Brave New World? Bitcoin is not the New Gold: Understanding Cryptocurrency Price Dynamics

Sangyup Choi[1] Junhyeok Shin[2]

Yonsei University Yonsei University

February 2020

Abstract

While the many commonalities shared by Bitcoin and gold raise a question of whether Bitcoin is a safe-haven like gold, relevant empirical evidence to date is mixed. Unlike existing empirical studies, we derive a simple estimable model of Bitcoin price dynamics from the quantity equation, which allows for structural interpretation of our findings; we then estimate the dynamic effects of macro factors, including income, inflation, and interest rates on Bitcoin prices at a weekly frequency. Unlike gold, Bitcoin prices are vulnerable to financial risk or uncertainty shocks, which is inconsistent with safe-haven quality. When the empirical model is augmented with Bitcoin-specific variables, such as its supply, transactions, and velocity, a major share of Bitcoin price dynamics is explained by these variables. We also find an interesting nonlinearity in the drivers of Bitcoin price dynamics between bullish and bearish market: the role of Bitcoin-idiosyncratic shocks increases when it appreciates, while the effects of macro factors dominate when it depreciates.

JEL Classification: E41; E44; F31; G10

Keywords: Cryptocurrencies; Bitcoin; safe-haven; gold; quantity equation; Vector Autoregressions

[1] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea. Email address: sangyupchoi@yonsei.ac.kr.

[2] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea. Email address: junhyeok.shin2@gmail.com.

I. INTRODUCTION

The global financial crisis in 2008 showed the vulnerability of the international financial system, as well as the limitations of central banks and their conventional monetary policy. Since then, there have been diverging views about the future of the international financial system and the role of central banks. Against this background, various types of cryptocurrencies have emerged as new forms of digital money and payment structures that allow users to make peer-to-peer transactions without the intervention of financial intermediaries (Nakamoto, 2008).

Rapidly-growing markets for trading cryptocurrencies based on block-chain technologies have attracted investors worldwide. The most prominent among them is Bitcoin, both in terms of its impressive price development and price volatility. For example, Bitcoin prices increased by a factor of 100 between April 2011 and April 2013. Bitcoin prices continued to increase, surpassing the threshold of $1,000 in November 2013 and $10,000 in December 2017. However, Bitcoin prices plunged after peak value in December 2017, implying that Bitcoin might be a typical example of an expectation-driven bubble. While Bitcoin as of today has become a major interest of not only investors but also academics and policymakers, existing theoretical and empirical attempts have not reached consensus about its true colors.[3]

The lack of consensus is driven by the ambiguous nature of Bitcoin as a currency or an asset, which makes it difficult to apply any established theoretical model or empirical approach (e.g., Glaser et al., 2014; Yermack, 2015; Baur et al., 2018; Schilling and Uhlig, 2019).[4] While the fundamental value of a financial asset is determined by the future cash flows it is expected to generate, Bitcoin does not generate any income streams. It does not have a fundamental value in the same way as bonds or stocks. This feature of cryptocurrencies prevents the application of a standard asset pricing model. At the same time, Bitcoin is not fully qualified as a currency because it only partly satisfies the functions of money (Yermack, 2015). Thus, Bitcoin prices cannot be

[3] See Böhme et al. (2015) and Bank for International Settlements (2018) for a general illustration of Bitcoin and blockchain technologies from an economist's perspective.

[4] For this reason, the terms Bitcoin, cryptocurrencies, and cryptoassets are used interchangeably throughout the paper.

fully understood by any single existing approach, which highlights the theoretical and empirical difficulties in modeling its price dynamics.

We contribute to this emerging literature by providing a systematic analysis of Bitcoin price dynamics. Our analysis is simple but allows for structural interpretation of the estimation results, which is in contrast to existing empirical studies, which have used reduced-form statistical analysis. We apply the theory of money demand to derive an estimable structural relationship between Bitcoin prices and standard macro factors. We then use VIX to test the safe-haven property of Bitcoin under financial market distress or uncertainty. Considering the well-known safe-haven property of gold, and gold's similarities to Bitcoin, we compare Bitcoin price dynamics with gold price dynamics, thereby facilitating an economic interpretation of our findings.

Our findings suggest that Bitcoin price dynamics are consistent with the theoretical prediction of money demand. Bitcoin prices increase in response to rises in real income, price levels, and Bitcoin's own velocity the velocity of Bitcoin, while they decline with respect to rises in the nominal interest rate. However, these macro factors from money demand theory explain only a limited share of the variation in Bitcoin prices, allowing us to attribute an asset-like nature to Bitcoin and justifying the inclusion of VIX—a strong driver of risky asset prices worldwide (Rey, 2015)—in the empirical analysis. Importantly, Bitcoin prices decrease significantly in response to VIX, suggesting that Bitcoin is not a safe haven. Moreover, the response of Bitcoin prices to macro factors in our empirical models is totally different from that of gold, which strongly repudiates the recent claim that Bitcoin is the "new gold" or "digital gold." However, uncertainty about future government policy as measured by the Economic Policy Uncertainty (EPU) index has no negative effect on Bitcoin prices, which is consistent with the claim that the increasing popularity and the rapid appreciation of Bitcoin prices are largely driven by Bitcoin's independence from government authorities.

When the baseline model is augmented with variables that are specific to Bitcoin, such as its supply, transactions, and velocity, a major share of the variation in Bitcoin prices is explained by these variables, calling for balanced consideration between macro and market-specific determinants in understanding Bitcoin price dynamics. We also find an interesting nonlinearity in the drivers of Bitcoin price dynamics between bullish and bearish markets. While Bitcoin-specific variables explain most movements during upturns, the role of macro variables, especially VIX, becomes important during the downturn. Taken together, our findings emphasize the importance of considering both the money demand approach and the speculative asset demand approach in understanding Bitcoin's true colors.

While the emerging literature on Bitcoin or cryptocurrencies, in general, is too vast to be summarized here, Corbet et al. (2019) provide a systematic review of existing studies on the characteristics of cryptocurrencies (e.g., bubble dynamics, regulation, cyber criminality, diversification, and efficiency). Among these various characteristics, we attempt to understand Bitcoin's price dynamics in order to determine its safe-haven property. Despite the rapid expansion of empirical studies, most analyses have investigated only the statistical properties of Bitcoin, such as its standard deviation, or have used correlation and volatility clustering with other financial assets to determine its safe-haven status (e.g., Dyhrberg, 2016; Bouri et al., 2017; Shahzad et al., 2019; Smales, 2019; Urquhart and Zhang, 2019).

Together with the increasing attention that economists are paying to cryptocurrencies, there has been parallel progress in building a theoretical model of Bitcoin (e.g., Hendrickson et al., 2016; Abadi and Brunnermeier, 2018; Kang and Lee, 2018; Pagnotta and Buraschi, 2018; Sockin and Xiong, 2018; Schilling and Uhlig, 2019; Bolt and Van Oordt, forthcoming). However, these studies mostly aimed at providing a normative framework for evaluating Bitcoin as a substitute for traditional money or at understanding Bitcoin's interplay with central bank monetary policy, without much emphasis on empirical evidence of Bitcoin price dynamics.[5] We aim to fill this gap in the literature by providing a set of empirical findings from structural VARs derived from the quantity equation, which will allow for structural interpretation of our findings, unlike many previous studies that have used ad-hoc specifications.

The novelty of our paper is fourfold. First, we develop a structural VAR model from a simple theoretical model of money demand in which Bitcoin prices are (partially) determined by macro factors, such as inflation, nominal interest rate, and the wealth of investors. While previous

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[5] Easley et al. (2019) is a notable exception. They built a game-theoretic model to explain both the factors leading to the emergence of Bitcoin transaction fees and the strategic behavior of miners and users; they then tested theoretical predictions using daily data.

analytical studies have relied only on sets of ad-hoc variables, we choose relevant variables guided by the theoretical model, thereby providing a framework that mitigates omitted variable bias and facilitates economic interpretation of the estimation results. Second, we estimate the dynamic responses of Bitcoin prices to various structural shocks and compare these with the responses of traditional safe-haven assets considered in the literature, such as gold. Third, we extend the model to consider non-macro factors specific to the Bitcoin market. The inclusion of these factors allows for an evaluation of the relative importance between macro and non-macro factors in understanding Bitcoin price dynamics. Lastly, we perform a battery of robustness checks by employing an alternative measure of each structural shock in the system and comparing Bitcoin dynamics with those of other popular asset classes, which enhances the credibility of our results.

The remainder of the paper is organized as follows. Section II outlines a simple theoretical framework to motivate the structural VAR model used in the empirical analysis. Section III describes the data, explains the econometric methodology, and summarizes the main empirical results as well as a battery of sensitivity tests and the extension of the baseline model. Section IV concludes the paper.

II. SIMPLE THEORETICAL FRAMEWORK

In this section, we outline a simple theoretical relationship between the nominal Bitcoin exchange rate (i.e., Bitcoin prices in USD) and macro factors motivated by the quantity equation. Any theoretical analysis of Bitcoin price dynamics is challenging because Bitcoin has characteristics of both assets and currencies. Bitcoin's nature is ambiguous because agents hold it for completely different purposes. Some hold Bitcoin for real transactions due to its anonymity and transactional flexibility, while others hold Bitcoin for speculative motives under the belief that its price will increase in the future.

To shed light on this issue, we first divide demand for Bitcoin into categories of (i) medium of exchange (i.e., as a digital currency), assuming that some real goods and services in the economy have to be purchased by Bitcoin; and (ii) instrument of speculative motive for capital gains (i.e., as a financial asset), similar to the model of Bolt and Van Oordt (forthcoming).[6] To the extent to which Bitcoin does not provide any meaningful cash flow, standard asset pricing theory cannot be applied to Bitcoin pricing. By considering its currency-like nature We apply the theory of money demand to Bitcoin prices. We then attribute Bitcoin price dynamics that are not explained by the monetary theory to speculative demand, which is supported by Bitcoin's asset-like nature. Our approach provides a useful benchmark for understanding Bitcoin price dynamics as balanced between the two extreme views.

Suppose there are two currencies in the economy used for real transactions: USD and Bitcoin. The well-known quantity equation applied to Bitcoin states that

$$P_t^B T_t^B = M_t^B V_t^B, \tag{1}$$

where P_t^B is the weighted average price of goods and services purchased by Bitcoin, denominated in number of units of Bitcoin, with T_t^B as their quantity. M_t^B is the (nominal) quantity of money in circulation, defined as the number of units of Bitcoin; V_t^B denotes the velocity of Bitcoin. Note that Equation (1), by definition, holds for any period *t*.

However, due to speculative motives for holding Bitcoin, not all of the stock of Bitcoin supplied is used for making real payments:

$$M_t^B = \overline{M_t^B} - M_t^{B,S}, \tag{2}$$

where $\overline{M_t^B}$ is a total stock of Bitcoin in period *t*; this stock grows exogenously and deterministically. $M_t^{B,S}$ is the stock of Bitcoin that is held only for speculative motive and never used for real payments. It is important to note that $\overline{M_t^B}$ is trivially observable from the data, but $M_t^{B,S}$ is not. Because the quantity equation is silent on speculative motives for holding Bitcoin, we assume that

[6] See Cheah and Fry (2015) for modeling of Bitcoin price dynamics under the assumption that Bitcoin prices are solely driven by speculative demand.

$M_t^{B,S} = 0$ and attribute the speculative holding of Bitcoin to error terms that are not explained by our model.[7]

Now we introduce the nominal Bitcoin exchange rate E_t (i.e., Bitcoin prices in USD) by rearranging Equation (1):

$$\frac{P_t^B}{P_t} \times (P_t T_t^B) = M_t^B V_t^B, \tag{3}$$

where P_t is the price level quoted in USD, so that $P_t T_t^B$ denotes the amount of trade in goods and services purchased by Bitcoin when quoted in USD. USD is the unit of account in the model. The nominal Bitcoin exchange rate is defined as $E_t = P_t / P_t^B$, under the assumption that the prices of goods and services expressed in Bitcoin are completely determined by the exchange rate and their price level in USD.[8]

We make the following assumption to link Bitcoin price dynamics to standard macroeconomic factors:

$$T_t^B = \Lambda_t Y_t, \tag{4}$$

where Λ_t is the share of Bitcoin used in total monetary transactions in the economy ($0 \leq \Lambda_t \leq 1$) and Y_t is the real income of the economy that is observable from the data. This simplifying assumption implies that agents in this economy purchase the same kind of goods with both USD

[7] In reality, the holding of Bitcoin stock for speculative purposes and therefore the stock of Bitcoin in effective circulation could be affected by Bitcoin prices (i.e., $\frac{\partial M_t^{B,S}}{\partial E_t} \neq 0$), which could result in an endogeneity problem when estimating Equation (7). While the stock of Bitcoin in effective circulation, driven by money demand, cannot be directly observed, one should note that the stock of Bitcoin held for speculative motive has zero velocity (Bolt and Van Oordt, forthcoming), so that changes in relative demand can be inferred from fluctuations in Bitcoin velocity. The excessive volatility of our proxy for Bitcoin velocity, shown in Figure A.2 in the appendix, echoes this concern. Although we cannot fully address this problem without data on the amount of Bitcoin in effective circulation, we can still test the robustness of our findings by including a proxy for the Bicoin in effective circulation.

[8] In other words, the law of one price holds here. This is not an unrealistic assumption given the practice of many online stores of instantly adjusting prices quoted in Bitcoin to the latest available exchange rate (see Bolt and Van Oordt, forthcoming).

and Bitcoin.[9] Although the value of λ_t is likely very small, the near-perfect pass-through helps us pin down the Bitcoin exchange rate in relation to standard macro factors. The share of Bitcoin used in a total monetary transaction is likely to remain constant in the short run, so we first treat Λ_t as a constant in the empirical analysis. We then allow it to vary over time given the rapidly-increasing role of Bitcoin in real payments.[10] It is important to note that Λ_t can be still proxied in the data according to Bitcoin usage.

To the extent that the velocity of Bitcoin cannot be observed directly in the data, we need to assume that this velocity depends negatively on the nominal interest rate. As long as we treat Bitcoin as a substitute currency for USD, this is not an unreasonable assumption.

$$V_t^B = k(i_t). \tag{5}$$

Plugging Equation (2), (3), and (4) into (5) and using the definition of the nominal Bitcoin exchange rate, and assuming $M_t^{B,S} = 0$, we obtain:

$$\frac{E_t}{P_t} = \frac{\Lambda_t k(i_t) Y_t}{\overline{M_t^B}}, \tag{6}$$

where the left-hand-side of Equation (6) denotes the nominal Bitcoin exchange rate normalized by the U.S. price level (i.e., the *real* prices of Bitcoin in USD).[11] Note that the equilibrium relationship in Equation (6) holds in the long run and in the absence of bubble dynamics;[12] as such, through the lens of the theory of money demand, we can interpret short-run fluctuations in real prices of Bitcoin as outcomes of shocks to the right-hand-side variables.

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[9] Of course, this is not simply true in reality due to Bitcoin usage for illegal activity. Foley et al. (2019) estimate that approximately one-quarter of bitcoin users are involved in illegal activity. However, this simplifying assumption is necessary to derive any meaningful relationship between Bitcoin prices and macro factors.

[10] Bitcoin usage is still limited, but increasing. See Figure A.2. in the appendix.

[11] One can derive a similar relationship assuming the Bitcoin standard in analogy to determining the price level and the dollar exchange rate under the gold standard (for example, see Barro, 1979).

[12] While understanding whether Bitcoin prices follow bubble-like dynamics is an important question, our model does not provide any theoretical framework for determining a bubble. Nevertheless, in the following empirical analysis, forecast errors of Bitcoin prices not explained by macro factors (i.e., idiosyncratic shocks) can be seen as proxies for bubble-like dynamics in explaining Bitcoin prices.

Equation (6) demonstrates the importance of the economy-wide price level in a correct understanding of Bitcoin price dynamics. Given the near-perfect pass-through from USD to Bitcoin, ignoring the price level in the U.S. can bias the estimation results. To the best of our knowledge, however, none of the existing studies has considered this possibility, probably due to the lack of a high-frequency measure of the price level.[13] We overcome this limitation of the previous literature by employing the daily online price index (OPI), constructed by Cavallo and Rigobon (2016).

Next, we derive an estimable equation from the equilibrium relationship suggested in Equation (6):

$$\frac{e_t}{p_t} = \alpha + \beta_1 y_t + \beta_2 i_t + \beta_3 \overline{m_t^B} + \beta_4 \lambda_t + \varepsilon_t, \tag{7}$$

where the lower-case variables now denote the percentage change from trends in the original upper-case variables. ε_t captures real Bitcoin price dynamics that are not explained by the theory of money demand (e.g., driven by speculative motive) as well as measurement errors in our empirical proxies. According to the quantity equation, the signs of the coefficients should be the following: $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 < 0$, and $\beta_4 > 0$. Importantly, although Equation (6) describes an equilibrium relationship among variables, the exogeneity of the right-hand-side variables with respect to the left-hand-side variable allows for estimation of Equation (7) without concern for reverse causality.[14]

One should note that some variables are directly observed in the data (e.g., Bitcoin/USD exchange rates or the total stock of Bitcoin supplied), while others are observed with (potentially significant) errors (e.g., the share of Bitcoin in the monetary transaction) or cannot be directly observed (e.g., the velocity of Bitcoin). Thus, we need to apply behavioral assumptions to some

[13] Although the Consumer Price Index is readily available at a monthly frequency, most empirical studies on cryptocurrencies have relied on high-frequency (daily, weekly, or even intra-daily) data because of the short-span of time-series data on cryptocurrencies (typically only several years).

[14] This interpretation is analogous to the small open economy assumption often employed in International Macroeconomics, in which each domestic economy (e.g., Bitcoin economy) is too small to affect the rest of the world (traditional economy), such that world variables are treated exogenously with respect to studying the domestic economy.

variables before estimation. Seeking parsimony, we start from the simplest model with the minimum set of observable variables; we then expand the model by embedding additional variables.

III. EMPIRICAL ANALYSIS

A. Data

This section describes how we choose proxies for macro factors in Equation (7), used in the following empirical analysis. We face a trade-off here. While Equation (7) provides a structural relationship between Bitcoin prices and standard macro factors based on the quantity equation, these variables are available at a monthly frequency at best (e.g., real income and price level). However, employing variables at a monthly frequency results in a lack of the degree of freedom because of the short span of Bitcoin-related data, thereby preventing proper estimation of the relationship.[15]

To account for this trade-off, we employ various proxies for macro factors in Equation (7) at a weekly frequency. We employ the daily online price index (OPI) constructed by Cavallo and Rigobon (2016) to obtain real Bitcoin prices (the left-hand-side variable); this process eases economic interpretation. The daily OPI is calculated with price data from numerous websites across the internet. The prices collected by automatized "scraping" programs are put together in a way similar to how the usual CPI is produced. This index is not only conceptually consistent with the CPI but also closely tracks fluctuations in the CPI during the sample period at higher frequency (see Figure A.1 in the appendix).

Though imperfect, we use the S&P 500 index, which is normalized by the OPI, to proxy real income of households at a weekly frequency. Although stock market investment is only a part of an average household's wealth portfolio, there is a strong positive relationship in the data between aggregate consumption, which translates into real money demand, and aggregate stock

[15] Bitcoin price series show excessive volatility within any given month or quarter, which further limits the use of low-frequency data in the empirical analysis.

prices.[16] In addition, using the stock market index to explain Bitcoin price dynamics allows for a convenient comparison of our results with existing empirical studies that compare Bitcoin with other traditional assets, including stocks.

Instead of the Federal Funds rate, we use the one-year Treasury bill rate as a benchmark interest rate to proxy the velocity of Bitcoin. This reflects the binding zero-lower-bound (ZLB) constraint during most of the sample period. By investigating the response of the real Bitcoin exchange rate to the interest rate, we can also infer the effect of monetary policy on Bitcoin price dynamics. Because the supply of total Bitcoin stock is perfectly inelastic to Bitcoin prices, we do not include a proxy for Bitcoin in circulation in the baseline analysis; this ensures the parsimony of the empirical model.

To determine the safe-haven nature of Bitcoin, we include the VIX index in the following analysis, given the ample theoretical and empirical literature on VIX as a measure of risk (or uncertainty) in financial markets (Bloom, 2009; Bekaert et al., 2013). A safe-haven asset is defined to hold its value in adverse market conditions, which are proxied by an increase in VIX. Instead of looking at the correlation between Bitcoin returns and stock returns during market distress, we decide to include VIX as an independent variable to link our findings to other emerging works in the literature on uncertainty shocks (e.g., Bloom, 2009; Baker et al., 2016). The recent finding that VIX is an important driver of risky asset prices across the globe and international capital flows (Rey, 2015) further justifies its use for testing the safe-haven property of Bitcoin. On top of other structural shocks identified in the VAR system, the response of Bitcoin prices to a shock to VIX illustrates how demand for Bitcoin as a financial asset would change under financial risk or uncertainty.

The data used for the following empirical analysis include weekly (Wednesday) observations between July 21, 2010, and April 11, 2018 (total 400 weekly observations).[17] The

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[16] For our purposes, it does not matter whether the positive link stems from the direct effect of financial wealth on consumption or from a signaling channel (Cooper and Dynan, 2016).

[17] Although daily data are also available for every variable, we choose a weekly frequency to minimize the persistence in the data and the influence of time-zone differences, which is standard in the finance literature. We test the robustness of our findings using daily data.

beginning date of the sample is governed by the introduction of Bitcoin exchanges and the ending date is determined by the availability of the daily OPI. The Bitcoin exchange rate data are taken from www.investing.com, while the total number of Bitcoins in circulation, the number of transactions, and the days destroyed for any given transaction (days destroyed)[18] are taken from www.blockchain.com. Other standard macro variables are taken from Federal Reserve Economic Data.

Figure 1 plots the evolution of the main variables used in the empirical analysis. Other than the variables explained above, we include real prices of gold—one of the best known safe assets—to ease the interpretation of our VAR analysis.[19] To the extent to which Bitcoin and gold share some similarities (e.g., exogenous supply, pseudo-medium of exchanges, and speculative demand), comparison with gold price dynamics should shed further light on Bitcoin price dynamics.[20] Figure A.2 in the appendix illustrates the evolution of the variables specific to the Bitcoin market.

Table 1 provides summary statistics on weekly compounded (log) returns on Bitcoin prices as well as statistics on the other variables shown in Figure 1. Given that most data series are non-stationary, we use the growth of these variables except for VIX and the one-year Treasury bill rate. Real Bitcoin prices during the sample period are characterized by a strong upward trend (the average weekly return of 2.75%) as well as excessive volatility (standard deviation of 17.4%, which is roughly ten times larger than that of the S&P 500). One should note that our sample period is characterized by the relatively tranquil financial market after the historic financial crisis in the last decade.

Table 2 summarizes the correlations between the main variables of interest. Bitcoin does not show any strong unconditional correlations with other financial assets (except for VIX),

[18] This variable is calculated by taking the number of Bitcoins in a transaction and multiplying it by the number of days since those coins were last spent.

[19] There is a vast empirical literature on the safe-haven quality of gold (e.g., Economist, 2005; Baur and Lucey, 2010; Baur and McDermott, 2010; Joy, 2011; Ciner et al., 2013; Reboredo, 2013).

[20] However, note that there exists a fundamental difference between gold and Bitcoin. While the former has intrinsic value and is used as an intermediate good in production, the latter (arguably) has no intrinsic value. See, for example, Dyhrberg (2016), Gronwald (2019), Shahzad et al. (2019), and Smales (2019) for a comparison of the properties of Bitcoin with those of gold.

somewhat consistent with previous studies concluding that Bitcoin can be used as a hedge against investment in other financial assets such as stocks and bonds (Dyhrberg, 2016; Bouri et al., 2019). However, it shows a strong unconditional negative correlation with VIX, suggesting that Bitcoin returns might be particularly vulnerable to heightened risk or uncertainty in financial markets or to the period of financial distress or turmoil. We delve into a more formal analysis in the following section to qualify the statistical evidence suggested in Tables 1 and 2.

B. Structural Vector Autoregressions

Guided by the theoretical model in the previous section, our baseline VAR model includes four variables: the log of the real U.S. stock market index (normalized by the OPI), the VIX index, the one-year U.S. Treasury bill rate, and the log of real Bitcoin prices (normalized by the OPI). The real stock market variable proxies real income at a high frequency and also captures the overall condition of financial markets. Many previous studies have defined a safe-haven asset as one with no or negative correlation with stock returns under market distress. To explicitly account for market distress, we include VIX—often called the fear index—as an additional variable in the VARs. Although most existing studies on Bitcoin price dynamics focused on statistical properties of Bitcoin returns (e.g., dynamic conditional correlation with other asset returns), analyzing their responses to shocks to VIX leads to a more qualified metric for gauging the safe-haven nature of Bitcoin from a macroeconomic perspective.[21]

Seeking parsimony, we treat the share of the Bitcoin economy as a constant and do not include a proxy for λ_t in the preliminary VAR model. This is not an unreasonable assumption given the weekly frequency of the data. The fact that the Bitcoin supply is fully exogenous and deterministic simplifies the understanding of its price dynamics because fluctuations in Bitcoin prices can be fully attributable to changes in the numerators on the right-hand-side of Equation (6), especially in the short run. For this reason, we do not include a proxy for $\overline{m_t^B}$ in the preliminary model either. Both of these assumptions will be relaxed later.

[21] An alternative interpretation of these two variables is that the former represents the first moment, while the latter represents the second-moment shock hitting the economy (Bloom, 2009).

To simplify the notation, let $Y_t = [sp500_t, VIX_t, i_t, btc_t]'$ be a 4×1 column vector of interest observed at time *t*. The individual elements indicate the log of the real S&P 500 index, the log of VIX, the one-year Treasury bill rate, and the log of real Bitcoin prices, respectively. We model the data in (log) levels to preserve the cointegrating relationships among the variables.[22] Then, the baseline VAR model can be represented in matrix form as follows:

$$A_0 Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + \varepsilon_t, \tag{8}$$

where A_0 is the lower triangular matrix that reflects the structural assumptions we imposed on the variables. p is the lag length and four lags have been chosen in our preliminary model given the weekly frequency of data.[23] ε_t is a 4×1 column vector of structural shocks at time *t*. Starting from the most parsimonious model with four variables, in the next section we include additional variables suggested by Equation (6) and check how results vary over different model specifications.

We impose structural assumptions on the variables equivalent to Cholesky identification arranging of the variables in the above order, implying that a variable is affected by contemporaneous changes in the variables listed before it, while this variable is exogenous to the variables listed after it. Given the small share of Bitcoin in all monetary transactions, it is reasonable to treat real Bitcoin prices as the least exogenous variable in the VAR system.[24] Other than the presence of Bitcoin prices, this identifying assumption is largely compatible with the vast literature on risk or uncertainty shocks and the macroeconomy, in the sense that the second-moment shock to the economy is purged of the first-moment shock (e.g., Bloom, 2009).

C. Main Results

[22] A large body of literature on this issue suggests that it is still desirable to estimate a VAR model in levels, even if the variables have unit roots (Sims et al., 1990).

[23] In the baseline model, the Akaike information criterion suggests two lags, whereas the Schwarz information criterion and the Hannan-Quinn information criterion suggest one lag. In the following section, we confirm that our results are not sensitive to the lag selection.

[24] Consistent with the small open economy-like assumption applied to the Bitcoin economy, we also impose a block recursive structure, assuming that a shock to the real Bitcoin prices does not affect other economic and financial variables contemporaneously, nor does it cause lags. The empirical results hardly change, which reinforces our identifying assumption.

Figure 2 shows the main empirical findings in this paper, obtained by estimating the four-variable preliminary model. This figure shows the response of real Bitcoin prices to one standard shock to the real S&P 500 index, to VIX, and to the one-year Treasury bill rate, respectively. First, real Bitcoin prices increase significantly in response to a positive shock to the stock market, consistent with the prediction of the quantity equation when treating the stock market as a measure of income. Moreover, the positive response suggests that Bitcoin does not serve as a hedge for investment in stock markets, in contrast to recent empirical evidence based on GARCH models (e.g., Dyhrberg, 2016).

Second, real Bitcoin prices do not respond to shocks to the nominal interest rate. While this finding is not consistent with the prediction of the quantity equation, it implies that Bitcoin could be a useful hedge for investment in bond markets.[25] Third and most importantly, real Bitcoin prices decline significantly in response to shocks to VIX. The one standard deviation increase in VIX is followed by a nearly 10% decline in real Bitcoin prices after three months. This is equivalent to a more than 30% decline in its prices when translated into the latest spike in VIX during early February 2018, driven by financial market turmoil.[26]

Overall, our results are in sharp contrast to statistical analysis concluding that Bitcoin returns are uncorrelated with traditional asset classes such as stocks, bonds, and commodities, suggesting that structural analysis is important in determining whether Bitcoin acts as a safe haven. We provide additional empirical results by re-estimating Equation (8), in which real Bitcoin prices are replaced by real gold prices. This is not an arbitrary exercise because one can derive a similar kind of structural relationship between real gold prices and the right-hand-side variables using implications from the gold standard (e.g., Barro, 1979). Moreover, given the traditional role of gold as a safe-haven asset and the many similarities between the two, analyzing the response of gold prices to the same macro factors can help illuminate Bitcoin price dynamics.

[25] The negative finding might be driven by the binding ZLB constraint during most of our sample period. We test the possibility of this case in the later section.

[26] After a long period of tranquil market, VIX jumped in the first week of February 2018 from its historically low value (about 9) to 27 without a particular exogenous cause.

Figure 3 shows results sharply contrasting from those of the case of Bitcoin. Real gold prices decrease significantly in response to the S&P 500 index, implying that gold is qualified as a (strong) hedge for stocks. Moreover, real gold prices do not respond to shock to VIX at all, indicating that gold is qualified as a (weak) safe-haven asset. This safe-haven nature of gold in response to global uncertainty or risk shocks is also consistent with Piffer and Podstawski (2017), who identified uncertainty shocks using gold prices as an instrument for a proxy-SVAR model. Real gold prices appreciate in response to rises in the interest rate, which is also different from the case of Bitcoin and suggests that gold is an effective hedge for bonds.

We confirm that our findings are robust for the joint inclusion of Bitcoin and gold prices in the VAR system (i.e., the five-variable VARs), in which real gold prices are placed before real Bitcoin prices given that markets for trading gold are much larger, more established, and more liquid than the Bitcoin market (i.e., information is likely to flow from the gold market to the Bitcoin market). To ease the comparison between Bitcoin and gold price dynamics, we use the five-variable VARs as a baseline model for the rest of the results. Figure A.3 in the appendix shows the residuals of real Bitcoin and gold prices after estimating the baseline model.

Figure 4 shows the response of real Bitcoin and gold prices to structural shocks in the new baseline model; results are consistent with the evidence from the preliminary model with four variables. We find no significant dynamic interaction between Bitcoin and gold prices. Taken together, the findings from the baseline VAR model suggest that Bitcoin is far from qualifying as a safe haven, acting nothing like gold in response to various shocks hitting the economy. Our findings complement the conclusions of recent studies that Bitcoin exhibits distinctively different returns, volatility, and correlation characteristics compared to other assets, including gold and the USD (e.g., Baur et al., 2018; Klein et al., 2018).

The forecast error variance decomposition of real Bitcoin and gold prices from the baseline model, shown in Figure 5, provides further insight into the nature of Bitcoin price dynamics. First, essentially none of the macro factors can explain real Bitcoin dynamics in the very short-run (i.e., within a month). This is in sharp contrast to the case of real gold price dynamics, in which a nonnegligible share is explained by the interest rate, even in the short run. Second, while the interest rate does not play any role, VIX is the most important variable in explaining real Bitcoin price dynamics. Given that VIX shocks do not explain variation in real gold prices, this exercise confirms that Bitcoin is far from a safe haven.

A historical decomposition of real Bitcoin and gold prices is provided in Figure 6, showing fluctuations in real prices of Bitcoin and gold are attributed to structural shocks over the sample period. One can find an interesting pattern in Bitcoin price dynamics. While the increase in real Bitcoin prices is almost exclusively explained by an idiosyncratic shock to Bitcoin prices, the decrease is relatively well-explained by other macro factors—except for the beginning of the sample period—especially by VIX. The asymmetry in the role of idiosyncratic shocks that we document is consistent with Makarov and Schoar (2019), who find that idiosyncratic components of Bitcoin trading volume can explain arbitrage spreads between Bitcoin exchanges, particularly when Bitcoin appreciates.

The asymmetric drivers of the real Bitcoin price dynamics between bullish and bearish markets also imply that Bitcoin prices follow bubble-like dynamics and are vulnerable to swift changes in investor sentiment in the face of risk or uncertainty in financial markets. Apart from fundamental differences between Bitcoin and gold regarding their intrinsic value, concerns about the complexity and opaqueness of Bitcoin markets might explain the vulnerability. Gorton (2017) has defined a "safe asset" as an asset about which an investor can be confident that no other investor has private information. Although the idea of Bitcoin is consistent with this definition, the reality is not. For example, Gandal et al. (2018) identify price manipulation in the Bitcoin exchange. Taken together with the evidence from the impulse response functions and forecast error variance decomposition, we find no evidence of Bitcoin as a safe haven under heightened uncertainty or risk in financial markets.

D. Robustness Checks

In this section, we provide a battery of robustness checks for our conclusion that Bitcoin behaves nothing like gold and therefore is not a safe haven. To save space, we will provide a brief discussion of the results here and move the relevant figures to the appendix.

Alternative lags in the VAR system. Our baseline specifications include four lags of the variables based on the Akaike, Schwarz, and Hannan-Quinn information criteria. Nevertheless, given the potential presence of residual serial correlation, we confirm the main findings by re-estimating our baseline model using eight lags. Figure A.4 in the appendix shows that none of our findings are affected by the lag length selection.

Alternative identification scheme. Our structural VAR model is identified using simple economic theory and the assumption that movements in the rest of the economy are largely exogenous to the Bitcoin system. Although our assumptions are quite reasonable, any recursive assumption could be problematic in the presence of financial variables, especially at a low frequency (e.g., Furlanetto et al, 2017). Because there is no easy solution under our framework for this problem, we simply test whether our main findings are affected by reversing the Cholesky ordering of the VAR system. Figure A.5 in the appendix confirms our main findings, except that now the response of real Bitcoin prices to a shock to the S&P 500 becomes statistically insignificant. The difference in responses to VIX shocks between Bitcoin and gold is even more dramatic: gold becomes a strong, not a weak, safe-haven asset in this case.

Daily data. So far, we have relied on weekly (Wednesday) data because changes in daily data tend to be too noisy. However, this practice might have ignored important short-run changes that are particularly relevant to Bitcoin price dynamics. For example, Bouri et al. (2017) find that the hedge and safe-haven nature of Bitcoin depend on the horizon of study. Moreover, in the presence of financial variables in the VAR system, employing high-frequency data alleviates concerns from the recursive identification used in the baseline VAR model. Thus we re-estimate the baseline model using daily data.[27] Figure A.6 in the appendix shows that all results using weekly data are preserved.

Structural breaks in the Bitcoin market. The perception of cryptocurrencies in general and the trading system of Bitcoin, and its market behavior in particular, have experienced dramatic changes over the last decade. At the beginning of the sample period, Bitcoin trading volume was very low and most of the general public had no idea about Bitcoin as an investment option. Although it is difficult to pin down the exact timing of when Bitcoin became an accessible investment option, we assume there exists a structural break in the Bitcoin prices between 2013

[27] For this exercise, we drop the weekend data. While Bitcoin prices are available for the weekend, other variables are not. We use 20 lags in the daily VARs.

and 2015. As shown in Figure A.2. in the appendix, Bitcoin prices increased from below $100 in early 2013 to above $1,000 by the end of 2013. Although this jump in Bitcoin prices is dwarfed by the recent spike in prices, the sharp increase in Bitcoin prices during 2013 suggests a dramatic increase in investor attention paid to Bitcoin markets. Figure A.7 in the appendix shows that our results hardly change when limiting the analysis to data since 2014.[28]

Alternative proxies for macro factors. We have used various proxies for the macro factors suggested by the equilibrium relationship in Equation (7). In this section, we replace these variables with their alternatives to confirm whether our results are driven by a particular variable employed in the baseline VAR model.

First, we used the S&P 500 index normalized by the price index as a measure of real income, as well as a first-moment shock to the economy. Despite the important role of the U.S. stock market in driving global stock markets, the S&P 500 index might not necessarily capture income factors at the global level. Thus, we replace the S&P 500 index with the MSCI World index, which is a more representative measure of global stock markets. As shown in Figure A.8 in the appendix, none of our results are changed in this case.

Second, we replace the VIX index with the U.S. EPU index, developed by Baker et al. (2016), given the emerging literature on policy uncertainty as a driver of financial markets and asset prices (e.g., Karnizova and Li, 2014; Brogaard and Detzel, 2015). While uncertainty about financial markets has a negative effect on Bitcoin prices, Figure A.9 in the appendix shows that uncertainty about future government policy does not have any negative effect. The (weak) safe-haven nature of Bitcoin with respect to policy uncertainty echoes the claim that the increasing popularity and rapid appreciation of Bitcoin prices are largely driven by its independence from government authorities.

Third, we have found an insignificant effect on Bitcoin prices of shocks to the nominal interest rate, which is somewhat inconsistent with the prediction of the quantity equation. This finding might have been driven by the binding ZLB constraint; therefore, the one-year Treasury bill rate failed to capture the opportunity cost of holding Bitcoins. To account for this possibility,

[28] We also tested the robustness of our findings using the data from 2013 and 2015, and obtained similar results.

we instead use the shadow short rate constructed by Krippner (2013) at a weekly frequency. The shadow short rate measures the area between the expected path of the shadow rate (the policy rate if above zero) and the estimated neutral rate, giving a forward-looking view of the strength of any monetary stimulus. As shown in Figure A.10 in the appendix, we indeed find a negative effect of the nominal interest rate on Bitcoin prices in this case, although the effect is statistically significant only in the short run.

Alternative benchmark assets other than gold. We find that the responses of Bitcoin prices to macro factors suggested by the quantity equation as well as to risk or uncertainty shocks proxied by VIX are sharply different from those of gold. Based on this observation, we reject the popular claim that Bitcoin is a safe haven or "new gold." Now, to enhance our understanding of Bitcoin price dynamics, we compare the empirical properties of Bitcoin with those of other financial assets.

First, Gronwald (2019) argues that Bitcoin behaves similarly to commodities like crude oil and gold because Bitcoin shares characteristics such as the fixed supply with exhaustible resource commodities. Given a much longer history of crude oil and gold traded in financial markets, he emphasizes the importance of understanding commodity price dynamics to shed light on Bitcoin price dynamics. Thus, we compare the response of Bitcoin with that of crude oil prices to macro factors in the VAR model, in which real gold prices are replaced by real crude oil prices.[29] While real oil prices respond to the S&P 500 positively, they do not respond to VIX, suggesting that the empirical properties of Bitcoin and crude oil are not necessarily similar (Figure A.11 in the appendix). Interestingly, we find that real Bitcoin prices respond positively to real oil prices, which is different from the case of gold.[30]

Second, following much of the literature on the link between Bitcoin and traditional currencies (Yermack, 2015; Baur et al., 2018; Urquhart and Zhang, 2019), we replace real gold prices with the U.S. dollar index, which measures the value of the dollar against a basket of foreign currencies. Figure A.12 in the appendix shows that the responses of the dollar index are sharply different from those of Bitcoin prices. Real Bitcoin prices decline in response to dollar

[29] Real crude oil prices are obtained by normalizing West Texas Intermediate crude oil prices by the OPI.

[30] We find qualitatively similar results when using the commodity price index instead.

appreciation, suggesting that Bitcoin can serve as a hedge for investors against USD.[31] Taken together, our findings, in general, differ from those of Liu and Tsyvinski (2018), who used factor analysis to determine that cryptocurrencies have no exposure to common stock market factors or the returns to commodities and currencies.

E. Extension of Preliminary Model

In this section, we extend the preliminary model in Equation (7) by adding Bitcoin-specific variables we ignored in the baseline analysis. This is an important analysis given that a substantial share of Bitcoin price dynamics is not explained by the variables suggested by the theory of money demand. Our ultimate interest is whether the inclusion of variables specific to the supply, usage, or velocity of Bitcoin will affect our main conclusion and demonstrate additional explanatory power for Bitcoin price dynamics.

First, we have normalized the nominal Bitcoin/USD exchange rate by the U.S. price index, as suggested by the quantity equation. However, one might be interested in understanding the nominal Bitcoin/USD exchange rate itself (i.e., Bitcoin prices in USD) and its response to inflation, which is a far more intuitive measure for investors. Thus, we replace real Bitcoin prices with nominal Bitcoin prices and include the price index as an independent variable.

Figure 7 summarizes the response of nominal Bitcoin prices to shocks in the extended VAR system. While responses to the real S&P 500 index, the VIX, and the one-year U.S. treasury rate are nearly identical, as shown in Figure 2, Bitcoin prices increase significantly after a positive shock to the price level. This finding is consistent with the prediction of the quantity equation (from a money demand perspective) and also implies that Bitcoin could be a useful hedge against inflation (from an asset perspective). Figure 8 shows the results of the forecast error variance decomposition. The one notable difference from Figure 5 is that a non-negligible share of Bitcoin price fluctuations is now explained by inflation shocks.

Second, given the exogenous and deterministic nature of the supply of Bitcoin in the economy, we ignored the proxy for $\overline{m_t^B}$ in the baseline analysis (see Figure A.2 in the appendix).

[31] Although real Bitcoin prices increase on impact, this effect is not statistically significant.

A possible way to justify our assumption is to include this variable in the VARs and confirm that the effect of an increase in the stock of Bitcoin does not have any significant effect on its prices.[32] Thus, we add the log of the total number of Bitcoins in circulation to the preliminary VAR model. Given the exogeneity of the supply of Bitcoin with respect to its prices, we place the Bitcoin stock variable before the price variable in the Cholesky ordering. In this augmented VAR model I, real Bitcoin prices do not respond significantly to shocks to Bitcoin supply (Figure A.13 in the appendix) and fluctuations in real Bitcoin prices are not explained by supply over any horizon (Figure A.14 in the appendix). These findings are fully consistent with the implication of the deterministic supply of Bitcoin and support our identifying assumption.

Third, by ignoring variation in the relative size of the Bitcoin economy (i.e., Bitcoin usage) over time, the baseline analysis does not include a proxy for λ_t. This is because we are interested in the short-run dynamics of Bitcoin prices. However, as shown in Figure A.2 in the appendix, Bitcoin usage has substantially increased over time. To account for the expansion of λ_t over time, we further include the log of the number of transactions to the augmented model I. Thus, this augmented model II includes six variables in total. Consistent with the theoretical prediction of the quantity equation, an increase in the relative size of the Bitcoin economy (i.e., a shift in demand for real payment given the price and real income) is followed by the appreciation of Bitcoin (Figure A.15 in the appendix). However, the effect is statistically significant only on impact and the variation in the number of Bitcoin transactions hardly explains the variations in real Bitcoin prices (Figure A.16 in the appendix).

Lastly, because velocity cannot be directly observed, we have included the nominal interest rate to proxy the velocity of Bitcoin in the quantity equation. We add an alternative proxy for the velocity of Bitcoin (the days destroyed of any given transaction) to the VAR model for further study of its role. The occurrence of dramatic changes in the velocity already suggests an important role of speculative demand in determining Bitcoin prices. Augmented model III includes seven variables in which the real Bitcoin price variable is placed last in the Cholesky ordering; this model is the most comprehensive description of Bitcoin price dynamics. Interestingly, the inclusion of the velocity proxy seems important in understanding Bitcoin price dynamics. Consistent with the

[32] Of course, this argument is only true when there is no change in speculative demand for Bitcoin.

prediction of the quantity equation, an increase in the velocity is followed by an increase in real Bitcoin prices, and this effect is highly statistically significant (Figure 9).

Moreover, Bitcoin velocity now explains a substantial share of the variation in Bitcoin price dynamics over every horizon (Figure 10). Among the Bitcoin-specific variables, Bitcoin velocity seems the most important variable in understanding Bitcoin price dynamics. One month after the shock, more than 90% of the variation in real Bitcoin prices can be explained by the idiosyncratic components. One year after the shock, about 65% of the variation is still explained by these components, consistent with Liu and Tsyvinski (2018), who find that cryptocurrency returns can be predicted by factors that are specific to cryptocurrency markets.

IV. CONCLUSION

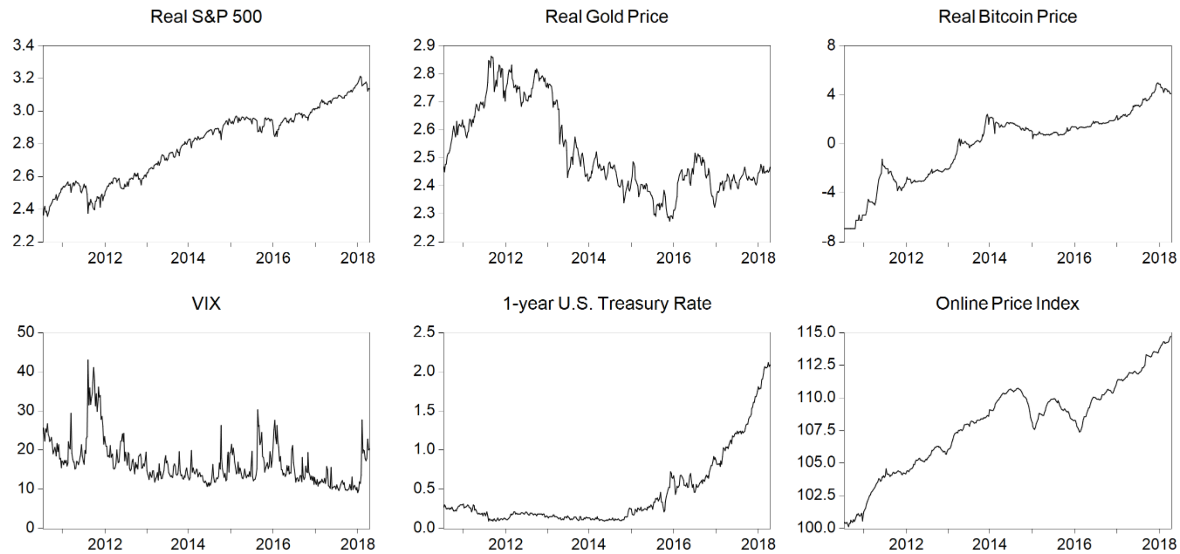
Since Bitcoin, or cryptocurrencies in general, has emerged as a new form of digital money and payment structure, the literature on understanding cryptocurrency price dynamics has rapidly expanded. However, theoretical and empirical attempts to understand Bitcoin price dynamics have not reached a consensus because of the inherent ambiguity of Bitcoin as an asset or a currency. We contribute to this emerging literature by providing a systematic analysis that encompasses both the currency- and asset-like nature of Bitcoin, allowing an easy structural interpretation of our findings.

Despite the many interesting empirical regularities discovered in the paper, our results are subject to some caveats. First, while the main findings, as well as a battery of sensitivity tests and extensions of the baseline model, shed new light on Bitcoin price dynamics, the rapidly changing environment regarding cryptocurrency markets urges caution in interpreting our findings. Especially, we have ignored any impact on Bitcoin prices of regulatory changes or the increasing number of new cryptocurrencies available. Second, compared to previous analyses of other safe-haven assets such as gold, the sample period in our analysis is limited to the early stages of cryptocurrency market development. Thus, important market characteristics such as trading volume or liquidity may suddenly change in the future, which would challenge our findings. A fruitful direction for future research should provide a fully coherent theoretical and empirical framework encompassing both the currency- and asset-like features of cryptocurrencies.

As an interim step, however, we believe our analysis provides a useful benchmark for understanding Bitcoin price dynamics, as well as Bitcoin's safe-haven nature. Will Bitcoin (or cryptocurrencies, in general) act as a safe haven during the next financial crisis or heightened global uncertainty? We are skeptical about the brave new world envisioned by Satoshi Nakamoto.

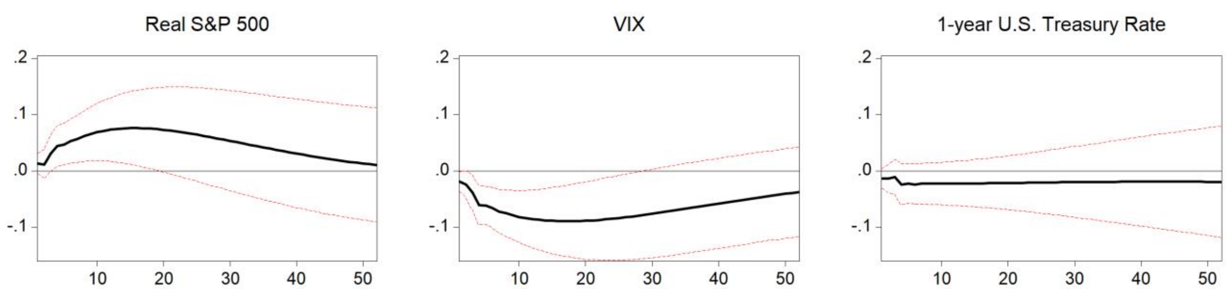
Figures and tables

Figure 1. Evolution of real Bitcoin prices and other variables.



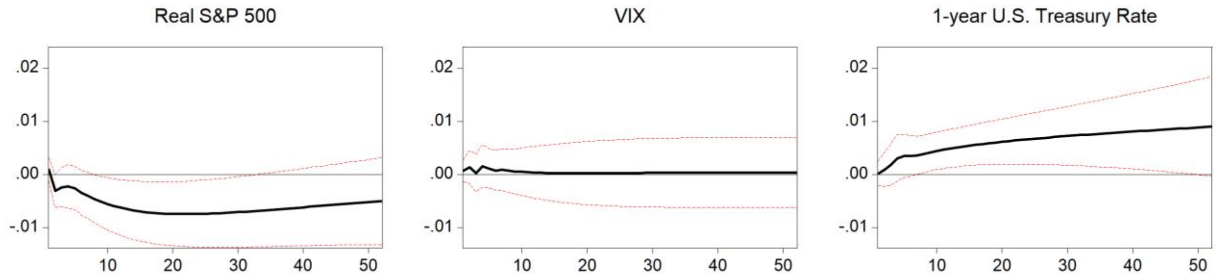
Note: This graph plots the time series of real Bitcoin prices and other macroeconomic and financial variables. Natural logarithms are taken on the S&P 500, gold prices and Bitcoin prices after normalized by the OPI. The natural logarithm is taken on the OPI. VIX and one-year Treasury bill rates are in level.

Figure 2. Response of real Bitcoin prices: preliminary model



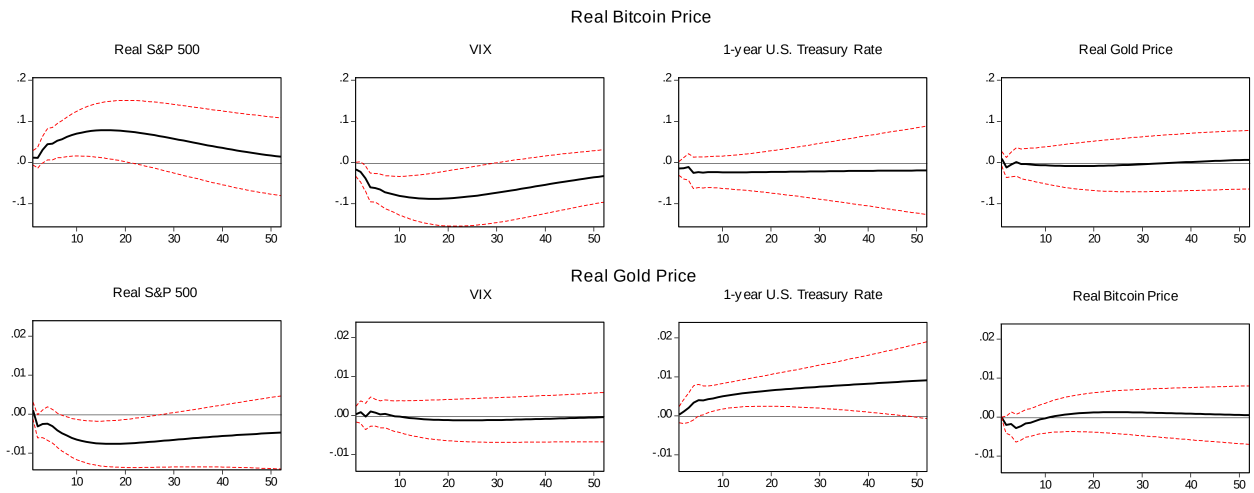
Note: This graph shows impulse responses of Bitcoin prices to one-standard-deviation shocks in other variables and their 95% confidence bands from the four-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 3. Response of real gold prices: preliminary model



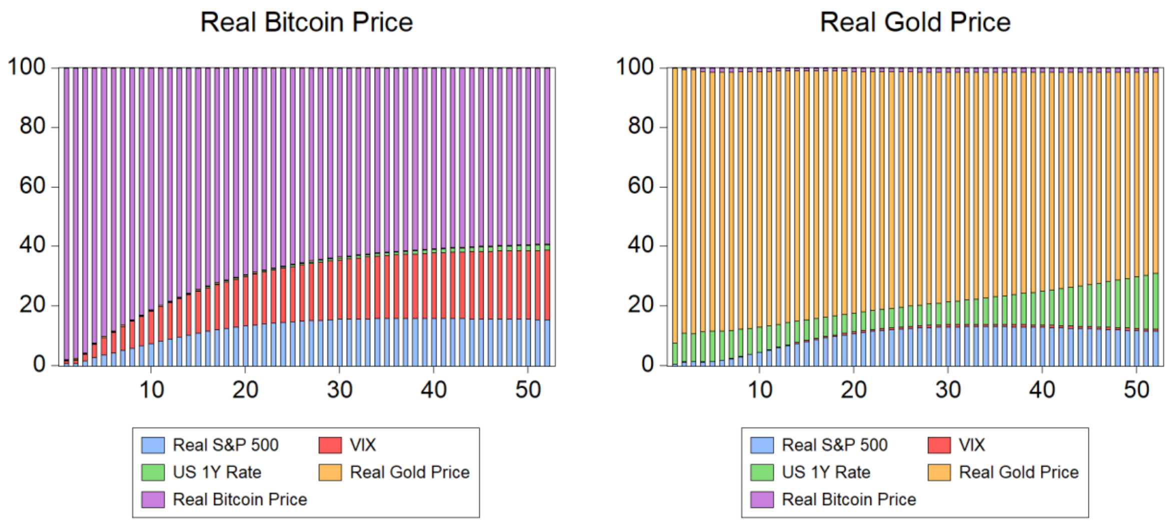
Note: This graph shows impulse responses of the gold price to one-standard-deviation shocks in other variables and their 95% confidence bands from the four-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 4. Response of real Bitcoin and gold prices: baseline model



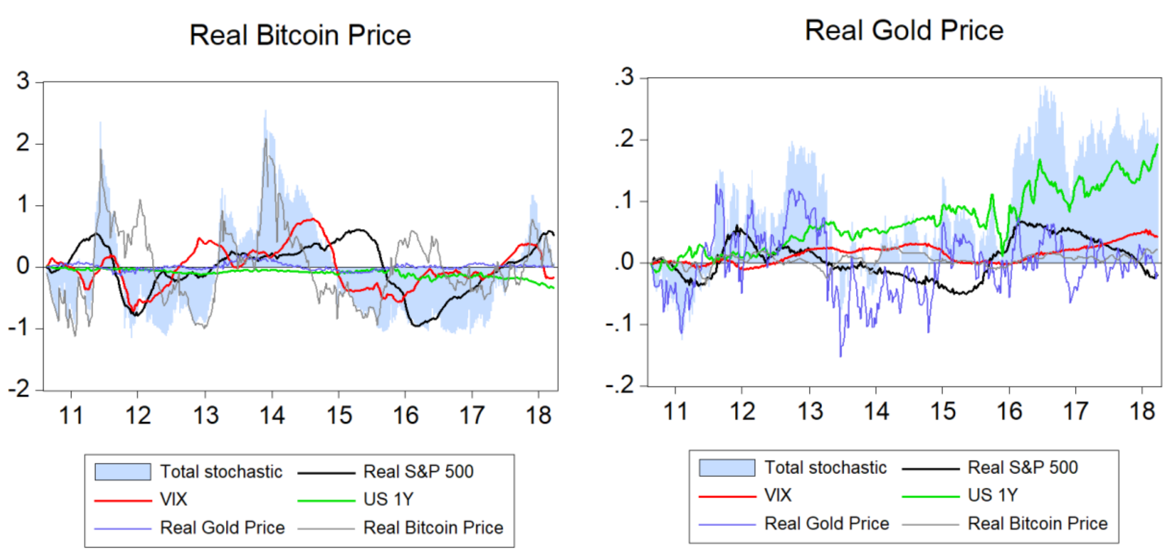
Note: This graph shows impulse responses of real Bitcoin and gold prices to one-standard-deviation shocks in other variables and their 95% confidence bands from the five-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 5. Forecast error variance decomposition of real Bitcoin and gold prices



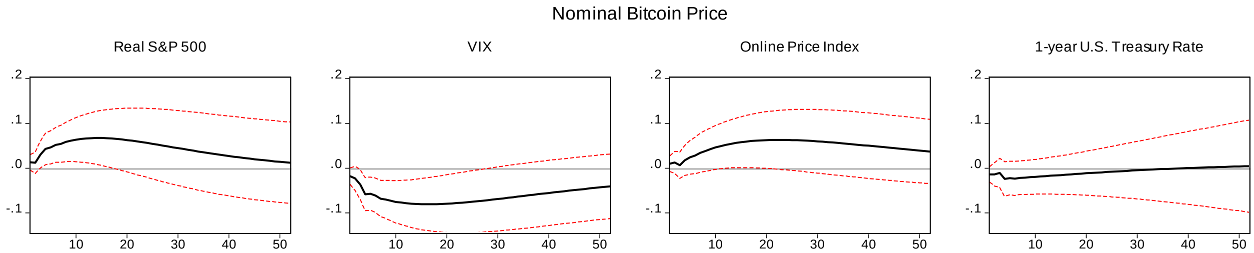
Note: This graph shows the forecast error variance decomposition of real Bitcoin prices and gold prices derived from the five-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 6. Historical decomposition of real Bitcoin and gold prices



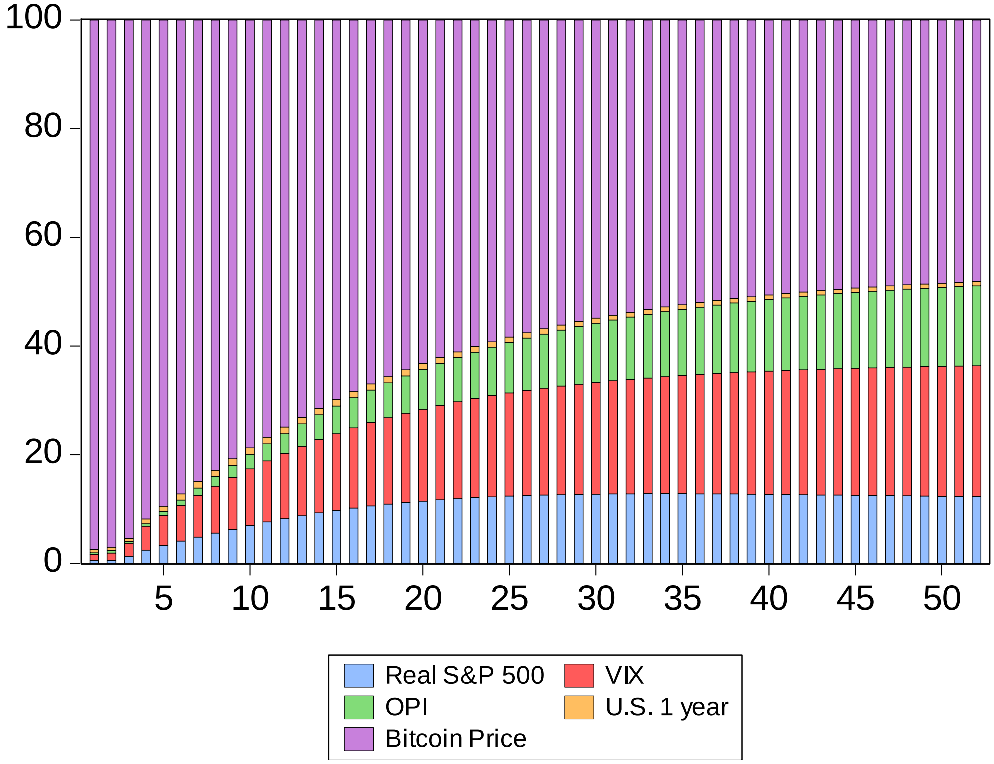
Note: This graph shows the historical decomposition of real Bitcoin prices and gold prices derived from five-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 7. Response of nominal Bitcoin prices



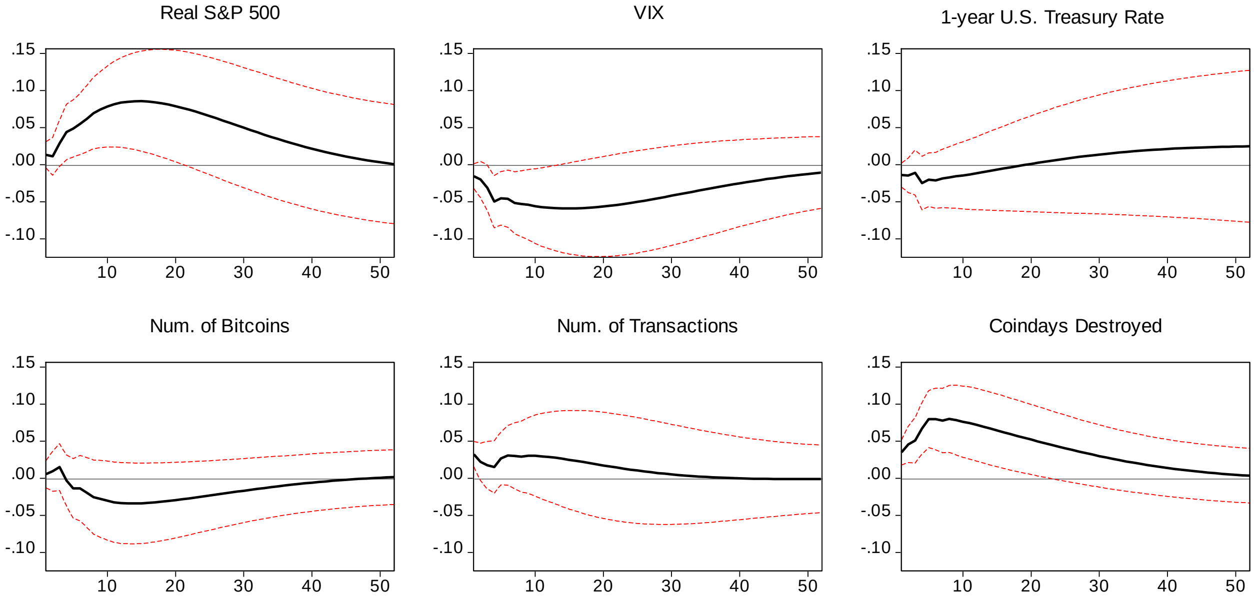
Note: This graph shows impulse responses of nominal Bitcoin prices to one-standard-deviation shocks in other variables and their 95% confidence bands from the five-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 8. Forecast error variance decomposition of nominal Bitcoin prices



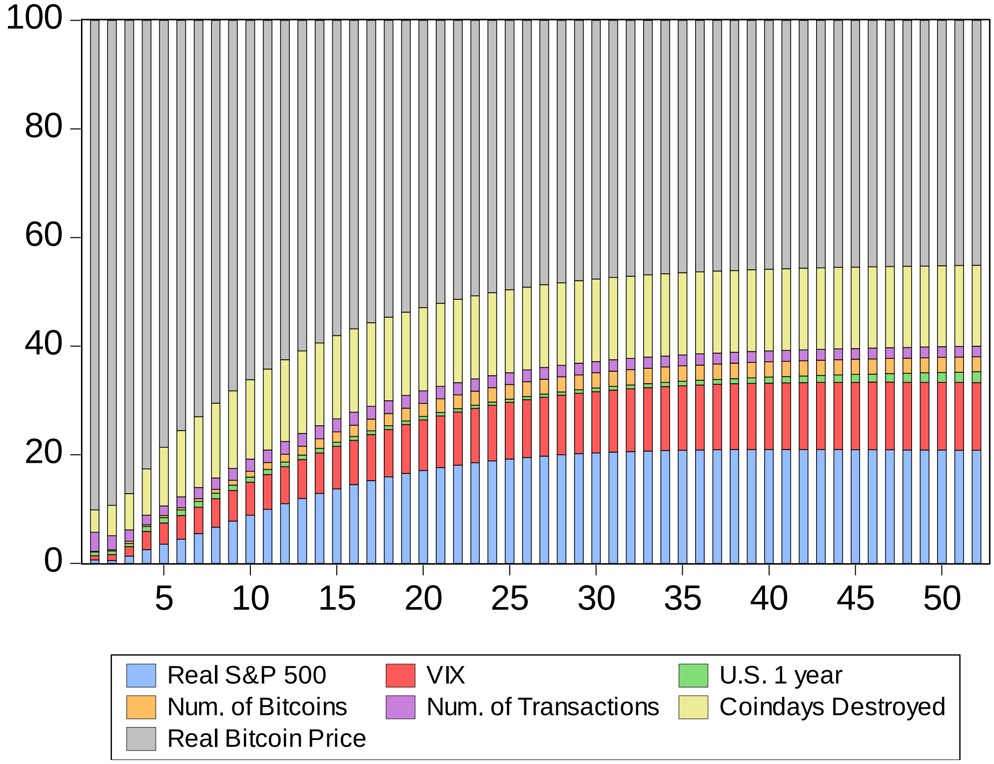
Note: This graph shows the forecast error variance decomposition of nominal Bitcoin prices, derived from the five-variable VARs for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 9. Response of real Bitcoin prices: augmented model III



Note: This graph shows impulse responses of real Bitcoin prices to one-standard-deviation shocks in other variables and their 95% confidence bands from the augmented-VAR model III for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure 10. Forecast error variance decomposition of real Bitcoin prices: augmented model III



Note: This graph shows the forecast error variance decomposition of real Bitcoin prices derived from the augmented-VAR model III for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Table 1. Summary Statistics

	S&P 500 (%)	Gold Prices (%)	Bitcoin Prices (%)	OPI (%)	VIX	US1Y (%)
Mean	0.1929	-0.0002	2.7545	0.0191	16.6715	0.4464
Median	0.3455	0.0753	0.4308	0.0177	15.31	0.23
Max	7.1323	7.8137	112.3410	0.2692	42.9900	2.12
Min	-11.6702	-12.4535	-71.0255	-0.7234	9.15	0.09
Std. Dev.	1.8175	2.2142	17.7419	0.0592	5.5532	0.4777
Observations	400	400	400	400	400	400

Note: This table shows summary statistics for real Bitcoin prices and other macroeconomic and financial variables. S&P 500, gold prices, and Bitcoin prices are log-differenced after normalization by the Online Price Index. The Online Price Index is log-differenced. VIX and the one-year Treasury bill rate are in level.

Table 2. Correlation matrix of Bitcoin price and other macroeconomic and financial variables

	S&P 500	Gold	Bitcoin	OPI	VIX	US1Y
S&P 500	1	0.0831	0.0636	-0.0511	-0.2859	-0.0189
Gold	0.0831	1	0.0430	-0.0986	0.0480	0.0213
Bitcoin	0.0636	0.0430	1	-0.0105	-0.1502	-0.0133
OPI	-0.0511	-0.0986	-0.0105	1	-0.0271	-0.1236
VIX	-0.2859	0.0480	-0.1502	-0.0271	1	-0.2854
US1Y	-0.0189	0.0213	-0.0133	-0.1236	-0.2854	1

Note: This table shows the correlation between the main variables in the analysis. S&P 500, gold prices, and Bitcoin prices are log-differenced after normalization by the Online Price Index. The Online Price Index is log-differenced. VIX and the one-year Treasury bill rate are in level.

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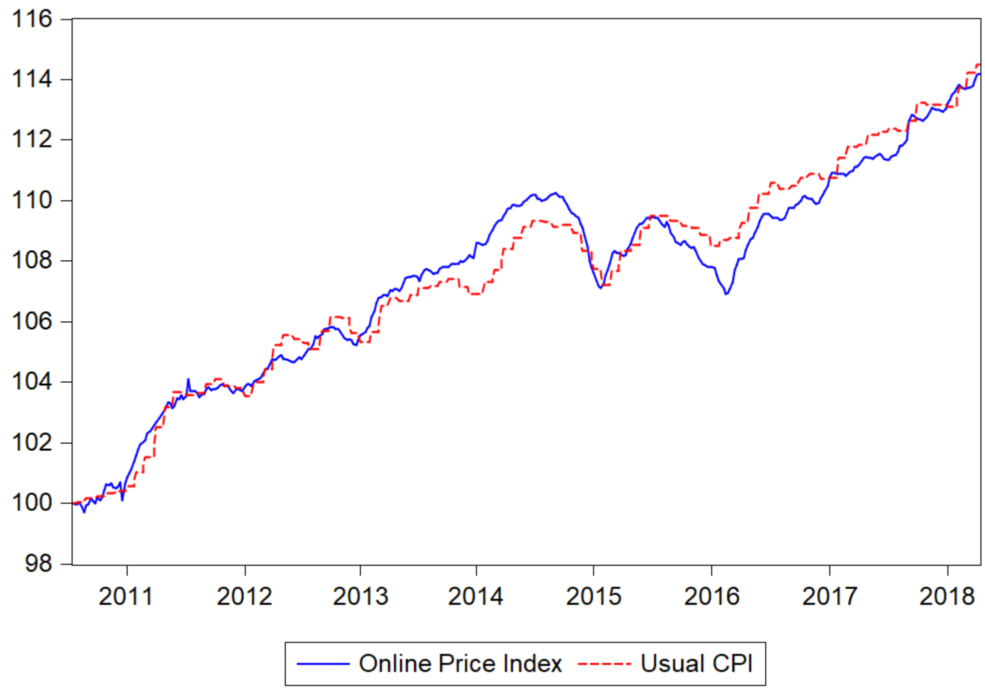
Appendix

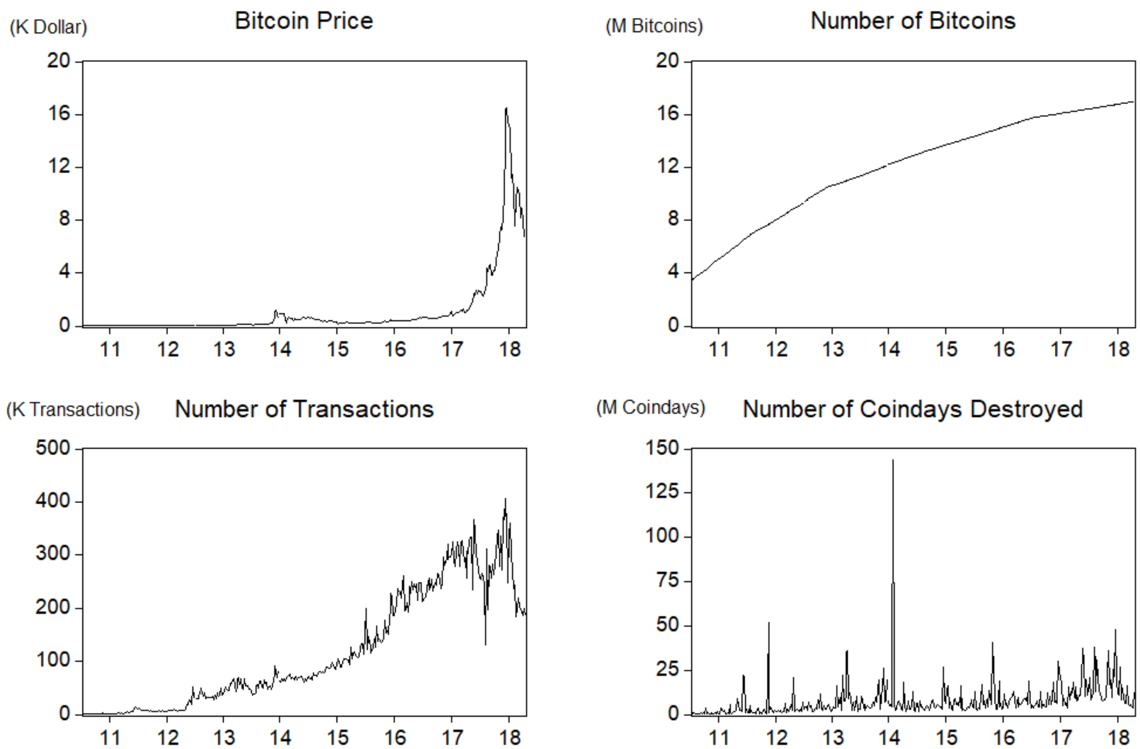
A. Additional figures and tables

Figure A.1. Online Price Index and Consumer Price Index at a weekly frequency



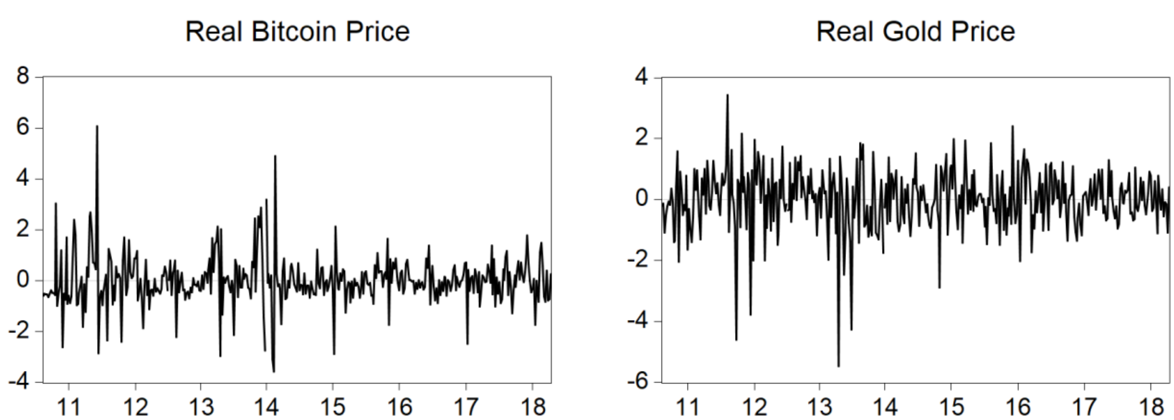
Note: This graph plots weekly time series of the U.S. daily Online Price Index and the Consumer Price Index released by Bureau of Labor Statistics for the sample period between July 21, 2010, and April 11, 2018. The indices are normalized by the first observation of each series.

Figure A.2. Evolution of Bitcoin-specific variables



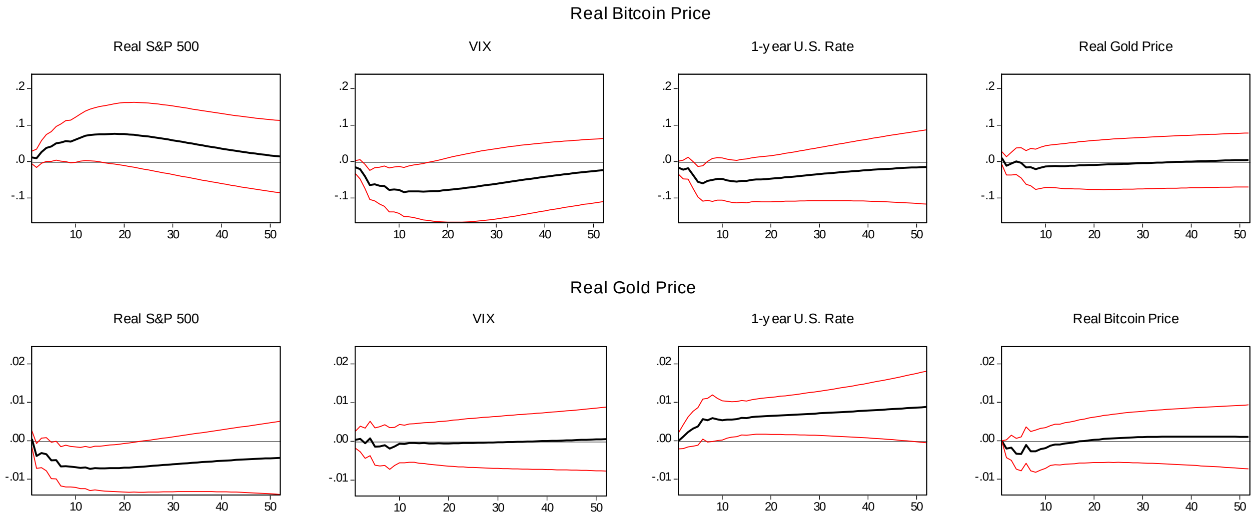
Note: This graph plots weekly time series of the Bitcoin-specific variables. The units of each axis are as follows: Bitcoin prices in thousand dollars; the number of Bitcoins in million; the number of transactions in thousand; the number of days destroyed in million (sum of the number of days past from the last transaction for each Bitcoin transacted on a day)

Figure A.3. Structural residuals of real Bitcoin and gold prices



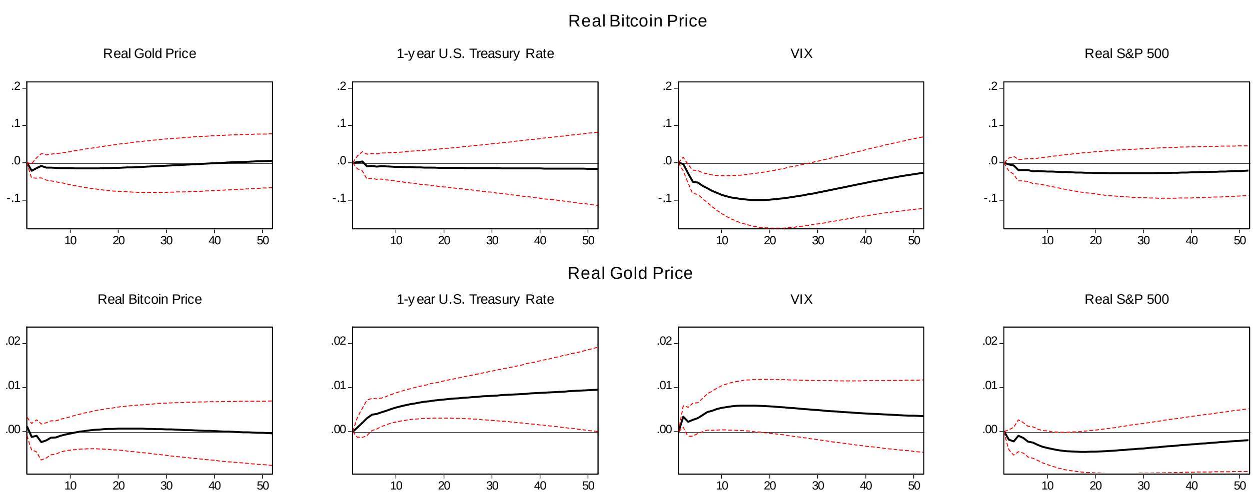
Note: This graph plots the structural residuals of real Bitcoin and gold prices derived from the five-variable VAR model for the sample period between July 21, 2010, and April 11, 2018.

Figure A.4. Robustness checks: alternative lags



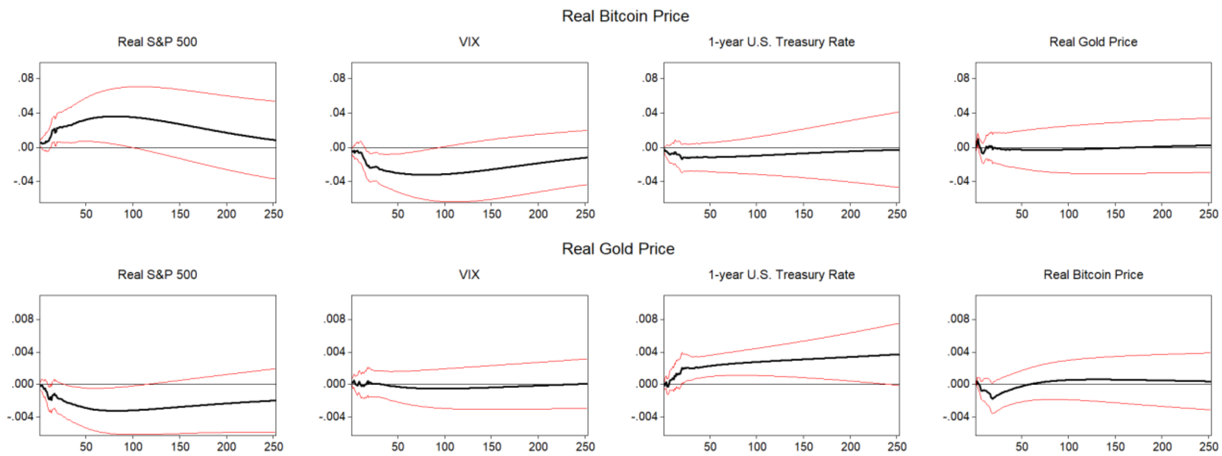
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but using the eight lags. The units of the horizontal axes are weeks.

Figure A.5. Robustness checks: reverse ordering



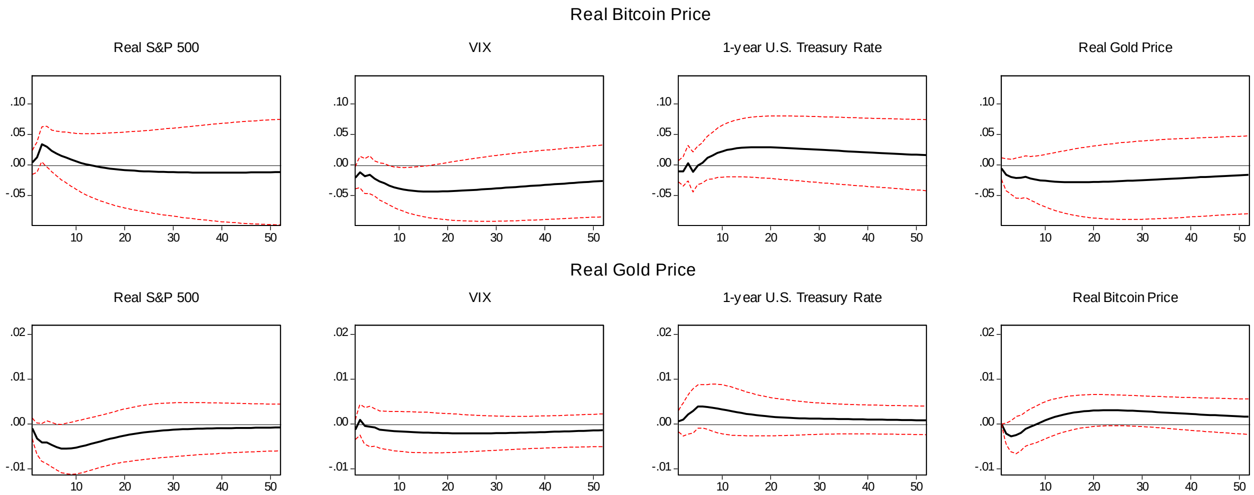
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but using the reverse Cholesky ordering. The units of the horizontal axes are weeks.

Figure A.6. Robustness checks: using daily data



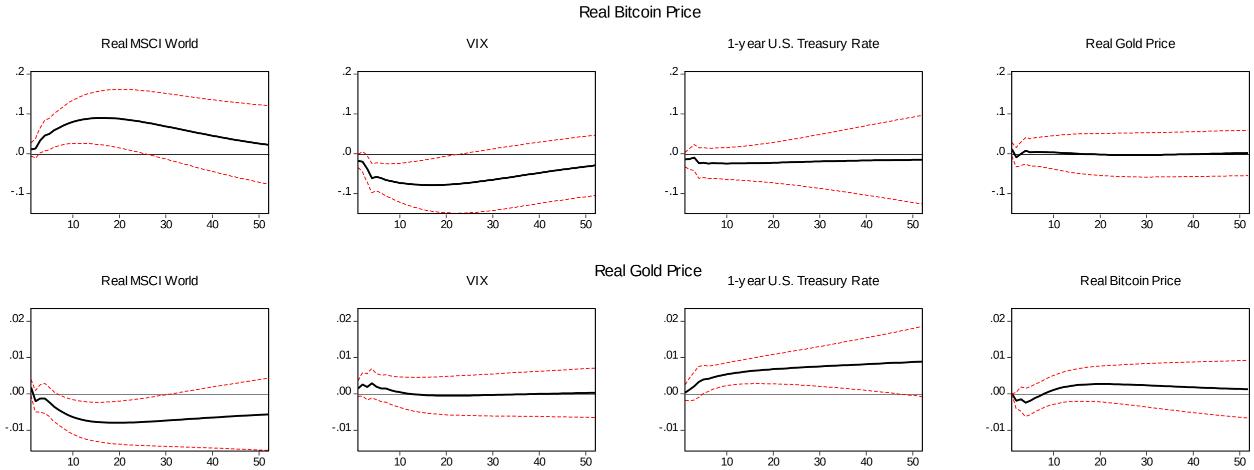
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but using daily data. The units of the horizontal axes are weeks.

Figure A.7. Robustness checks: using data from 2014



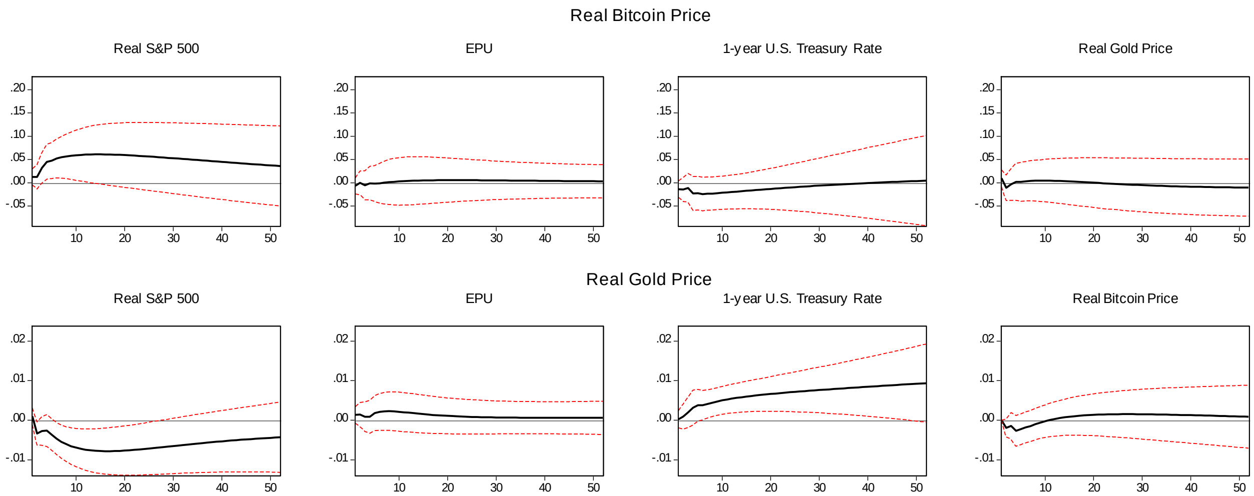
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but using the data from 2014 only. The units of the horizontal axes are weeks.

Figure A.8. Robustness checks: the MSCI World index



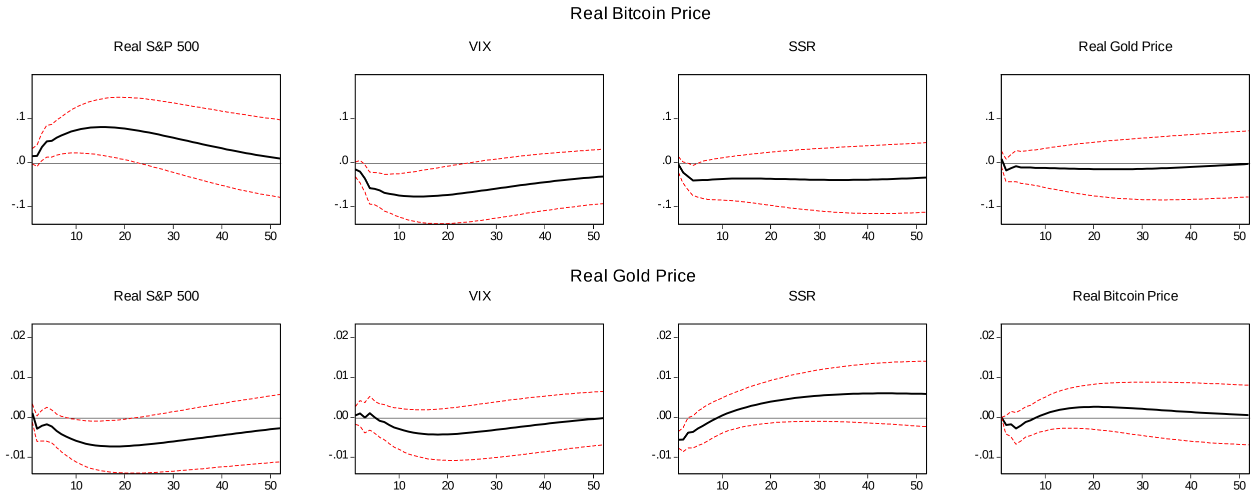
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but replacing the S&P 500 with the MSCI World index. The units of the horizontal axes are weeks.

Figure A.9. Robustness checks: U.S. economic policy uncertainty index



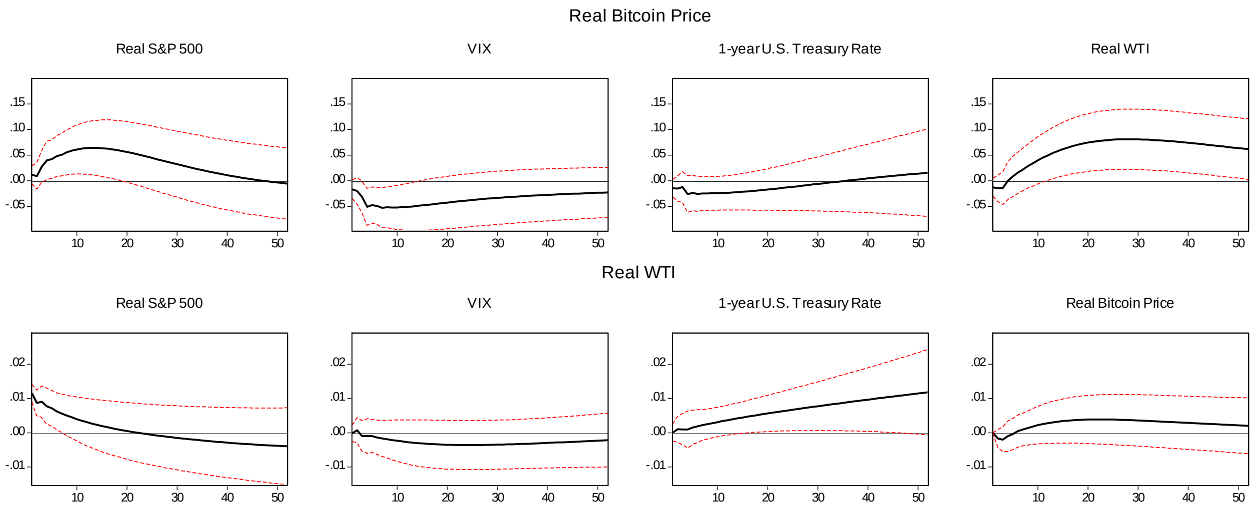
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but replacing the VIX with the U.S. economic policy uncertainty index. The units of the horizontal axes are weeks.

Figure A.10. Robustness checks: the shadow short rate



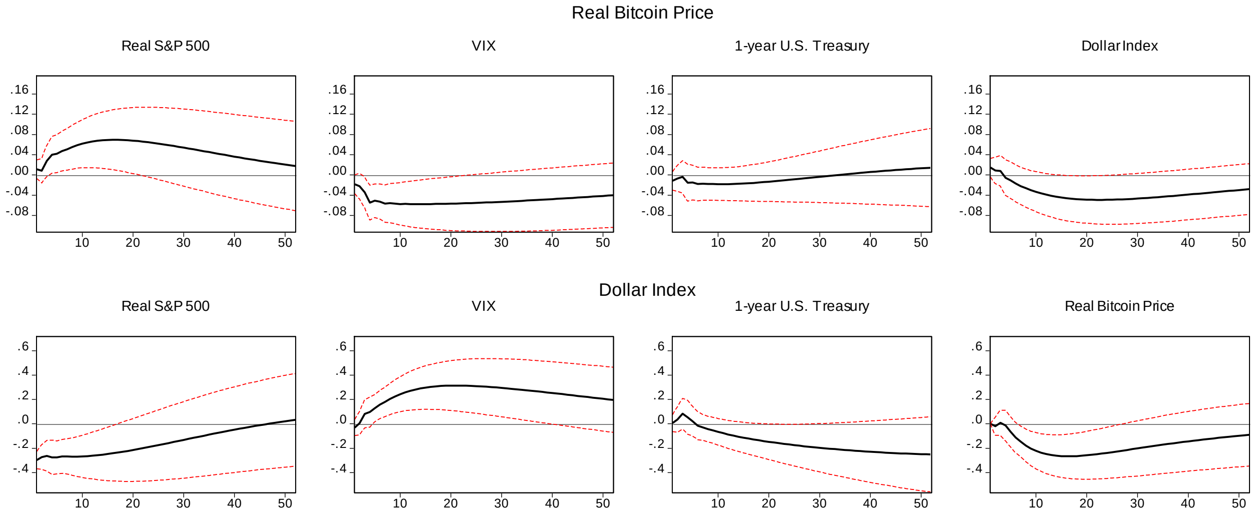
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but replacing the federal funds rate with the shadow short rate. The units of the horizontal axes are weeks.

Figure A.11. Robustness checks: real oil prices



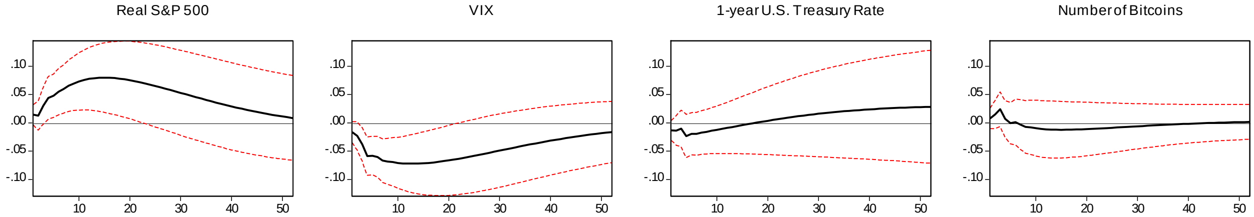
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but replacing real gold prices with real oil prices. The units of the horizontal axes are weeks.

Figure A.12. Robustness checks: dollar index



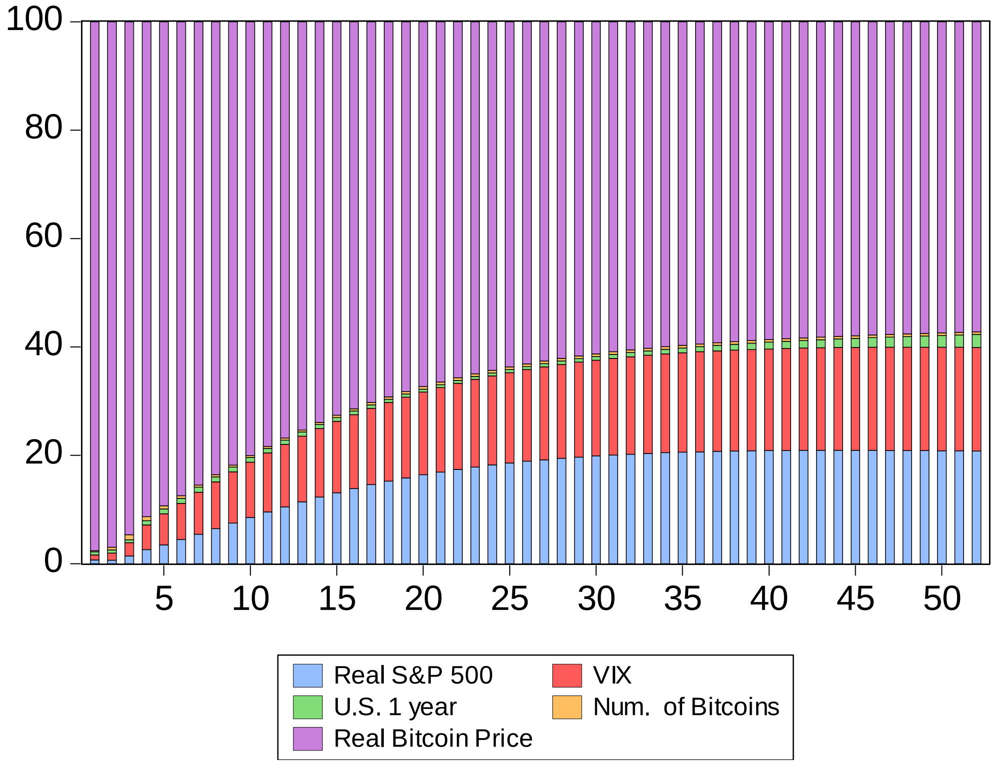
Note: This graph shows impulse responses of real Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the baseline model but replacing real gold prices with the dollar index. The units of the horizontal axes are weeks.

Figure A.13. The response of real Bitcoin prices: augmented model I



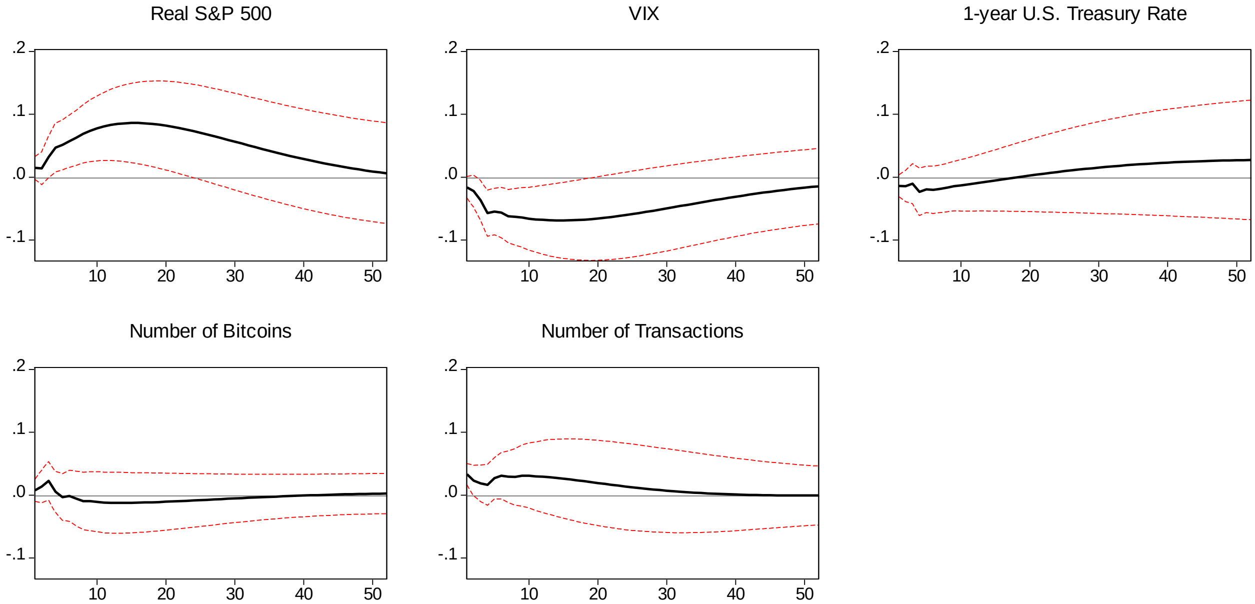
Note: This graph shows impulse responses of real Bitcoin prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the augmented-VAR model I for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure A.14. Forecast error variance decomposition of real Bitcoin prices: augmented model I



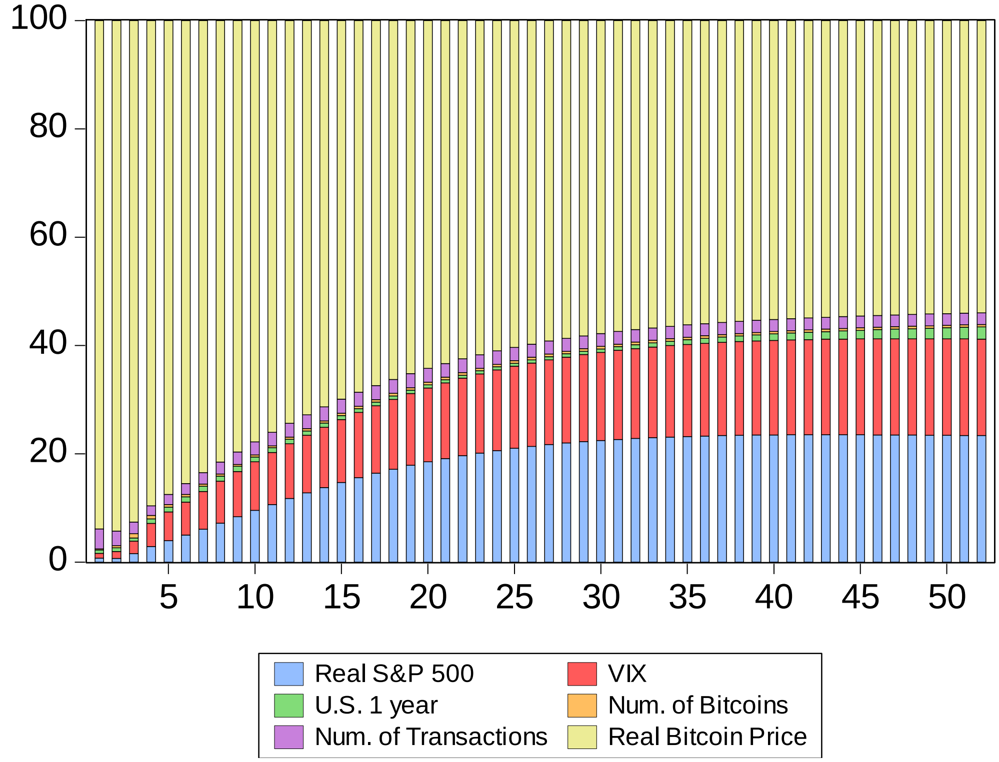
Note: This graph shows the forecast error variance decomposition of real Bitcoin prices derived from the augmented-VAR model I for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure A.15. The response of real Bitcoin prices: augmented model II



Note: This graph shows impulse responses of real Bitcoin prices to the one-standard-deviation shock in other variables and their 95% confidence bands from the augmented-VAR model II for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.

Figure A.16. Forecast error variance decomposition of real Bitcoin prices: augmented model II



Note: This graph shows the forecast error variance decomposition of real Bitcoin prices derived from the augmented-VAR model II for the sample period between July 21, 2010, and April 11, 2018. The units of the horizontal axes are weeks.