracts

Figure 7: Model 2, Bernanke et al. (2005) FAVAR IRFs of BPI 2-day return to



Note: IRFs with 90% confidence intervals in red. For more on Model 2 see Table 3.

Table 9: Effects on bitcoin from shocks to variables

Variable	Models (1)	Models (2)
Brent oil price (in USD per barrel)	NG	+
Gold price (in USD per troy ounce)	+	+
Fed Funds effective rate	NG	+
ECB deposit facility rate	NG	-
EUR/USD exchange rate	NG	+
GBP/USD exchange rate	NG	INS
CNY/USD exchange rate	NG	INS
JPY/USD exchange rate	INS	INS
Dow Jones NYSE index	+	+
Nasdaq index	+	+
Nikkei225 index	NG	INS
S&P350 index	NG	+
Shanghai Composite Index (SSEC)	NG	INS
CBOE DJIA Volatility Index (VXD)	-	+
US policy uncertainty index	INS	+
Europe policy uncertainty index	NG	+
China policy uncertainty index	INS	+
Above-trend Google feedback	NG	+
Below-trend Google feedback	INS	+
Above-trend Wikipedia feedback	INS	+
Below-trend Wikipedia feedback	INS	+

Notes: NG stands for no Granger causality (for the variables not included in the first model), while INS,+ and - for insignificant, positive and negative impulse responses, respectively (sign of the first response). Models (1) and (2) refer to the ones described in Table 3.

period until September 2016, while the second is extended to August 2018, the shift of significance from the Asian market to the US market documented in the results of the third and fourth models is strongly supported.

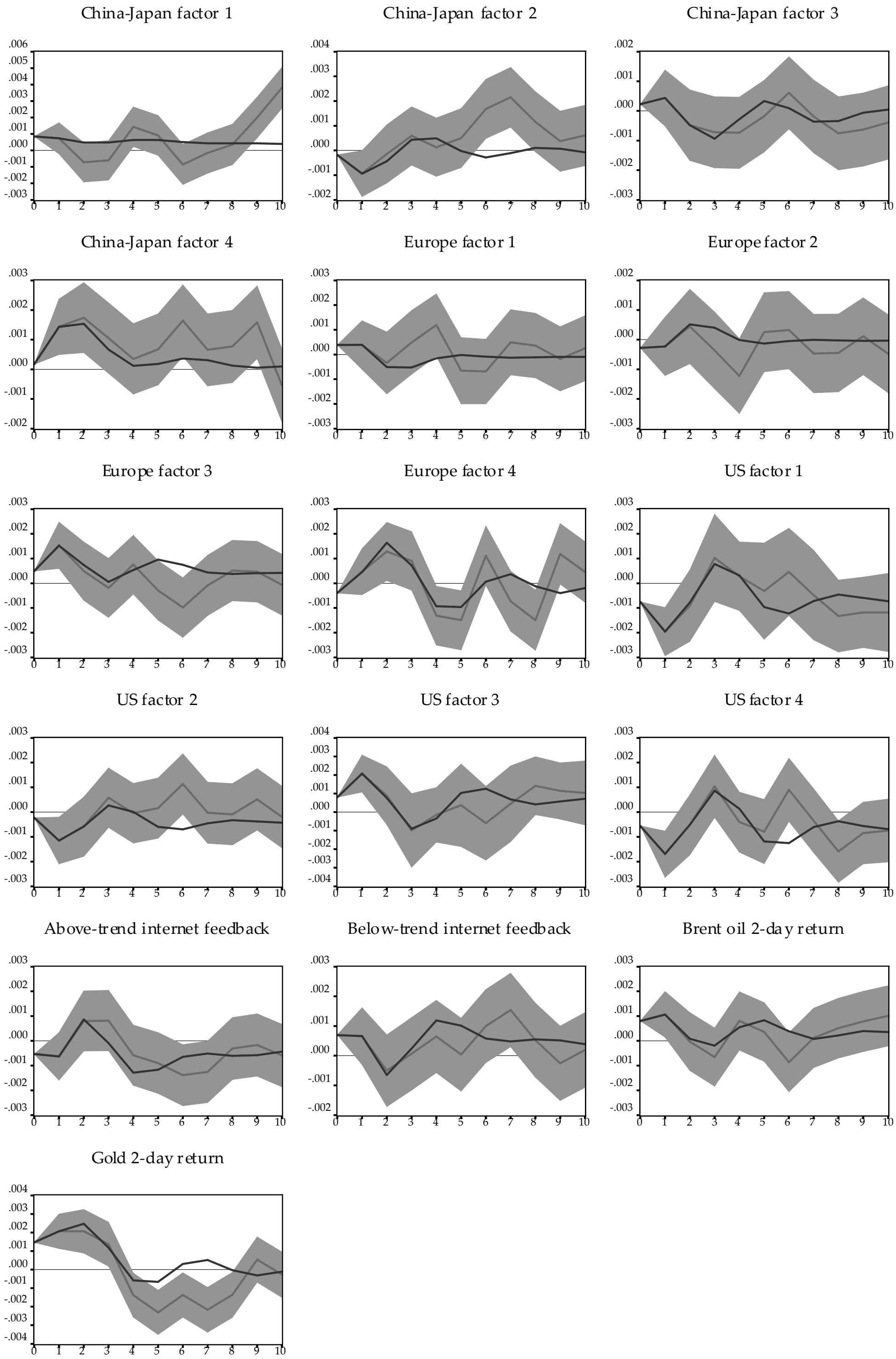
Table 10: Regional market effects on bitcoin

	Models					
	(3)			(4)		
Markets	# of +	# of -	# of INS	# of +	# of -	# of INS
China-Japan	1	1	2	1	0	2
US	1	3	0	2	1	1
Europe	1	0	3	2	0	2

Notes: the three columns under each model show the number of factors/principal components, which bitcoin has a positive, negative or insignificant local impulse response to. Models (3) and (4) are presented in Table 3 and the number of significant responses is derived from Figures 8 and 9.

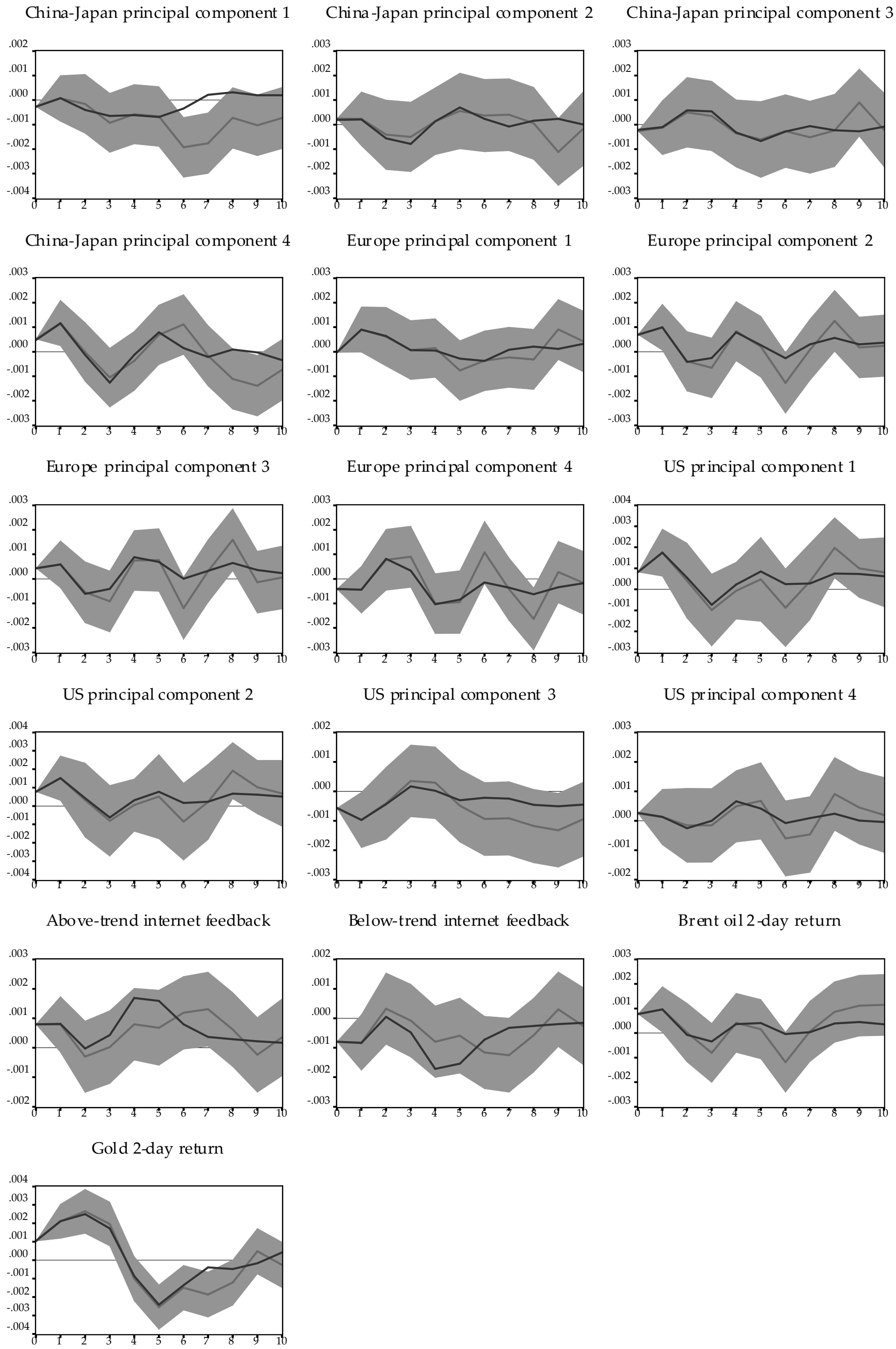
linked to the price of bitcoin with its clients (see https://www.nytimes.com/).

Figure 8: Model 3, VAR(3) after factor analysis GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 90% confidence intervals in red. For more on Model 3 see Table 3.

Figure 9: Model 4, VAR(4) with principal components GIRFs of BPI 2-day return to



Note: GIRFs in blue and Jordà (2005, 2009) LPs with 90% confidence intervals in red. For more on Model 4 see Table 3.

7. Concluding remarks

This study examines the response of bitcoin returns to shocks generated in the financial markets, uncertainty indices and search intensity. We provide an extensive review of the empirical literature on bitcoin. Given that the number of variables needs to be reduced, we employ four alternative models: (i) a standard VAR with Granger causality, (ii) a FAVAR, (iii) factor analysis and (iv) principal components analysis. These procedures result in four alternative VAR models. Generalized and local impulse response functions are produced to assess the effect of a number of variables (19 in total) on bitcoin returns.

Compared to previous studies, our results show a reduced impact of popularity (search intensity), proxied by Google and Wikipedia trend, on bitcoin. In this sense, internet trends seem to be now less likely to aggravate bitcoin bubbles. Gold shocks appear to have a robust positive effect on bitcoin, while there is also some evidence of a positive response to oil. We trace a considerable degree of connection with traditional financial markets, as bitcoin reacts to shocks in these (especially Dow Jones and Nasdaq) and to uncertainty shocks in the traditional markets, indexed by the CBOE VXD. However, the results for volatility (VXD) are mixed.

On the other side, weak influence from the currency markets is traced, as out of the four exchange rates examined, we find only some evidence of a positive response to a Yen depreciation. The results also show that bitcoin may react positively to a federal funds rate rise, but negatively to one in the ECB deposit facility rate. The first has been attributed to the increased online purchases using bitcoin caused by a federal funds rate hike and the subsequent appreciation of the US dollar (Dyhrberg, 2016b). However, such an argument is hard to corroborate, as transactions using bitcoin are anonymous and, thus, no regional data are available. Therefore, further research on bitcoin's response to central bank rates shocks is required.

Bitcoin's response to the US and European policy uncertainty shocks is positive. These results may suggest that increased policy uncertainty increases volatility in traditional markets rendering bitcoin's returns more attractive. The latter emphasizes the nature of bitcoin as an alternative asset minimally affected by the macroeconomy. Although policy uncertainty in China appears to have a pronounced impact on bitcoin, the sign of the effect is not robust.

Lastly, we employ factor and principal component analyses to provide systematic evidence on the effects of different geographically defined markets on bitcoin. Shocks in Asian markets, represented by China and Japan, appear to have the most pronounced impact, those in the USA a moderate one, while shocks in the European market seem to have a less important impact on bitcoin. Combined with the frequent interventions of Asian regulatory authorities on bitcoin, this result highlights the importance of Asian markets for bitcoin. Nevertheless, when the most recent sample is taken into account, the significance of the Asian market for bitcoin appears reduced, while that of the US enhanced, which is in agreement with the sudden contraction of CNY's share in bitcoin trading volume in early 2017 after Chinese regulatory authorities' intervention and the simultaneous rapid expansion of USD's share.

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A. Appendix

Table 1: Econometric literature on bitcoin in chronological order

Authors	Period	Empirical Results
van Wijk (2013)	July 19th 2010 to June 13th 2013 (759 daily obs.)	Dow Jones, EUR/USD and WTI oil price significantly affect Bitcoin in the long run. Dow Jones Index in the short run. Most influencing variables related to the U.S.
Ennis (2013)	July 19th 2010 to June 21st 2013 (717 daily obs.)	Bitcoin statistically independent of equity and bond markets. Bitcoin has a (weak) hedge and safe haven role for sovereign debt markets in the US and Europe and for the euro, but not dollar.
Kristoufek (2013)	May 1st 2011 to June 30th 2013 (788 daily obs. for Wikipedia, 113 weekly obs. for Google)	Strong correlation between bitcoin and both search queries. When prices high (i.e. above trend), increasing interest pushes them further up and when below trend, even deeper resulting in frequent emergence of bubble behaviour
Sàfka (2014)	July 17th 2010 to February 25th 2014 (1,320 daily obs., 1st of August 2010 to 7th of February 2014 used)	Incorporating structural breaks important for the explanation of conditional heteroskedasticity of bitcoin. Relationship between bitcoin and real economy indicators inconsistent and mostly insignificant in time.
Garcia et al. (2014)	Data for the whole bitcoin block chain up to November 5th 2013 (daily)	Two positive feedback loops lead to price bubbles: one driven by word of mouth and the other by new Bitcoin adopters. Spikes in information search precede drastic price declines.
Fink and Johann (2014)	January 1st 2011 to May 22nd 2014 (two datasets of 1,275,126 and 137,410 per minute obs.)	Bitcoin experienced extreme returns at high volatility. Price not informationally efficient. Market fragmentation and liquidity increased in the last years. Price determined by investors' attention, user and transaction characteristics. Bitcoin cannot be considered a currency.
MacDonell (2014)	July 18th 2010 to August 25th 2013 (163 weekly obs. plus 22 for out-of-sample tests)	Bitcoin mostly an investment vehicle. Speculation the primary force driving bitcoin values.

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Table 1 – continued from previous page

Authors	**Period**	**Empirical Results**
Huhtinen (2014)	July 17th 2010 to January 31th 2014 (1,289 daily obs.)	Momentum effect in price returns. Inflationary effect caused by increasing supply. Network hash rate found to forecast future bitcoin returns. Unpredictable speculative element of bitcoin valuation dominates utility valuation.
Vagstad and Valstad (2014)	January 1st 2014 – February 28th 2014 (ultra-high frequency; 873,560 obs. for bitcoin; over 10 million for gold)	Bitcoin far more risky than Gold and EUR. Applicability as medium of transaction challenged, but risk not large enough to outweigh potential benefits.
Glaser et al. (2014)	January 1st 2011 to October 8th 2013 (998-1,005 daily obs. in models)	New bitcoin and uninformed users rather use it as investment asset than as currency. Bitcoin users limited in their level of professionalism and objectivity and biased towards positive news.
Sapuric and Kokkinaki (2014)	19th July 2010 to April 9th 2014 (1,361 daily obs.)	Volatility of bitcoin exchange rate subsides substantially.
Gronwald (2014)	February 7th 2011 to February 24th 2014 (daily)	Bitcoin price strongly characterized by extreme price movements; immature market.
Gronwald (2015)	February 7th 2011 to February 24th 2014 and August 8th 2011 to August 27th (daily)	Evidence of both volatility clusters and extreme price movements. Bitcoin price more sensitive to news than other markets; immature market. No uncertainty on the supply-side; all extreme price movements driven by demand-side factors.
Kristoufek (2015)	September 9th 2011 to February 24th 2014 (daily)	Usage in trade, money supply and price level play a role in the long term. Increasing price of the bitcoin motivates users to become miners; effect vanishing over time, as hash rates and difficulty increase. Bitcoin driven by investors' interest; during episodes of explosive prices, interest drives prices further up, and during rapid declines, it pushes them further down.
Polasik et al. (2015)	April 2011 to March 2014 (26 monthly obs.)	Bitcoin returns primarily driven by popularity, sentiment expressed in newspapers and total number of transactions. Bitcoin not well-integrated with traditional currency markets and the macroeconomy.

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Table 1 – continued from previous page

Authors	**Period**	**Empirical Results**
Yelowitz and Wilson (2015)	January 2011 to July 2013 (31 monthly obs. for each state). Sample size varies from 580 to 794 in models.	Computer programming enthusiasts and illegal activity drive interest in bitcoin, while limited or no support for political and investment motives.
Brière et al. (2015)	July 23rd 2010 to December 27th 2013 (179 weekly obs.)	Bitcoin investment exhibits very high volatility, but also very high returns. Including a small proportion of bitcoins in a well-diversified portfolio may dramatically improve risk-return characteristics.
Vockathaler (2015)	August 19th 2010 to May 27th 2015 (1,743 daily obs.)	Speculative bubbles more significant in the past and not significant when tested in a larger sample size. Large spikes in the price of bitcoin less likely to occur again. Unexpected shocks by far the largest contributor to bitcoin price fluctuations.
Cheah and Fry (2015)	July 18th 2010 to July 17th 2014 (daily)	Bitcoin prone to speculative bubbles. Fundamental value of bitcoin is zero.
Bartos (2015)	March 4th 2013 to July 31st 2014 (349 daily obs.)	Price of bitcoin follows the efficient market hypothesis, immediately reacts to publicly announced information. No significant impact of macro-financial development or speculative investors on bitcoin.
Chu et al. (2015)	September 13th 2011 to May 8th 2014 (nearly 1,000 daily obs.)	The generalized hyperbolic distribution gives the best fit for bitcoin.
Baek and Elbeck (2015)	July 2010 to February 2014 (daily, monthly)	Bitcoin 26 times more volatile than the S&P 500 Index. Bitcoin returns driven by buyers and sellers and not by fundamental economic factors. Bitcoin market highly speculative.
Bouoiyour and Selmi (2015)	December 5th 2010 to June 14th 2014 (daily)	Extremely speculative behavior of bitcoin, partial usefulness in trade transactions, dependence to the Shangai stock market and the hash rate. No sign of bitcoin being a safe haven. Bitcoin still perceived as speculative foolery.

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Authors	Period	Empirical Results
Hencic and Gouriéroux (2015)	February 20th to July 20th 2013 (150 daily obs.)	Noncausal autoregressive model results show that bitcoin experiences episodes of local trends, which can be modelled and interpreted as speculative bubbles. The bubbles may result from the speculative component in the on-line trading.
Mai et al. (2016)	January 1st 2011 to March 21st 2014 (1,901 daily obs.), 89 hourly obs. for VECM	Predictive ability of social media in the short run. Internet forum and Twitter affect future returns depending on positive and negative news.
Dyhrberg (2016a)	July 19th 2010 to May 22nd 2015 (1,769 daily obs.)	Bitcoin can be used as a hedge against stocks in the FTSE Index. Also, USD in the short-term. It has some of the same hedging abilities of gold. Bitcoin traded at high and continuous frequencies with no days where trading is closed; it has speed advantages.
Dyhrberg (2016b)	July 19th 2010 to May 22nd 2015 (1,769 daily obs.)	Bitcoin reacts to fed funds rate and to similar variables in GARCH model, has similar hedging capabilities to gold and reacts symmetrically to good and bad news (as gold does). Bitcoin's position between gold and the dollar. Useful tool for portfolio management, risk analysis and market sentiment analysis.
Ciaian et al. (2016a)	2009–2014 (daily)	Bitcoin attractiveness the strongest driver of bitcoin price followed by market forces. Macro-financial developments no impact on bitcoin in the long-run.
Ciaian et al. (2016b)	November 2009 to May 2015 (daily)	Market forces and bitcoin attractiveness for investors and users significantly affect bitcoin. Macrofinancial developments not found to affect bitcoin in the long run.
Moore and Stephen (2016)	November 2010 to April 2015 (monthly)	Had the Central Bank of Barbados held a relatively small proportion of bitcoins, there would have been a significantly higher return with no significant difference in realized volatility.
Urquhart (2016)	August 1st 2010 to July 31st 2016 (2,183 daily obs.)	Based on multiple robust tests, bitcoin returns are significantly inefficient over our full sample. When sample split into two subsample periods, some tests show that bitcoin is efficient in the second period. Bitcoin is an inefficient market, but maybe in the process of moving towards an efficient market.

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Authors	Period	Empirical Results
Bukovina and Marticek (2016)	December 12th 2013 to December 31st 2015 (daily)	Sentiment, proxied by data mainly from the website reddit.com, explains a minor part of total bitcoin volatility. During periods of excessive volatility its explanatory value increases. Positive sentiment more influential for bitcoin excessive volatility.
Wang et al. (2016)	January 2011 to April 2016 (daily)	Short run: oil price and trading volume little influence on bitcoin price. Stock price index relatively larger impact. Long run: stock price index and oil price negative effect on bitcoin price, while daily trading volume positive.
Bouoiyour and Selmi (2016)	December 1st 2010 to July 22nd 2016 (daily)	Start-2014: bitcoin's conditional variance tending to follow an "explosive" process. Since January 2015, volatility much less persistent. Bitcoin price dynamics more driven by bad than good news. Bitcoin market remains far from mature.
Bouri et al. (2016)	August 19th 2011 to April 29th 2016 (1,226 daily obs.) and July 18, 2010 to December 15, 2015 (1,977 daily obs.)	Strong evidence of permanency of the shocks, lack of mean reversion in the level series, evidence of structural changes. After accounting for structural breaks, evidence of mean reversion uncovered in some cases. More evidence of long memory than short in volatility.
Li and Wang (2017)	January 1st 2011 to December 31st 2014 (1,096 daily obs. in model)	Short term: bitcoin adjusts to changes in economic fundamentals and market conditions. Long term: more sensitive to economic fundamentals and less sensitive to technological factors after Mt. Gox closed. Significant effect of mining technology and decreasing importance of mining difficulty.
Nadarajah and Chu (2017)	August 1st 2010 to July 31st 2016 (2,191 daily obs.)	A simple power transformation (not leading to any information loss) of the bitcoin returns satisfy the efficient market hypothesis based on eight different tests.
Lintilhac and Tourin (2017)	January 4th 2014 to June 3rd 2016	Pairs trading in bitcoin markets has been possible historically, but investors should use such strategies with caution. Despite the care taken to avoid certain pitfalls in backtesting, operational risks involved in an automated trading strategy, limited liquidity and market depth could distort the results of the strategies examined.

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Authors	**Period**	**Empirical Results**
Bouri et al. (2017a)	August 18th 2011 to April 29th 2016 (1,226 daily obs.)	After price crash in 2013 safe-haven property observed before vanishes. Adding bitcoin to US equity portfolios leads to risk reduction. However, bitcoin is less liquid than conventional assets.
Bouri et al. (2017b)	March 17th 2011 to October 7th 2016 (1,452 daily obs.)	Bitcoin reacts positively to uncertainty acting as a hedge against uncertainty at the extreme ends of the bitcoin market and global uncertainty, mainly at shorter investment horizons.
Bouri et al. (2017c)	July 18th 2011 to December 22nd 2015 (1,133 daily and 226 weekly obs.)	Bitcoin poor hedge, suitable for diversification only. It can only serve as strong safe haven against weekly extreme downfalls of Asian stocks. Bitcoin hedging and safe haven properties vary between horizons.
Balcilar et al. (2017)	December 19th 2011 to April 25th 2016 (1,587 daily obs.)	Volume predicts returns over the quantile range of 0.25 to 0.75. No evidence of predictability emanating from volume for volatility of bitcoin returns.
Baur and Dimpfl (2017)	January 1st 2014 to January 25th 2017 (high-frequency)	Bitcoin cannot be considered a currency, as high volatility undermines its reliability as a medium of exchange and the store of value and unit of account properties. Bitcoin might better be classified as a speculative asset class.
Bouoiyour and Selmi (2017)	November 8th 2016 to February 15th 2017 (99 daily obs.)	Bitcoin‘s safe-haven properties against the US stock market are time-varying. It acts as a weak safe haven in the short-run and as a hedge in the medium- and the long-run.
Stavroyiannis and Babalos (2017)	July 1st 2013 to December 27th 2016 (1,276 daily obs.)	Bitcoin does not act as a hedge, diversifier, or safe-haven against the US market (S&P500). It possesses intrinsic risk attributes reflected in the absence of regulation and cryptomoney specific crimes.
Urquhart (2017a)	May 1st 2012 to April 30th 2017 (daily)	Significant evidence of price clustering around whole numbers, with over 10% of prices ending with decimal digits of 00; however, no predictable pattern traced in prices after a round number. Clustering in bitcoin is consistent with the negotiation hypothesis of Harris (1991), as price clustering is significantly related to price and volume.

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Authors	Period	Empirical Results
Urquhart (2017b)	January 1st 2012 to December 31st 2016 (24-hour 5-minutely data)	No evidence of leverage effect in bitcoin. HAR models superior in modelling bitcoin volatility to traditional GARCH models. Significant evidence of jumps and continuous components in the HAR models. Superiority of high frequency based volatility forecasting models over traditional GARCH models for bitcoin supported.
Scaillet et al. (2017)	June 2011 to November 2013 (high-frequency data, 6.4 million transactions)	Jumps are frequent: 124 jump days out of the 888 sample days. In contrast to the intuition that relates jumps to crash events, most jumps are in fact positive and economically significant. Jumps cluster in time. Illiquidity, order flow imbalance and the preponderance of aggressive traders significantly drive the occurrence of jumps. Jumps have a positive impact on market activity and a negative impact on liquidity.
Katsiampa (2017)	July 18th 2010 to October 1st 2016 (2,267 daily obs.)	The paper investigates the performance of alternate GARCH-type models to explain bitcoin volatility. The AR-CGARCH is found to possess the best goodness-of-fit to the data, stressing the importance of accounting both for the short-run and the long-run component of conditional variance.
Bariviera et al. (2017)	2011 to 2017 (daily) and March 31th 2013 to August 2nd 2016 (intraday)	High volatility of bitcoin, which has been decreasing over time. Long range memory not related to market liquidity. Similar long range memory across different time scales (5 to 12 hours) mostly similar, in terms of long range memory. Until 2014 bitcoin had a persistent behavior (H $>$ 0.5), but after that time the Hurst exponent has moved around 0.5.
Bariviera (2017)	August 8th 2011 to February 15th 2017 (1435 daily obs.)	Daily returns suffered a regime switch. From 2011 until 2014 bitcoin returns were persistent, but after that year they are compatible with a white noise process. Daily volatility exhibits a persistent behavior during all the period. The long memory content of daily volatility is stronger than in daily returns.
Baur et al. (2017a)	July 19th 2010 to July 14th 2017 (2,552 daily obs.)	Results contradict those of Dyhrberg (2016b). Bitcoin has different return, volatility and correlation characteristics compared to other assets including gold and the US dollar.

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Table 1 – continued from previous page

Authors	Period	Empirical Results
Baur et al. (2017b)	July 2010 to June 2015 (1,334 daily obs.)	Bitcoin is uncorrelated with traditional asset classes such as stocks, bonds and commodities. It is mainly used as a speculative investment and not as an alternative currency or medium of exchange.
Khuntia and Pattanayak (2018)	July 18th 2010 to December 21st 2017 (2,714 daily obs.)	Evidence of dynamic efficiency adheres to the proposition of the Adaptive market hypothesis. Crucial events coincide with episodes of efficiency/inefficiency.
Koutmos (2018)	January 2nd 2013 to September 20th 2017 (1,231 daily obs.)	Strong linkages between bitcoin returns and transaction activity, albeit returns explain relatively more of the variation in transaction activity than vice versa.
Blau (2018)	July 17th 2010 to June 1st 2014 (daily)	No evidence that speculative trading was significantly high during this period or that speculative trading contributes to bitcoin's volatility.
Takaishi (2018)	January 1st 2014 to December 31st 2016 (per minute obs.)	Negative skewness is observed in bitcoin returns at time scales shorter than one day. No evidence of volatility asymmetry. Both temporal correlation and broad return distribution contribute the multifractality of bitcoin.
Su et al. (2018)	June 16th 2011, to September 30th 2017 (weekly obs.)	There have been four explosive bubbles in China and the US market. A serious financial crisis may trigger long-term and large-scale bubbles, whereas relatively short-term bubbles are caused by domestic components. Bitcoin can be used as a hedge against market-specific risk. Bitcoin bubbles collapse due to administrative intervention by economic authorities.
Jiang et al. (2018)	December 1st 2010 to November 30th 2017 (2,551 daily obs.)	Bitcoin market is inefficient; returns series present strong persistence. Existence of long-term memory captured.
Urquhart (2018)	August 1st 2010 to July 31st 2017 (weekly, per 5 minutes obs.)	Previous day volatility and volume are significant drivers of attention of bitcoin, as well as two days previous returns. Testing in subsample, it is found that the latter holds only from October 2013 and therefore the results indicate that investors are attracted to bitcoin after large increases in volatility and trading volume.

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Authors	Period	Empirical Results
Feng et al. (2018)	September 13th 2011 to July 17th 2017	Evidence of informed trading in the bitcoin market ahead of cryptocurrency-related negative bitcoin market events, and ahead of large positive events. The profits of informed trading are estimated to be between $100,922 and $915,455 per event.
Aalborg et al. (2018)	March 1st 2012 to March 19th 2017 (daily and weekly obs.)	Realized volatility of bitcoin exhibits high persistence. Trading volume improves the volatility model for bitcoin, while the trading volume of bitcoin can be predicted from Google trends. None of the considered variables can predict bitcoin returns.
Corbet et al. (2018)	January 9th 2009 to November 9th 2017 (3,227 daily obs.)	No clear evidence of a persistent bubble in the bitcoin market. Evidence that bitcoin is currently in a bubble phase and has been since the price increased above $1,000 is found.
Vidal-Tomás and Ibañez (2018)	September 13th 2011 to December 17th 2017 (2,287 daily obs.)	Bitcoin has become more efficient over time in relation to its own events, as it responds to bitcoin-specific market news. Nevertheless, it is not affected by monetary policy news.
Demir et al. (2018)	July 18th 2010, to November 15th 2017 (2,678 daily obs.)	Economic policy uncertainty (EPU) has a predictive power on bitcoin returns with bitcoin returns being negatively associated with (EPU). However, the effect is positive and significant at lower and higher quantiles of bitcoin returns and the EPU. Thus, bitcoin can serve as a hedging tool against uncertainty.
Giudici and Abu-Hashish (2018)	May 18th 2016 to April 30th 2018 (daily obs.)	The proposed model is able to well describe the correlation structure between bitcoin prices in different exchange markets, which are rather strong, whereas the correlation of bitcoin prices with traditional assets is low. The model is also able to improve bitcoin price predictions compared to a simpler autoregressive model.
Ardia et al. (2018)	August 18th 2011 to March 3rd 2018 (2,355 daily obs.)	Strong evidence of regime changes in the GARCH process. MSGARCH models outperform single–regime specifications when predicting Value–at–Risk.
Dastgir et al. (2018)	January 1st 2013 to December 31st 2017 (weekly obs.)	Bi-directional causal relationship between bitcoin attention (Google trend) and bitcoin returns traced; the relationship mainly exists in the tails of the distribution.

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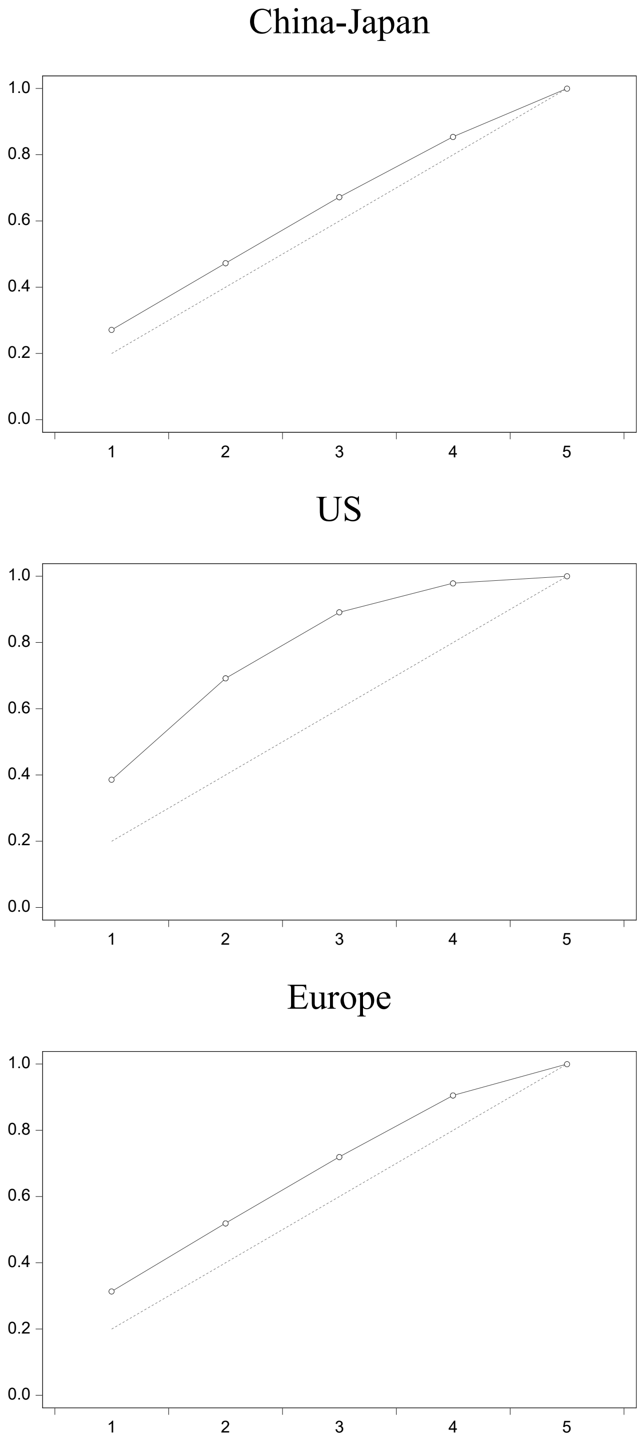
Authors	Period	Empirical Results
Thies and Molnár (2018)	September 2011 to August 2017 (2,170 daily obs.)	Structural breaks in average returns and volatility of bitcoin are very frequent. Several regimes with positive average returns and one regime with negative average returns are captured. Across regimes, higher volatility is associated with higher average returns, with exception of the most volatile regime, which is the only regime with negative average returns.
Sensoy (2018)	January 1st 2013 to March 5th 2018 (high frequency; multiple frequencies)	USD and euro bitcoin markets have become more informationally efficient at the intraday level since the beginning of 2016; the one in USD is slightly more efficient. The higher the data frequency, the lower the pricing efficiency. Liquidity (volatility) has a significant positive (negative) effect on the informational efficiency of bitcoin price.
Panagiotidis et al. (2018)	June 17th 2010 to June 23rd 2017 (2,533 daily obs.)	Lasso regression allows variable selection among the 21 variables examined and regularization. Search intensity (Google trend), gold returns and policy uncertainty are found to be the most important drivers of bitcoin returns.

Table 8: Bai and Ng (2002) criteria for the number of factors

China-Japan factors						
# of lags	PC1	PC2	PC3	IPC1	IPC2	IPC3
4	0.0005	0.0005	0.0005	-7.1359	-7.1341	-7.1369
3	0.00152	0.00152	0.00152	-5.6756	-5.6742	-5.6764
2	0.00341	0.00341	0.00341	-5.078	-5.0771	-5.0785
1	0.00603	0.00603	0.00603	-4.8003	-4.7999	-4.8006
Optimal	4	4	4	4	4	4
Europe factors						
# of lags	PC1	PC2	PC3	IPC1	IPC2	IPC3
4	0.00123	0.00123	0.00123	-6.238	-6.2363	-6.2391
3	0.00215	0.00215	0.00215	-5.456	-5.4547	-5.4568
2	0.00401	0.00401	0.00401	-4.9643	-4.9634	-4.9648
1	0.05544	0.05544	0.05544	-2.5735	-2.5731	-2.5738
Optimal	4	4	4	4	4	4
US factors						
# of lags	PC1	PC2	PC3	IPC1	IPC2	IPC3
4	0.00026	0.00026	0.00026	-7.8021	-7.8004	-7.8032
3	0.00333	0.00333	0.00333	-4.7731	-4.7717	-4.7739
2	0.01275	0.01275	0.01275	-3.7233	-3.7225	-3.7239
1	0.03038	0.03038	0.03038	-3.1731	-3.1727	-3.1734
Optimal	4	4	4	4	4	4

Note: the general form of the six criteria is: $PC(k) = V(k, \hat{F}^k) + k \cdot g(N,T)$, where k the number of factors estimated, $V(k, \hat{F}^k)$ the sum of squared residuals, $g(N,T)$ a penalty function. Optimal number of lags is selected, so that $\hat{F}$ has the most suitable dimension $r < 5$.

Figure 10: Model 4, cumulative proportion of explained variance in PCA



Note: the proportion of total variance explained for each number of PCs in blue and a diagonal reference line in red.