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Abstract

During the recent COVID-19 pandemic, many commonalities shared by Bitcoin and gold raise the question of whether Bitcoin can hedge inflation or provide a safe haven as gold often does. By estimating a Vector Autoregression (VAR) model, we provide systematic evidence on the relationship among inflation, uncertainty, and Bitcoin and gold prices. Bitcoin appreciates against inflation (or inflation expectation) shocks, confirming its inflation-hedging property claimed by investors. However, unlike gold, Bitcoin prices decline in response to financial uncertainty shocks, rejecting the safe-haven quality. Interestingly, Bitcoin prices do not decrease after policy uncertainty shocks, partly consistent with the notion of Bitcoin's independence from government authorities. We also find an interesting asymmetry in the drivers of Bitcoin price dynamics between the bullish and bearish market. The main findings hold with or without the COVID-19 pandemic episode.

JEL Classification: E41; E44; F31; G10

Keywords: Cryptocurrencies; Bitcoin; inflation-hedging; safe-haven; gold; COVID-19

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I. INTRODUCTION

Since the global financial crisis in 2008, various types of cryptocurrencies, including Bitcoin, 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). While Bitcoin has become a significant interest of not only investors but also academics and policymakers, existing theoretical and empirical attempts have not reached a consensus about its nature. Recently, the COVID-19 pandemic asked important questions regarding the nature of Bitcoin again. Does Bitcoin hedge inflation pressure caused by government stimulus measures? Does Bitcoin act as a safe haven for investors during market turmoil or heightened uncertainty? Recent studies have partly answered these questions but have not reached a consensus (Conlon and McGee, 2020; Dutta et al., 2020; Mariana et al., 2021).[1]

We contribute to this emerging literature and contemporary discussions by providing systemic evidence on the relationship among inflation (or inflation expectation), uncertainty, and Bitcoin prices. Despite the rapid expansion of empirical studies, many analyses have focused on the statistical properties of Bitcoin to understand its herding behavior or determine its safe-haven status, mostly from a portfolio diversification perspective (e.g., Dyhrberg, 2016; Bouri et al., 2017; Shahzad et al., 2019; Smales, 2019; Wang et al., 2019). Moreover, although few studies based on the money demand theory provide a link between Bitcoin prices and inflation (Ciaian et al., 2016), this link has not been tested empirically to our knowledge.[2] Given that many investors consider Bitcoin as an inflation hedge, especially during the recent pandemic (Bloomberg, 2020), the high-frequency analysis on the relationship between inflation and Bitcoin prices provides timely policy implications.

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[1] For example, while Mariana et al. (2021) argue that Bitcoin exhibits short-term safe haven properties during the pandemic, Conlon and McGee (2020) conclude that Bitcoin is not a safe haven for the majority of international equity markets examined.

[2] For example, Ciaian et al. (2016) build a simple conceptual framework of Bitcoin price formation by borrowing Barro's (1979) model for gold standards and test its predictions. Although the opportunity cost of holding Bitcoin crucially depends on inflation under the standard money demand theory, Ciaian et al. (2016) instead use the exchange rate between the U.S. dollar and Euro as a measure of the general price level due to the lack of data on prices at such a high frequency. However, the exchange rate can be driven by factors other than inflation and is too volatile to be rationalized by the changes in economic fundamentals.

Against this background, analysis of the response of Bitcoin prices to shocks to uncertainty and inflation within a Vector Autoregression (VAR) framework using high-frequency data provides a more qualified metric for gauging the nature of Bitcoin from a macroeconomic perspective. Considering the well-known safe-haven and inflation-hedging property of gold, as well as its similarities to Bitcoin (e.g., exogenous supply, pseudo-medium of exchanges, and speculative demand),[3] we compare the response of Bitcoin prices with that of gold prices to the same kind of shocks, which ease interpretation of our findings.[4]

We find that Bitcoin prices decrease significantly in response to financial uncertainty shocks—measured by the VIX, suggesting that Bitcoin is not a safe-haven asset. However, Bitcoin prices do not decline in response to policy uncertainty shocks—proxied by Economic Policy Uncertainty (EPU) constructed by Baker et al. (2016), lending support to the notion of Bitcoin's independence from government authorities. Bitcoin appreciates against positive inflation and inflation expectation shocks, suggesting its inflation-hedging property that has not been confirmed in the existing literature. Overall, these responses to the structural shocks sharply differ from those of gold prices to the same shocks, which strongly repudiate the recent claim that Bitcoin is the "digital gold."

II. EMPIRICAL ANALYSIS

A. Data

We estimate the VAR model at a weekly frequency to understand the short-run effect of uncertainty and inflation shocks on Bitcoin prices. We use the S&P 500 index to capture overall financial market conditions and test the robustness of our findings using the world stock market

[3] 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.

[4] There is a vast empirical literature on the safe-haven or inflation-hedging quality of gold (e.g., Economist, 2005; Baur and McDermott, 2010; Joy, 2011; Reboredo, 2013).

index. We measure the degree of uncertainty in the economy by the VIX and EPU index.[5] They capture uncertainty regarding different dimensions (financial vs. policy) of the economy.[6]

Motivated by the prediction of the money demand theory on Bitcoin or gold price formulation (Barro, 1979; Ciaian et al., 2016), we employ both inflation expectations—measured by the difference between the five-year nominal treasury yield and the five-year TIPS (Treasury Inflation-Protected Securities) yield—and the online price index (OPI) constructed by Cavallo and Rigobon (2016) to measure inflation pressures at a high frequency.[7] While investigating the prices on goods sold online is particularly relevant for capturing the inflation-hedging demand of Bitcoin, the OPI has never been used to understand the Bitcoin price behavior. Lastly, we use the one-year Treasury bill rate to measure the stance of monetary policy.

The data used for the following empirical analysis include weekly (Wednesday) observations between July 21, 2010, and December 31, 2020 (a total of 539 weekly observations).[8] The beginning date of the sample is governed by the introduction of Bitcoin exchanges. Figure 1 plots the evolution of the main variables used in the empirical analysis

[5] The VIX is a measure of market expectations of near-term volatility, as implied by S&P 500 stock index option prices, which becomes a standard measure of uncertainty in financial markets. The EPU index captures the uncertainty of "who will make economic policy decisions, what economic policy actions will be undertaken and when they will be enacted, the economic effects of past, present and future policy actions, and uncertainty induced by policy inaction." The index has been widely used in recent studies as an alternative to the VIX—the most popular uncertainty measure based on financial market data. In constructing the index, Baker et al. (2016) mainly adopted a narrative approach and utilized the news coverage of policy-related economic uncertainty. They counted the articles appearing in every newspaper containing terms related to economic and policy uncertainty. Each article should contain terms related to the three categories of uncertainty, economy, and policy to meet the criteria for inclusion.

[6] 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. The recent episodes of the Brexit and the U.S. presidential election demonstrate how empirical proxies for each uncertainty can diverge dramatically from one another. We choose the U.S. EPU index because of its high correlation with the world EPU index and its availability at a daily frequency.

[7] 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 (see Figure A.1 in Appendix).

[8] 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.

Table 1 provides summary statistics on weekly compounded (log) returns on Bitcoin prices and the other variables. As expected, Bitcoin prices during the sample period are characterized by a strong upward trend as well as excessive volatility. Table A.1 in Appendix summarizes the correlations between the main variables of interest. Bitcoin does not show any strong unconditional correlations with other financial assets, 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., 2017). We delve into a more formal analysis in the following section to qualify the suggestive evidence.

B. Vector Autoregressions Model

To test the effect of various structural shocks on Bitcoin prices, the baseline VAR model includes six variables and a linear and quadratic trend: the log of the U.S. stock market index, the VIX index, five-year-ahead inflation expectations,[9] the one-year U.S. Treasury bill rate, the log of gold prices, and the log of Bitcoin prices. ADF unit root test results in Table A.2 in Appendix indicate that Bitcoin and gold prices and the one-year U.S. Treasury bill rate are nonstationary, whereas other variables are stationary. We model the data in (log) levels to preserve the potential cointegrating relationships among the variables.[10]

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, whereas this variable is exogenous to the variables listed after it. Given the small share of Bitcoin in financial markets, it is reasonable to treat Bitcoin prices as the least exogenous variable in the VAR system.[11] The identifying assumption on

[9] In the previous draft, we analyzed inflation based on the high-frequency online price index. Since this index is not available for the pandemic period, we used inflation expectations for the baseline analysis and tested the robustness of our findings using the OPI.

[10] A large body of literature on this issue suggests that it is still desirable to estimate the VAR model in levels, even if the variables have unit roots (Sims et al., 1990). We still test the robustness of the main dynamic relationship we found by estimating the Vector Error Correction Model and confirm that the results hardly change. To save space, this result is available upon request.

[11] Gold prices are placed before Bitcoin prices because 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).

the rest of the variables is largely compatible with the vast literature on the monetary VAR model (e.g., Christiano et al., 2005) augmented with uncertainty shocks, 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

The top panel in Figure 2 shows the main empirical findings in this paper.[12] First, Bitcoin prices increase significantly in response to a positive shock to the stock market, suggesting that Bitcoin does not serve as a hedge for investment in stock markets, in contrast to the results using GARCH models (e.g., Dyhrberg, 2016). Second, Bitcoin prices decline significantly in response to the shock to the VIX. The one standard deviation increase in the VIX is followed by a more than 7% decline in Bitcoin prices after three months, corroborating the empirical evidence rejecting the safe-haven property using various statistical methodologies (e.g., Bouri et al., 2017; Shahzad et al., 2019; Smales, 2019; Conlon and McGee, 2020). Third, Bitcoin prices increase significantly after a positive inflation shock, suggesting that Bitcoin could be a useful hedge against inflation. Lastly, Bitcoin prices do not respond much to the shock to the nominal interest rate.[13]

The bottom panel in Figure 2 shows the estimation results of gold prices that are sharply contrasting from those of Bitcoin prices. Gold prices decrease in response to the S&P 500 index, implying that gold is qualified as a hedge for stocks. Moreover, gold prices increase significantly to the shock to the VIX, indicating that gold is qualified as a safe-haven asset. Gold prices do not respond much to the inflation shock but decrease significantly following the interest rate shock, which is also distinct from the case of Bitcoin. These findings suggest that Bitcoin acts nothing like gold in response to various shocks hitting the economy, thereby rejecting the popular claim that Bitcoin is a safe haven or "new gold."

The forecast error variance decomposition of Bitcoin and gold prices, shown in Figure 3, provides further insight into the nature of Bitcoin price dynamics and highlights the contrast from

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[12] For each impulse response function, the 90% bootstrap confidence intervals are plotted. Figure A.2 in Appendix plots the entire set of impulse response functions for a comprehensive picture. We confirm that our findings are robust for the exclusion of gold prices in the VAR system (i.e., the five-variable VARs). The results are available upon request.

[13] The negative finding might be driven by the binding ZLB constraint during most of our sample period. We test the possibility of this case by using the shadow short rate in Appendix.

gold price dynamics. For example, inflation expectation shocks explain an important share of Bitcoin price fluctuations, whereas they explain only a minor share of gold price fluctuations.

A historical decomposition of Bitcoin and gold prices is provided in Figure 4, showing fluctuations in prices of Bitcoin and gold that are attributed to the shocks over the sample period. One can find an interesting pattern in Bitcoin price dynamics. While the increase in Bitcoin prices is dominantly explained by a shock to Bitcoin price itself, the decrease is relatively well-explained by other shocks—except for the beginning of the sample period—, especially by the VIX and expected inflation. This is in sharp contrast to gold price dynamics, which do not show much asymmetry between a bullish and bearish market and are dominantly driven by the U.S. monetary policy recently. The asymmetry in Bitcoin price dynamics 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. Apart from fundamental differences between Bitcoin and gold regarding their intrinsic value, concerns about the complexity and opaqueness of Bitcoin markets might explain the difference. For example, Gandal et al. (2018) identify price manipulation in the Bitcoin exchange.

Figure 5 shows the estimation results parallel to Figure 2 but using a high-frequency online price index to capture inflation shocks directly. While investors often claim Bitcoin as a hedge against monetary stimulus prevalent during and after the Global Financial Crisis as well as during the recent COVID-19 pandemic, the inflation-hedging property has not been directly tested due to the lack of realized inflation data at a high frequency. Although high-frequency financial data from the TIPS market is useful in extracting financial market participants' expectations about future inflation, it might not necessarily capture actual inflation relevant to the public. To guard against this possibility, we replace the inflation expectation variable with the actual high-frequency price variable.[14] Bitcoin and gold prices respond to inflation shocks similarly to how they respond to inflation expectation shocks, further confirming the inflation-hedging property of Bitcoin.

Financial vs. economic policy uncertainty. We replace the VIX index with the U.S. EPU index, developed by Baker et al. (2016), given the increasing attention paid to the predictive power of EPU

[14] Due to the availability of the OPI, this exercise uses data up to April 11, 2018, which does not include the pandemic-related crisis.

on Bitcoin prices (Demir et al., 2018; Wu et al., 2019). While uncertainty about financial markets is followed by a decline in Bitcoin prices, Figure 6 shows that uncertainty about future government policy does not have any negative effect. This finding echoes the claim that the increasing popularity and rapid appreciation of Bitcoin prices are largely driven by its independence from government authorities.

Alternative benchmark assets other than gold. We find that the responses of Bitcoin prices to various structural shocks are sharply different from those of gold. To enhance our understanding of Bitcoin price dynamics, we compare the empirical properties of Bitcoin with those of other well-known financial assets.

First, 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 gold prices with the U.S. dollar index, which measures the value of the dollar against a basket of foreign currencies. Panel A of Figure 7 shows that the responses of the dollar index are sharply different from those of Bitcoin prices.

Second, Gronwald (2019) argues that Bitcoin behaves similarly to commodities like crude oil and gold, as 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. We also compare the response of Bitcoin with that of crude oil prices in the VAR model. Consistent with Gronwald (2019), oil prices respond to the S&P 500 and inflation expectations positively and respond to the VIX negatively (Panel B of Figure 7).[15] 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.

Robustness checks. Section B in Appendix provides a battery of sensitivity tests of our findings, including employing the alternative identification schemes, daily data frequency, alternative variables in the VAR model, different benchmark assets, excluding the COVID-19 pandemic period,

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

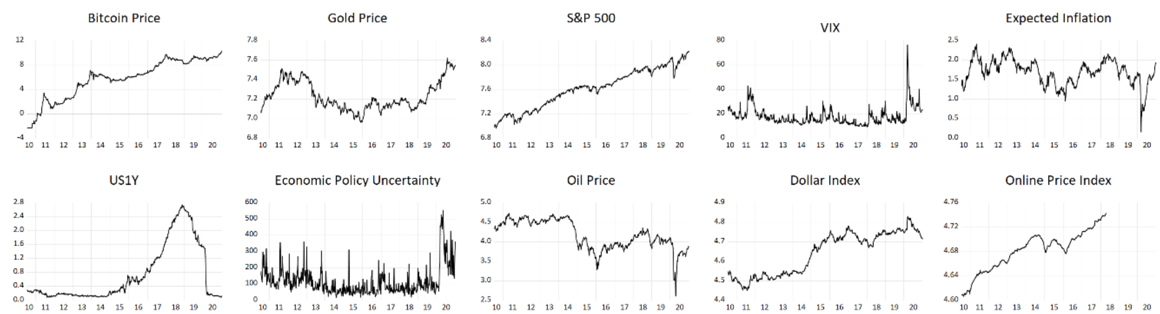
and considering structural breaks in the Bitcoin market. The estimation results are summarized in Appendix for the sake of brevity, but our key findings are robust to an exhaustive set of sensitivity checks.

III. CONCLUSION

Despite the many interesting empirical regularities discovered in the paper, our results are subject to some caveats. First, while the main findings, including a battery of sensitivity tests, 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.

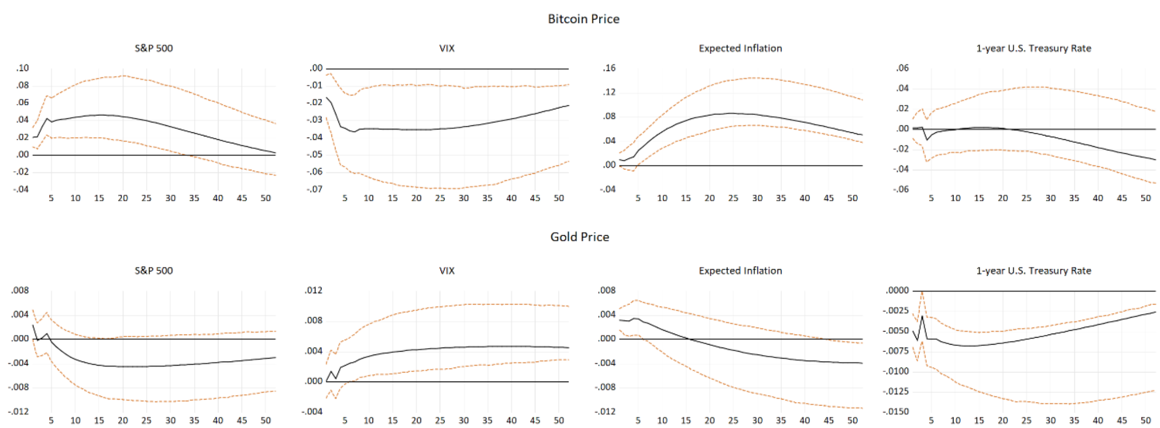
Figures and Tables

Figure 1. The evolution of the Bitcoin prices and other variables



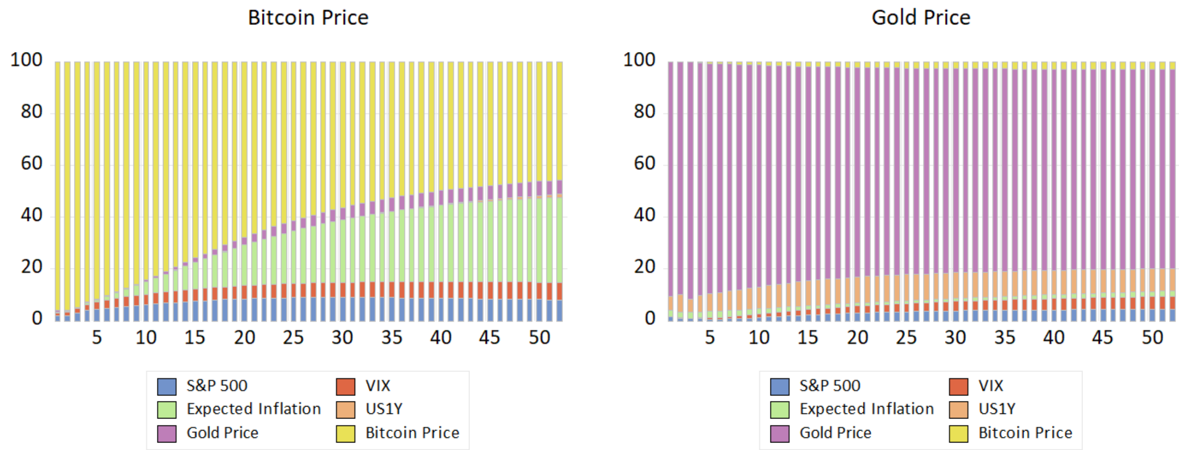
Note: This graph plots the time series of Bitcoin prices and other macroeconomic and financial variables. The natural logarithm is taken to Bitcoin and gold prices, S&P 500, oil prices, the dollar index, and the OPI.

Figure 2. The response of Bitcoin and gold prices: baseline model



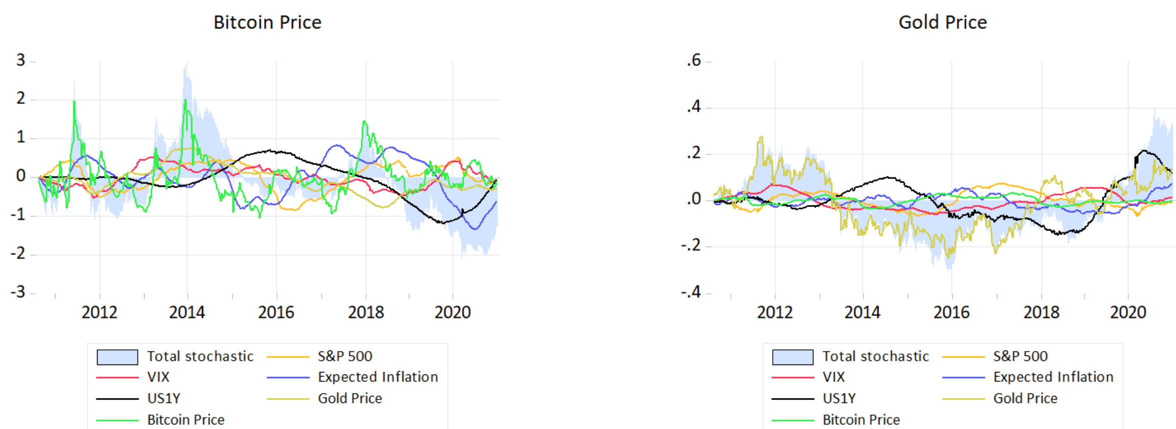
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the six-variable VARs for the sample period between July 21, 2010, and December 31, 2020. The units of the horizontal axes are a week. The graphs on the top illustrate the response of Bitcoin prices, and the graphs on the bottom illustrate the response of gold prices.

Figure 3. Forecast error variance decomposition of Bitcoin and gold prices



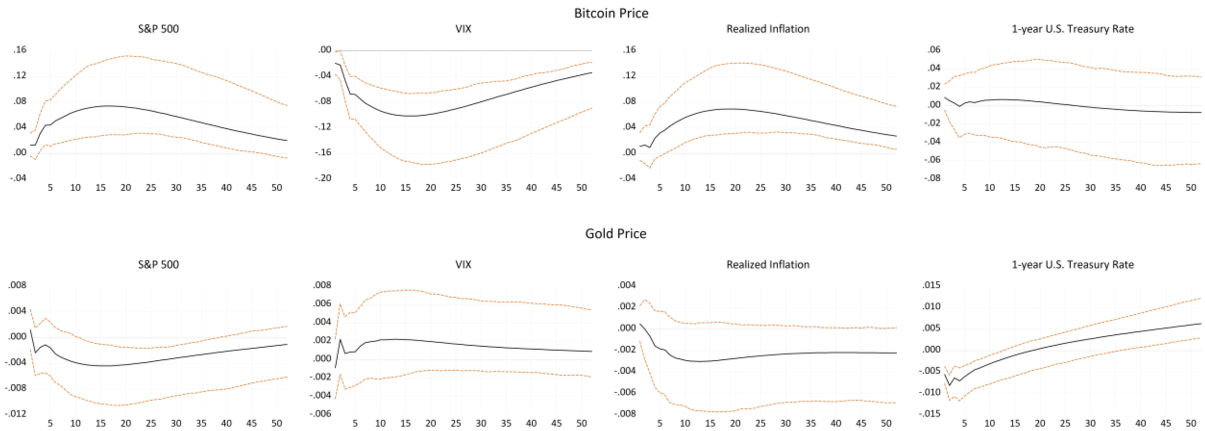
Note: This graph shows forecast error variance decomposition of Bitcoin and gold prices for the sample period between July 21, 2010, and December 31, 2020. The units of the horizontal axes are a week.

Figure 4. Historical decomposition of Bitcoin and gold prices



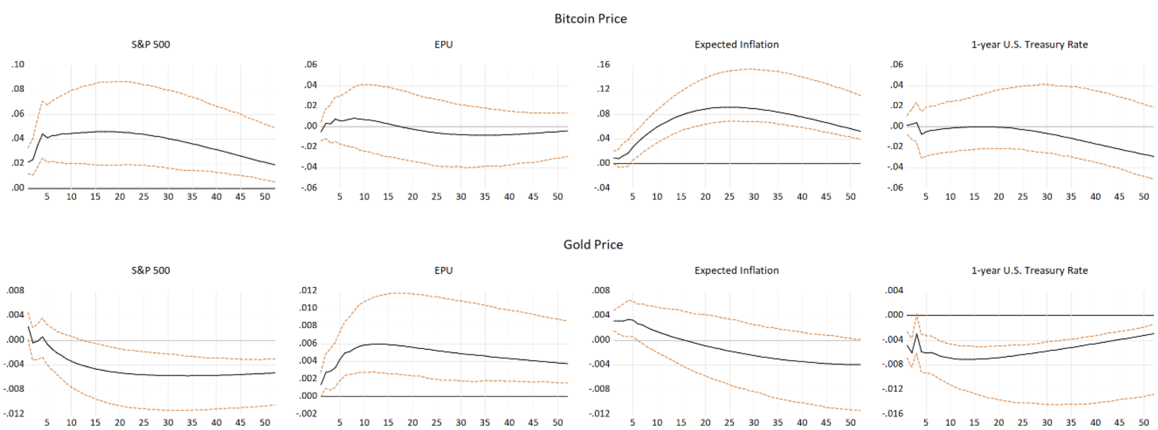
Note: This graph shows the historical decomposition of Bitcoin and gold prices for the sample period between July 21, 2010, and December 31, 2020.

Figure 5. The response of Bitcoin and gold prices: using the OPI



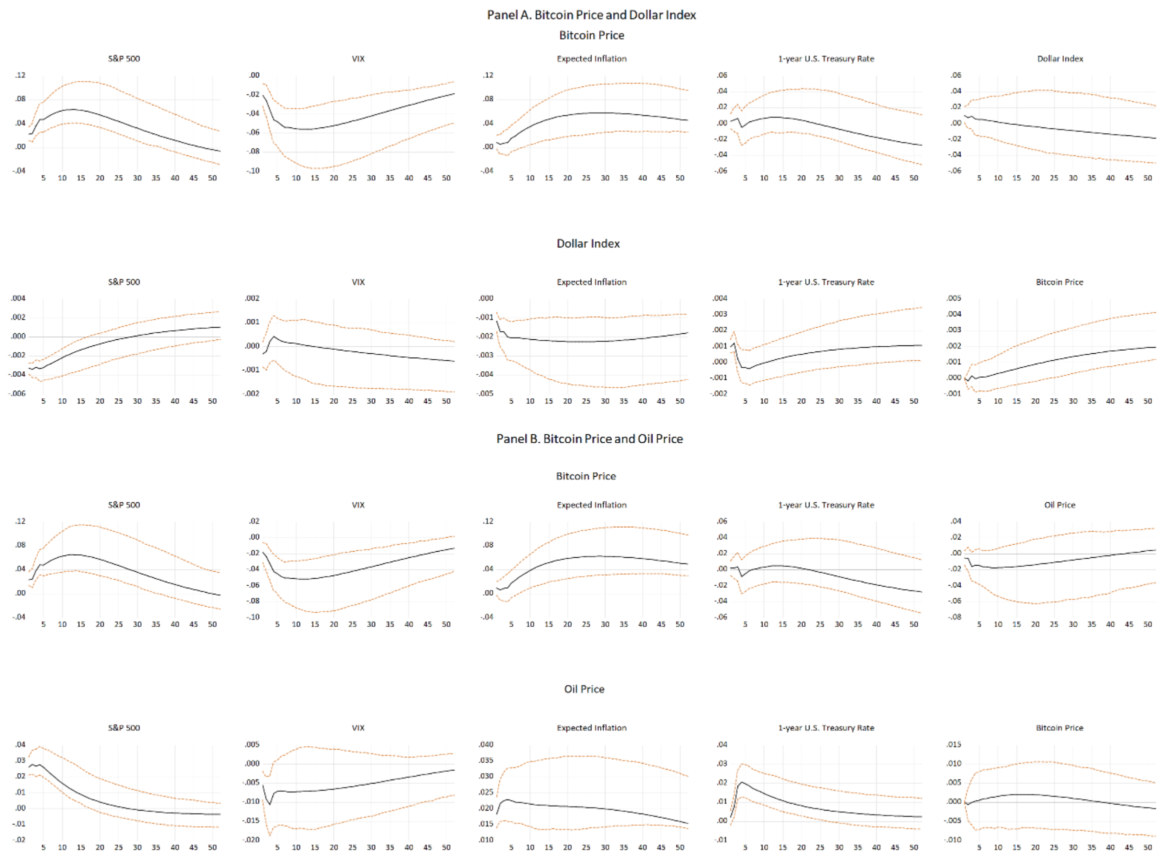
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the six-variable VARs using the OPI instead of inflation expectation derived from the financial market data. The sample period covers from July 21, 2010 to April 11, 2018. The units of the horizontal axes are a week. The graphs on the top illustrate the response of Bitcoin prices, and the graphs on the bottom illustrate the response of gold prices.

Figure 6. The response of Bitcoin and gold prices: using the EPU



Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the six-variable VARs for the sample period between July 21, 2010, and December 31, 2020. The units of the horizontal axes are a week. The graphs on the top illustrate the response of Bitcoin prices, and the graphs on the bottom illustrate the response of gold prices. We use the baseline specification but replace the VIX with the EPU index.

Figure 7. The response of Bitcoin prices: model with the dollar index and oil prices



Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but replacing gold prices with the dollar index (Panel A) and oil prices (Panel B). The units of the horizontal axes are weeks.

Table 1. Summary Statistics

	Bitcoin Prices (%)	Gold Prices (%)	S&P 500 (%)	VIX	π^e(%)	US1Y (%)	EPU	WTI	Dollar Index	OPI
Mean	2.337	0.087	0.232	17.718	1.689	0.724	116.602	-0.085	0.031	0.033
Median	0.797	0.154	0.449	15.590	1.710	0.260	90.420	0.067	0.001	0.027
Max	112.601	8.230	10.717	76.450	2.410	2.740	553.210	46.233	5.006	0.585
Min	-70.852	-12.398	-13.379	9.150	0.160	0.090	18.040	-48.099	-2.150	-0.595
Std. Dev.	16.161	2.182	2.144	7.296	0.323	0.806	86.071	5.981	0.719	0.123
Observations	539	539	539	539	539	539	539	539	539	400

Note: This table shows summary statistics of Bitcoin prices and other macroeconomic and financial variables. Bitcoin prices, gold prices, S&P 500, WTI, Dollar Index, and the Online Price Index are log-differenced. The VIX, expected inflation, the one-year Treasury bill rate, and the Economic Policy Uncertainty Index are in level.

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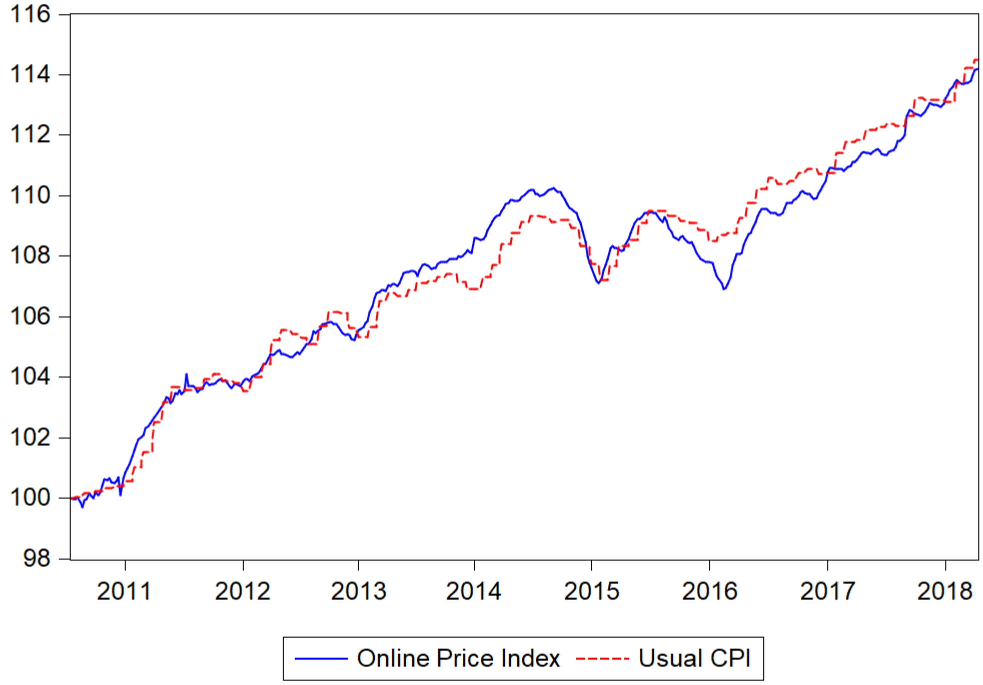
Appendix for online publication.

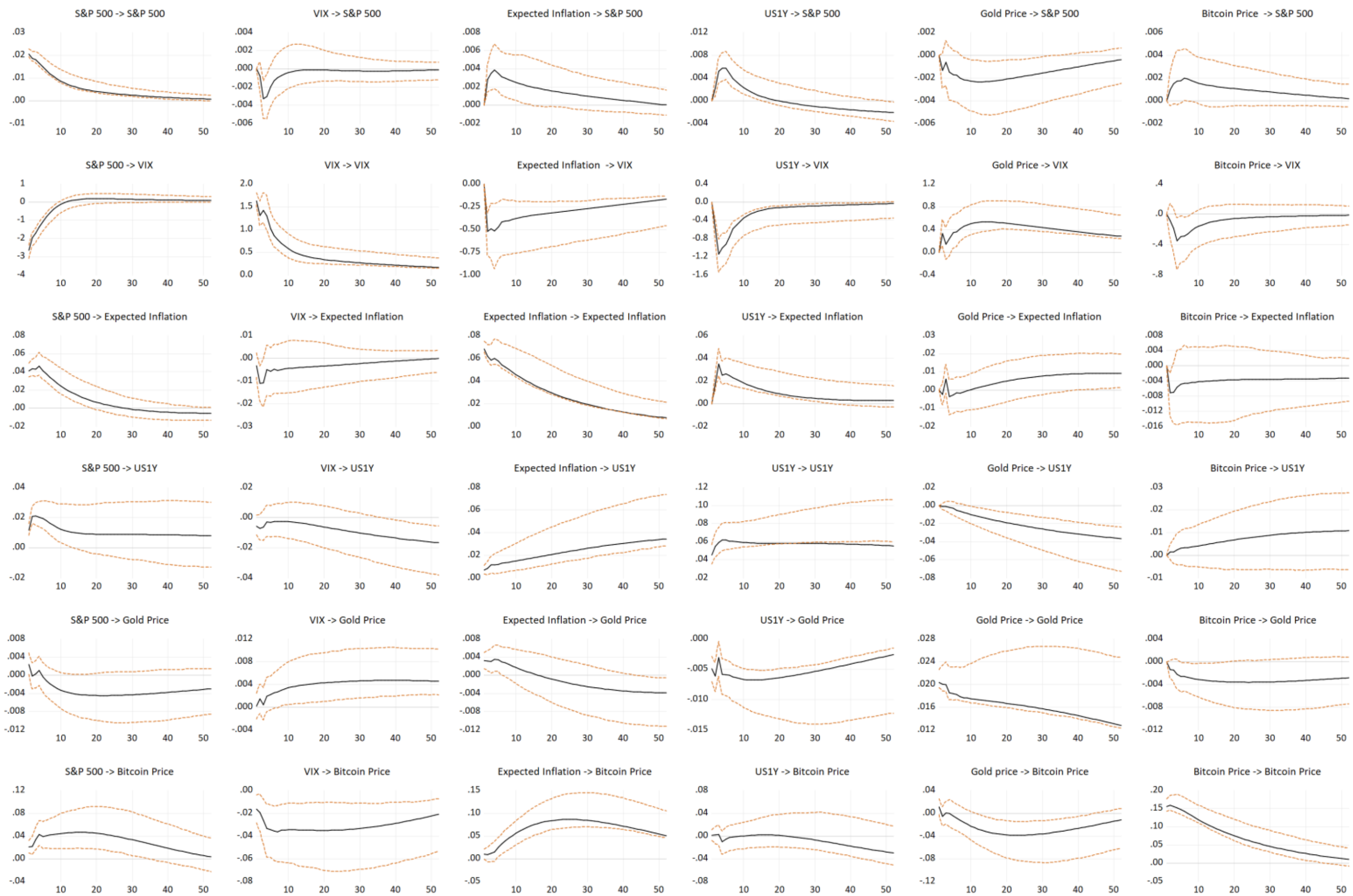
A. Additional results

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



Note: This graph plots the weekly time series of the U.S. daily Online Price Index and the Consumer Price Index released by the 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. Impulse response functions of variables



Note: This graph plots impulse responses of the six variables with a 90% confidence interval for the sample period between July 21, 2010, and December 31, 2020.

Table A.1. Correlation matrix of key variables

	Bitcoin	Gold	S&P 500	VIX	π^e (%)	US1Y (%)	EPU	WTI	Dollar Index	OPI
Bitcoin	1									
Gold	0.052	1								
S&P 500	0.074	0.082	1							
VIX	-0.150	0.040	-0.295	1						
π^e (%)	0.140	-0.017	0.054	-0.163	1					
US1Y (%)	-0.013	0.025	-0.015	-0.285	-0.040	1				
EPU	0.008	0.083	-0.024	0.351	0.219	-0.234	1			
WTI	-0.018	0.196	0.422	-0.098	0.109	0.071	0.003	1		
Dollar Index	0.047	-0.370	-0.405	0.141	-0.113	-0.086	-0.015	-0.397	1	
OPI	0.109	-0.015	0.037	-0.146	0.258	0.065	0.009	0.116	-0.118	1

Note: This table shows the correlation between the main variables in the analysis. Bitcoin prices, gold prices, S&P 500, WTI, Dollar Index, and the Online Price Index are log-differenced. The VIX, expected inflation, the one-year Treasury bill rate, and the Economic Policy Uncertainty Index are in level.

Table A.2. ADF tests of stationarity for key variables

	Level	Critical Values			Difference	Critical Values		
		1%	5%	10%		1%	5%	10%
Bitcoin	-2.641	-3.975	-3.418	-3.132	-21.601^{***}	-3.975	-3.418	-3.132
Gold	-1.202	-3.975	-3.418	-3.132	-23.806^{***}	-3.975	-3.418	-3.132
S&P 500	-4.185^{***}	-3.975	-3.418	-3.132	-23.473^{***}	-3.975	-3.418	-3.132
VIX	-4.561^{***}	-3.975	-3.418	-3.132	-28.675^{***}	-3.975	-3.418	-3.132
π^e (%)	-3.395^{*}	-3.975	-3.418	-3.132	-23.534^{***}	-3.975	-3.418	-3.132
US1Y	-0.186	-3.975	-3.418	-3.132	-17.634^{***}	-3.975	-3.418	-3.132
EPU	-4.092^{***}	-3.975	-3.418	-3.132	-21.278^{***}	-3.975	-3.418	-3.132
WTI	-3.140^{*}	-3.975	-3.418	-3.132	-20.220^{***}	-3.975	-3.418	-3.132
Dollar	-1.772	-3.975	-3.418	-3.132	-22.186^{***}	-3.975	-3.418	-3.132
OPI	-2.279	-3.981	-3.421	-3.133	-7.811^{***}	-3.981	-3.421	-3.133

Note: This table shows the t-statistics for the null hypothesis of a unit root in level or difference of each variable based on the ADF test with an intercept and a time trend. *, **, and *** denote statistical significance at the 1,5, and 10%, respectively.

B. 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.

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 B.1 shows that none of our findings are affected by the lag length selection.

Alternative identification scheme. Our structural VAR model is identified using an assumption that movements in the rest of the economy are largely exogenous to the Bitcoin system. Although our assumption is 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 B.2 confirms our main findings. In Figure B.3, we also report the estimation results using generalized impulse response functions, consistent with our main findings.

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.[16] Figure B.4 shows that all results using weekly data are preserved.

Dropping the COVID-19 pandemic episode. Although the COVID-19 pandemic is an interesting opportunity to test inflation-hedging and safe-haven properties of Bitcoin, our findings might have been driven by this outlier event. To guard against this possibility, we re-estimate the VAR model

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[16] 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.

using the sample up to December 2019. Figure B.5 shows that our results are preserved when excluding the COVID-19 pandemic episode.

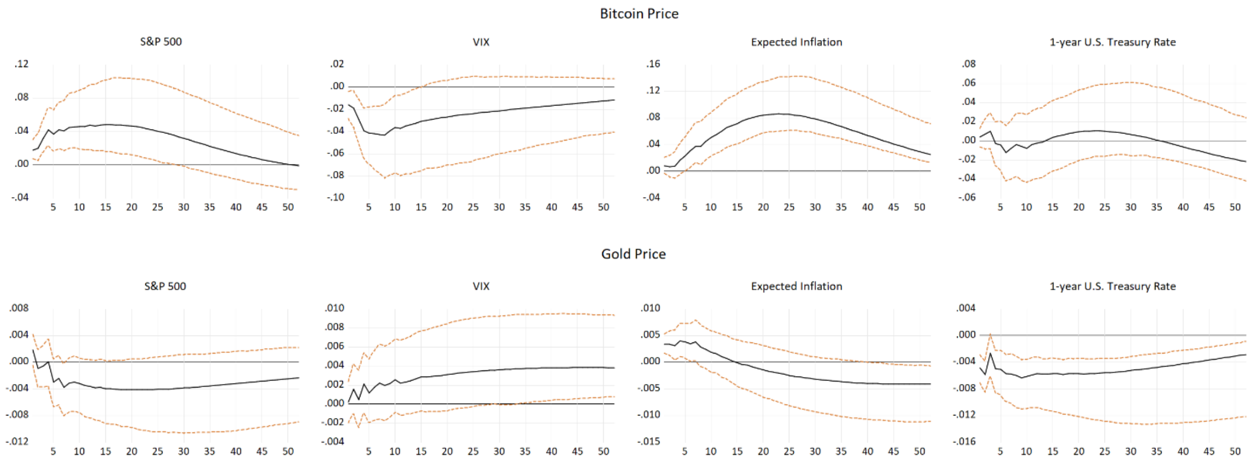
Structural breaks in the Bitcoin market. The perception of cryptocurrencies in general and the trading system of Bitcoin and its market behavior, in particular, have experienced dramatic changes over the last decade. At the beginning of the sample period, Bitcoin trading volume was very low, and most of the 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 market in 2013. 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 the Bitcoin market. Figure B.6 shows that our results are qualitatively similar when limiting the analysis to data since 2014.

Alternative proxies for macro variables. We replace some macro 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 as a measure of overall financial market conditions, 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 financial market conditions 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 B.7, none of our results are changed in this case.

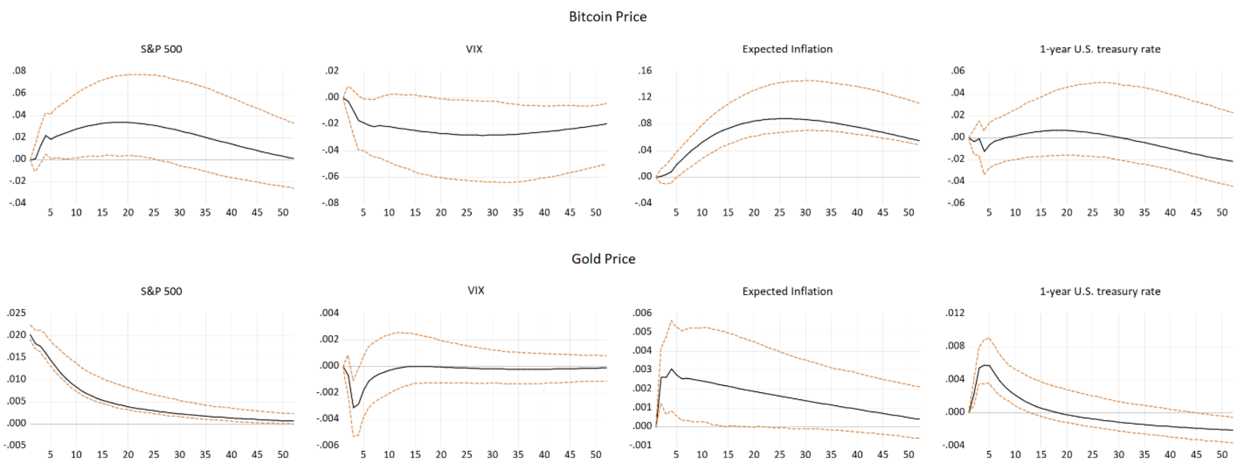
Second, we have found an insignificant effect on Bitcoin prices of shocks to the nominal interest rate. This finding might have been driven by the binding ZLB constraint; therefore, the one-year Treasury bill rate failed to capture the opportunity cost of holding Bitcoins. To account for this possibility, 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 B.8, 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.

Figure B.1. Robustness checks: alternative lags



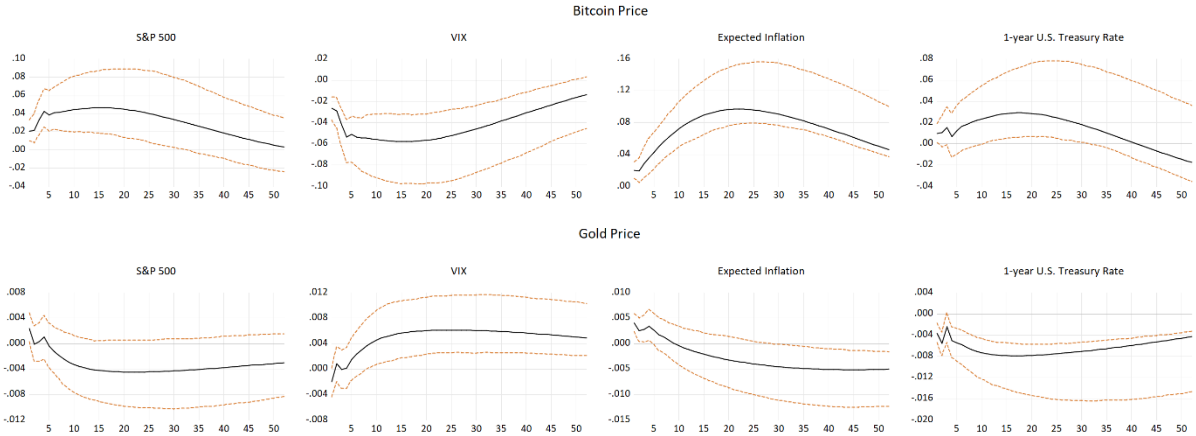
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but using the eight lags. The units of the horizontal axes are weeks.

Figure B.2. Robustness checks: reverse ordering



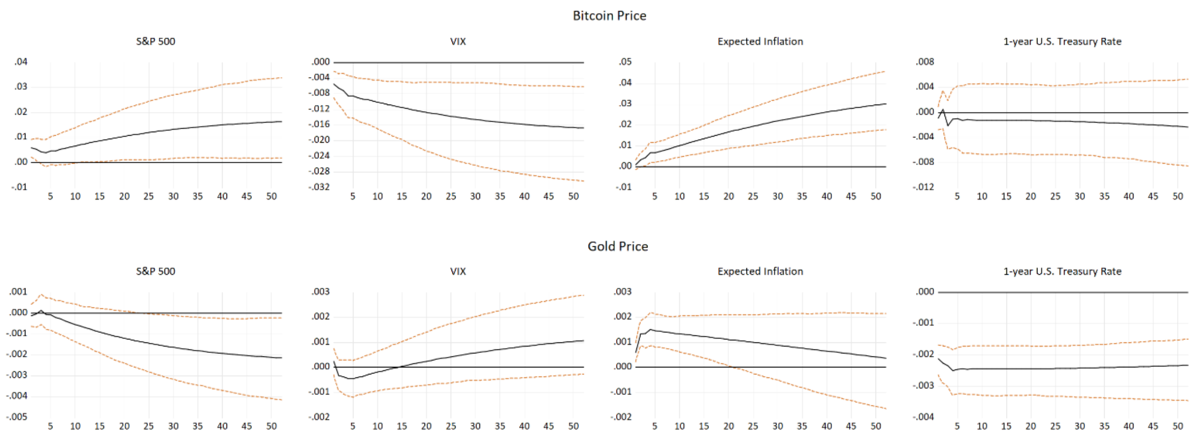
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but using the reverse Cholesky ordering. The units of the horizontal axes are weeks.

Figure B.3. Robustness checks: generalized IRF



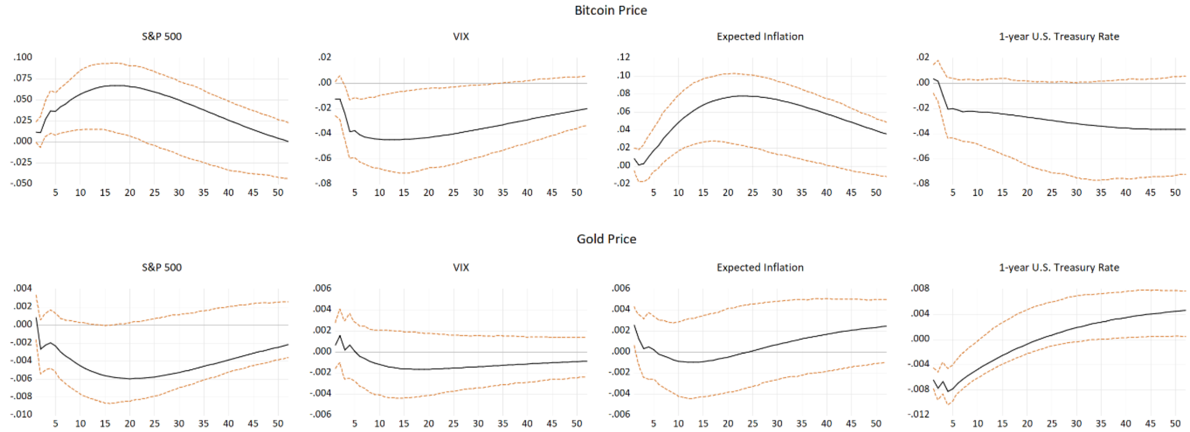
Note: This graph shows generalized impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model. The units of the horizontal axes are weeks.

Figure B.4. Robustness checks: using daily data



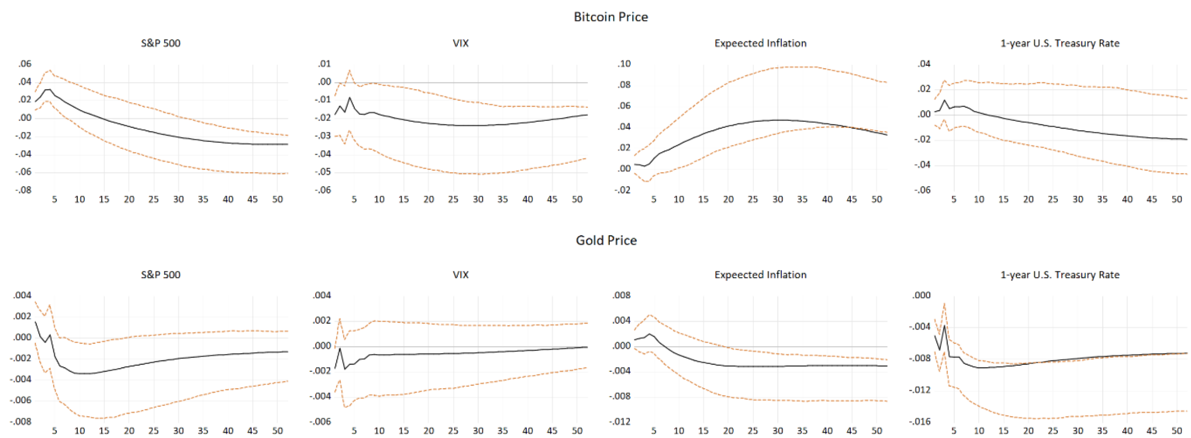
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but using daily data. The units of the horizontal axes are weeks.

Figure B.5. Robustness checks: excluding COVID-19 episode



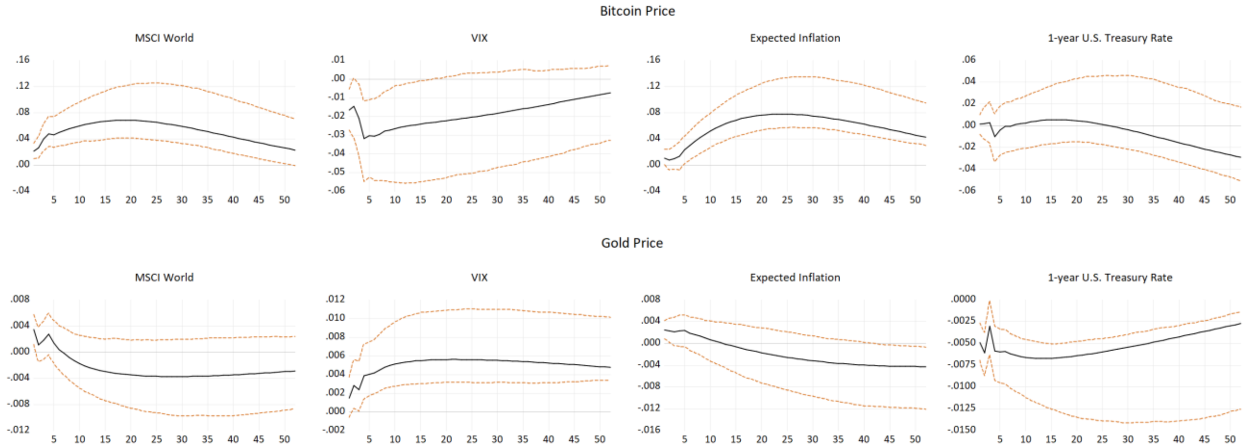
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but using sample excluding the COVID-19 period. The units of the horizontal axes are weeks

Figure B.6. Robustness checks: using data from 2014



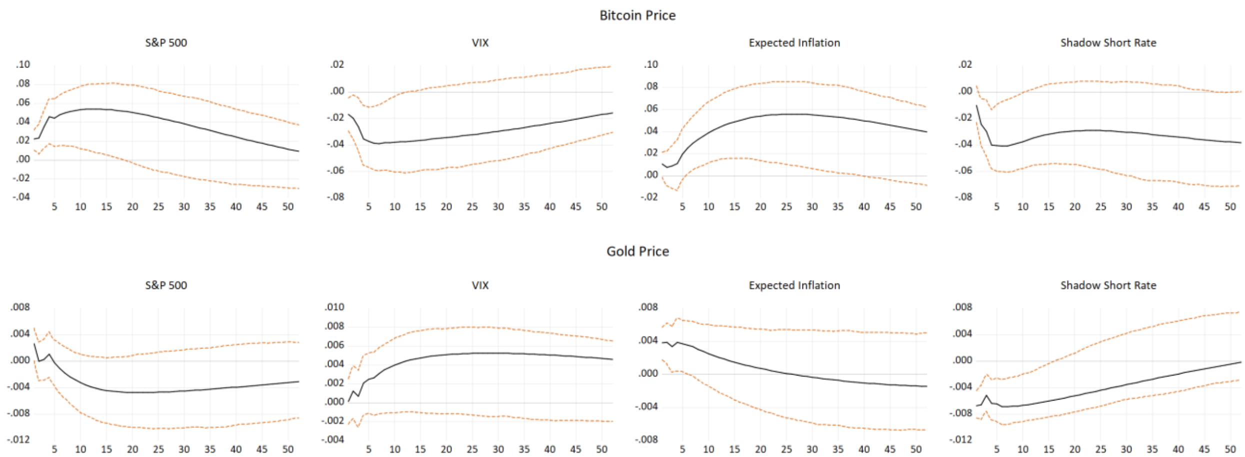
Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but using the data from 2014 only. The units of the horizontal axes are weeks.

Figure B.7. Robustness checks: the MSCI World index



Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% 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 B.8. Robustness checks: the shadow short rate



Note: This graph shows impulse responses of Bitcoin and gold prices to the one-standard-deviation shock in other variables and their 90% confidence bands from the baseline model but replacing the 1-year U.S. treasury Bill rate with the shadow short rate. The units of the horizontal axes are weeks.

References for Online Appendix

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