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Monetary policy and Bitcoin

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Non-technical summary

Research question

Bitcoin was created in the midst of the Global Financial Crisis in 2009. Its design, to some, represents a challenge not only to the role of established financial institutions but also to discretionary monetary policy. Via its peer-to-peer payment system, bitcoins can be transferred, also across-borders, with the help of just an internet connection, but without the involvement of regulated banks. And as Bitcoin's supply grows fairly mechanically and is ultimately finite, this is sometimes argued to insulate it from supposedly inflationary central bank policy. These design choices raise the question as to how Bitcoin valuations respond to changes in monetary policy. Not only would this speak to Bitcoin's role as an inflation hedge but also shine light on its interactions with the broader financial system.

Contribution

The paper goes beyond reduced-from analyses of previous work on Bitcoin and cryptocurrencies and instead features a structural analysis. First, I analyze changes in high-frequency price data of Bitcoin around monetary policy announcements by the FOMC and the ECB Governing Council. The main empirical analysis then identifies US and euro area monetary policy shocks in a macroeconometric framework in order to study their effects on Bitcoin valuations as well as its broader ecosystem. In particular, the paper adopts an international perspective by utilizing price differences of Bitcoin in local currencies relative to the US dollar. In addition, I exploit the unique availability of blockchain data. From hundreds of millions of transactions I construct time series estimates of cross-border flows and holdings of Bitcoin in different currency areas and study how these respond to monetary policy.

Results

Monetary policy shocks emanating from both the US and the euro area are found to have significant and persistent effects on Bitcoin valuations. Strikingly, however, I find that their effects differ in sign: a disinflationary monetary tightening by the Eurosystem lowers valuations, whereas a tightening by the US Federal Reserve increases Bitcoin prices. Whereas the response to euro area monetary policy therefore is consistent with Bitcoin's supposed role as an inflation hedge (*digital gold*), for US shocks this effect must be overcompensated by another channel. By linking the increased market value for Bitcoin to demand from emerging markets, I argue that the response to US monetary policy reflects the technological and institutional particularities of Bitcoin that make it sought after as global *digital cash* when economic and financial conditions deteriorate following the international ramifications of US monetary policy.

Nichttechnische Zusammenfassung

Forschungsfrage

Bitcoin ist inmitten der Finanzkrise 2009 entstanden. Für einige Beobachter stellt sein Design einen bewussten Gegenentwurf zum herkömmlichen Finanzsystem dar. Über Bitcoins dezentralisiertes Zahlungssystem können Werte mithilfe nur einer Internetverbindung auch über Ländergrenzen hinweg transferiert werden, ohne dass regulierte Finanzinstitutionen involviert wären. Und weil die Menge an Bitcoins endlich ist, wird mitunter argumentiert, dass Bitcoin einen Schutz gegen inflationäre Zentralbankpolitik biete. Diese Charakteristika werfen die Frage danach auf, wie Bitcoin-Preise auf geldpolitische Veränderungen reagieren. Nicht nur würde dies Einblicke in Bitcoins Rolle als Inflationsschutz gewähren, sondern auch auf Wechselwirkungen mit dem herkömmlichen Finanzsystem hinweisen.

Beitrag

Das Forschungspapier analysiert die kausalen Einflusseffekte der Geldpolitik auf die Bewertung von Bitcoin. Zunächst werden Veränderungen von Bitcoin-Preisen in engen Zeitfenstern um geldpolitische Ankündigungen des Fed-Offenmarktausschusses und des EZB-Rates untersucht. Die Hauptanalyse erfolgt dann auf Basis eines makroökonometrischen Modells, mit dem strukturelle geldpolitische Schocks aus den USA und dem Euroraum identifiziert und deren Wirkung auf Bitcoin untersucht werden. Ein besonderer Fokus liegt dabei auf internationalen Aspekten, weshalb Preisunterschiede zwischen Bitcoin in unterschiedlichen Währungen relativ zum US-Dollar in die Analyse einfließen. Zusätzlich werden aus Blockchain-Daten auf Basis von Hunderten von Millionen von Transaktionen Zeitreihen gewonnen, die gehaltene Bitcoin-Bestände und Bitcoin-Transfers zwischen Währungsräumen abbilden.

Ergebnisse

Das Forschungspapier dokumentiert signifikante und lang anhaltende Effekte geldpolitischer Schocks auf Bitcoin-Preise. Bemerkenswerterweise unterscheidet sich die Wirkungsrichtung dieser Effekte jedoch: Eine geldpolitische Straffung im Euroraum führt zu einem Rückgang, während eine ebensolche Straffung in den USA eine Erhöhung von Bitcoin-Bewertungen zur Folge hat. Während also die Reaktion auf Euroraum-Geldpolitik mit der Rolle von Bitcoin als Inflationsschutz vereinbar ist, muss im Falle US-amerikanischer Geldpolitik ein anderer Wirkungskanal eine bedeutendere Rolle spielen. Die Ergebnisse deuten darauf hin, dass Bitcoin aufgrund seiner technologischen und institutionellen Besonderheiten eine steigende Nachfrage vor allem aus Schwellenländern erfährt, wenn sich die finanziellen Bedingungen aufgrund der besonders ausgeprägten Ausstrahleffekte US-amerikanischer Geldpolitik eintrüben.

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Abstract

Bitcoin was conceptualized in response to perceived shortcomings in the monetary and financial system, not only related to large financial institutions but also to discretionary decision making in monetary policy. Using high-frequency data and a weekly proxy VAR model, I study the impact of monetary policy on Bitcoin. The paper shows that monetary shocks have sizable effects on Bitcoin prices, but that these differ in sign: a disinflationary monetary tightening by the ECB lowers valuations – consistent with the notion of Bitcoin as a *digital gold* –, whereas a Fed tightening increases Bitcoin prices. I document similar differences with respect to central bank information shocks and explore potential explanations by studying various aspects of the Bitcoin ecosystem. Exploiting both differences in Bitcoin valuations across currencies and blockchain transaction data, the paper shows that the increased demand for Bitcoin following a US monetary tightening is primarily driven by emerging markets. I argue that this likely reflects the technological and institutional particularities of Bitcoin that make it sought after as global *digital cash* when international economic and financial conditions deteriorate.

Keywords: Bitcoin, Blockchain, Monetary policy, Proxy VAR

JEL Codes: E42, G32, L14, O16

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1 Introduction

The root problem with conventional currency is all the trust that's required to make it work. The central bank must be trusted not to debase the currency, but the history of fiat currencies is full of breaches of that trust. Banks must be trusted to hold our money and transfer it electronically, but they lend it out in waves of credit bubbles with barely a fraction in reserve.

– Satoshi Nakamoto in P2P foundation forum post, Feb. 11, 2009.[1]

Cryptocurrencies were conceived more than ten years ago when Nakamoto (2008) conceptualized Bitcoin as a decentralized electronic cash system. What distinguishes Bitcoin from other globally traded financial assets is not only its establishing of a peer-to-peer payment system that does not rely on incumbent financial institutions. It is also the rules governing their supply that sets them apart. As these rules are typically fairly mechanical, this is argued to insulate cryptocurrencies from the discretionary decision-making of major commercial and central banks. Consequently, by some, cryptocurrencies are perceived as an explicit challenge to perceived shortcomings in monetary policy and the existing monetary and financial system.[2]

There is a growing literature on many aspects surrounding Bitcoin and the underlying blockchain technology. In particular, there is now a number of papers on cryptocurrency price behavior highlighting its large volatility and low connectivity to essentially any other traditional asset or macroeconomic activity (Yermack, 2015; Liu and Tsyvinski, 2018). However, this literature is almost entirely concerned with reduced-form analyses and has largely ignored the role of what Bitcoin was designed to challenge, if not replace – the discretionary decisions of monetary policy makers. Against this background, this paper conducts a systematic empirical analysis of the effects of monetary policy on Bitcoin. Not only is such a structural analysis important to understand Bitcoin's supposed role as a hedge against inflation, but it can also provide insights in what drives demand for Bitcoin more generally.

The analysis comprises two parts. First, using high-frequency price data, I document that the already high price volatility of Bitcoin is systematically elevated in narrow time windows around monetary policy announcements by the FOMC and ECB Governing Council, indicating that monetary news do contain relevant information for cryptocurrency markets. Regarding the direction of responses, there is no clear relation to changes in interest rates. However, there are a few occasions where price responses are in line with those of stocks and exchange rates for ECB announcements, whereas Bitcoin valuations respond inversely to other risky asset prices after several announcements by the Fed.

[1] See http://p2pfoundation.ning.com/forum/topics/bitcoin-open-source?id=2003008%3ATopic%3A9402&page=1.

[2] Bitcoin's inception coincides with the Great Financial Crisis 2008-09. Nakamoto's disdain for both the role of existing financial institutions and government involvement in their rescue cannot only be seen in the above quote but also found its way in the Bitcoin blockchain: the first block of transactions includes the now infamous text message "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks".

Second, motivated by these stylized facts, the main empirical analysis uses a weekly proxy VAR framework to study the effects of structural monetary policy shocks on Bitcoin prices. The analysis reveals a systematic pattern and long-lasting effects. In response to disinflationary euro area monetary policy shocks, I find that Bitcoin prices persistently decline – consistent with the view of Bitcoin as a form of *digital gold*: a hedge against supposedly inflationary monetary policy. In stark contrast, however, an exogenous monetary tightening by the Fed does not lead to a fall but an increase in Bitcoin valuations. I find that this pattern also extends to central bank information shocks – surprise increases in interest rates that are accompanied by rising stock market valuations (Jarociński and Karadi, 2020). Also here, Bitcoin prices rise in tandem with inflation expectations in response to euro area shocks, but fall after equivalent shocks emanating from the US.

In search for an explanation of these atypical responses to US monetary policy, I then study its effects on further aspects of the Bitcoin ecosystem. Whereas a more pronounced role of Bitcoin as a medium of exchange for day-to-day transactions does not seem to offer a compelling explanation, the evidence points to an international dimension. First, I utilize the established fact that cryptocurrency markets are not arbitrage-free but show sizable and persistent valuation differences in different currencies (Makarov and Schoar, 2020). My results show that Bitcoin prices expressed in emerging market currencies – above all the Chinese yuan – increase especially strongly following a contractionary US monetary policy shock. In contrast, this is not the case for the currencies of advanced economies. I then corroborate the notion that the increased demand for Bitcoin primarily stems from emerging markets by exploiting the availability of blockchain data. By constructing time series of Bitcoin flows and holdings from hundreds of millions of transactions, I find that those exchanges that support trading of Bitcoin against emerging market currencies experience net inflows of coins, both in absolute terms and directly from other exchanges. Conversely, fewer coins are held at advanced economy exchanges.

I interpret these findings in the context of the recently documented disproportionally large effects that a US monetary tightening has on economic and financial conditions globally (Rey, 2015; Miranda-Agrippino and Rey, 2020). The low correlation of Bitcoin prices with other assets as well as the fact that Bitcoin is borderless and technologically largely independent from incumbent (and regulated) financial institutions makes it suitable for capital flight or as a vehicle currency. In that sense then, in response to US monetary policy shocks, rather than serving as an inflation hedge (digital gold), Bitcoin seems to primarily operate as a global *digital cash* whose technological and institutional characteristics make sought after when pressure is put on the currencies of emerging economies in the face of deteriorating economic and financial conditions.

I further substantiate these notions in two ways. First, I find that the impact of US monetary policy shocks on Bitcoin prices is indeed mostly driven by monetary tightening rather than easing measures. Second, I study the response of Bitcoin valuations to *risk-shift* shocks that capture the willingness of investors to hold risky assets (Kroencke et al., 2021).

The results confirm the view that the positive Bitcoin price response to contractionary US shocks is not driven by changes in interest rates *per se*, but rather operate through their impact on economic and financial conditions as well as investor risk perceptions.

Related Literature. The paper contributes to various strands of the literature. Most fundamentally, it is related to the large literature on the effects of monetary policy on asset prices (Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Gilchrist et al., 2019; Gürkaynak et al., 2021; Kroencke et al., 2021), which I extend to cryptocurrency markets.[3] Notably, I uncover that Bitcoin prices respond qualitatively very differently to US monetary policy shocks compared to other financial assets. Relatedly, the paper extends the literature on the effects of monetary policy on capital flows (Kalemli-Özcan, 2019; Chari et al., 2020) to cryptocurrencies based on blockchain data. Whereas US monetary contractions are usually associated with net capital flows out of emerging markets, I find evidence of an increase in the demand for, and net inflows of, Bitcoin.

Second, the paper contributes to the growing literature on cryptocurrency price behavior as a guide to answer questions of whether Bitcoin is best thought of as a (speculative) asset or a currency. These studies are usually based on reduced-form analysis and find that cryptocurrency valuations have little if any relation to other financial assets (Liu and Tsyvinski, 2018; Corbet et al., 2018; Baur et al., 2018), whereas their volatility is much larger (Yermack, 2015). I focus on one particular driver of asset valuations – monetary policy – and extend the literature methodologically by conducting a structural analysis. The paper also relates to one strand of the literature that studies to what extent Bitcoin has safe haven properties. While some authors have found evidence that Bitcoin might be used as a hedge for exposure to several assets as well as global uncertainty (Dyhrberg, 2016; Bouri et al., 2017a), other studies argue against a safe haven status of cryptocurrencies such as Bitcoin (Smales, 2019; Baur and Hoang, 2020), with the exception of Asian stock markets (Bouri et al., 2017b). Consistent with an important role for Asian markets, I find that Bitcoin prices in Korean won and Chinese yuan appreciate particularly strongly following a US monetary contraction and that coins flow to emerging market exchanges, the largest of which for a long time operated in China.[4]

Third, the empirical literature on cryptocurrencies also encompasses work that studies user behavior and trading relations from blockchain transaction data (Athey et al., 2016; Tasca et al., 2016; Griffin and Shams, 2020), which here is adapted to an international context. In particular, I compute time series estimates of blockchain trading activity that

[3] There are only a few papers that include some form of analysis of monetary policy on cryptocurrencies. These, however, are narrowly focused on valuations, and are either concerned with volatility spillovers (Corbet et al., 2020b), identify structural shocks of financial market variables recursively (Choi and Shin, 2020) or employ daily data in an event study analysis (Pyo and Lee, 2019). Finally, in a companion paper (Karau, 2021a) I document the existence of pre-announcement drifts of Bitcoin prices to monetary news in the spirit of Lucca and Moench (2015).

[4] The role of Chinese economic conditions in particular for cryptocurrency markets has been emphasized also by Elsayed et al. (2020). They show that the Chinese yuan is the only major currency that affects Bitcoin prices in a volatility spillover analysis in the spirit of Diebold and Yilmaz (2009).

controls for transfers within different entities or users. A notable contribution of this paper lies in identifying exchanges and computing time series of Bitcoin flows between them according to which fiat currencies they support.[5] The paper is also the first to compute balances of these exchanges meant to proxy Bitcoin holdings in different currency areas.

Fourth, the paper contributes to the literature on the role of US monetary policy as a main determinant of monetary and financial conditions globally (Rey, 2015; Miranda-Agrippino and Rey, 2020). Degasperi et al. (2020) conduct a comprehensive analysis of the international spillover effects of US monetary policy in a VAR framework. They focus on macroeconomic variables and traditional financial markets and confirm that US shocks have profound effects globally. Jarociński and Karadi (2020) study the effects of both US and euro area monetary policy shocks and find them to yield broadly similar effects on the macroeconomy. I extend these analyses to variables related to Bitcoin. Walerych and Wesołowski (2020) show that US monetary policy shocks have larger spillover effects on emerging economies than those emanating from the euro area. Caporin et al. (2020) present a similar finding regarding the co-movement of global equity and CDS prices. I show that also Bitcoin markets are affected differently from US and euro area monetary policy shocks.

From a methodological standpoint, the paper is most closely related to the literature that uses instrumental variable techniques in a VAR framework (Mertens and Ravn, 2013; Stock and Watson, 2018) to identify monetary policy shocks (Gertler and Karadi, 2015). In particular, the paper relates to those isolating or controlling for information effects contained in monetary announcements (Miranda-Agrippino and Ricco, 2021; Jarociński and Karadi, 2020). I show that this approach works well in relatively short weekly instead of longer monthly time samples when using an instrument constructed via sign restrictions.

Outline. The paper is structured as follows. Section 2 presents some stylized facts of Bitcoin price behavior in narrow windows around monetary announcements. Part 3 conducts the main empirical analysis in a weekly proxy VAR framework. After outlining the model (Section 3.1) and data (Section 3.2), Section 3.3 establishes the main results, which are further explored in Section 3.4 and discussed in Section 3.5. Part 4 concludes.

2 Monetary Announcements and Bitcoin Prices – Some Stylized Facts

I begin the empirical analysis by studying how Bitcoin (BTC) valuations respond in short time windows around monetary announcements using high-frequency price data, following the literature on the effects of monetary policy on financial markets (Gürkaynak et al., 2005; Altavilla et al., 2019). This exercise serves two purposes. First, it establishes that monetary news are not non-events for the Bitcoin market in the first place. Second, it gives a first

[5] The analytical firm Bitfury Crystal publishes reports on Bitcoin with year-by-year estimates of flows between exchanges based on which countries these exchanges officially reside in, see Bitfury (2019).

indication of the direction of the responses that motivate much of the subsequent structural VAR analysis in Section 3.

Btc Price Volatility. It is well established that cryptocurrency prices feature significantly higher levels of volatility than other financial assets (Yermack, 2015). For instance, the standard deviation of daily Bitcoin returns in USD from January 2014 to June 2021 is almost 4 percent. This figure is roughly 4 times higher than that for returns of the S&P500 and 8 times higher than of the USD-EUR exchange rate.

Figure 1 shows that the already high volatility of Bitcoin prices is further elevated in narrow windows around monetary announcements by the ECB (left) and Federal Reserve (right panel).[6] I compute realized volatilities as the standard deviation of Bitcoin returns in five-minute spells in EUR (left) and USD (right boxes) in the same time period from January 2014 to June 2021. In each case, I compare the volatility around the announcement (light) with that in comparable time windows on days that do not feature monetary news (dark boxes).[7]

The box plots indicate that in all cases the distribution of volatilities is shifted upwards in monetary announcement windows.[8] This is the case irrespective of whether the monetary news stems from the ECB or the Fed and holds for both considered fiat currencies.[9] The difference is also visible when comparing the means of the distributions statistically. In all cases, a t-test on mean equality is rejected with p-values below 0.01. Hence, although cryptocurrencies are sometimes perceived as being detached from the drivers of other financial assets (Liu and Tsyvinski, 2018), monetary news appear to contain information of interest to participants in these markets as well. Revealing this information then leads to levels of valuation changes that are unusually high even for Bitcoin.[10]

Direction and Correlation of BTC Price Responses. The findings in Figure 1 raise the natural question as to the direction of Bitcoin price responses to monetary news. In particular, it will be interesting to see if there is a clear relation to changes in interest rates. A perhaps overly simplistic view based on standard asset pricing considerations would

[6] As in Gürkaynak et al. (2005), for FOMC announcements I use a time window of 10 minutes prior to 20 minutes after the FOMC press statement if there is no subsequent press conference. If there is one, the window extends to 60 minutes after the beginning of the press conference as in Cieslak and Schrimpf (2019). As in Altavilla et al. (2019), for the ECB I consider a window of 10 minutes prior to the press statement to 75 minutes after the beginning of the regularly held subsequent press conference.

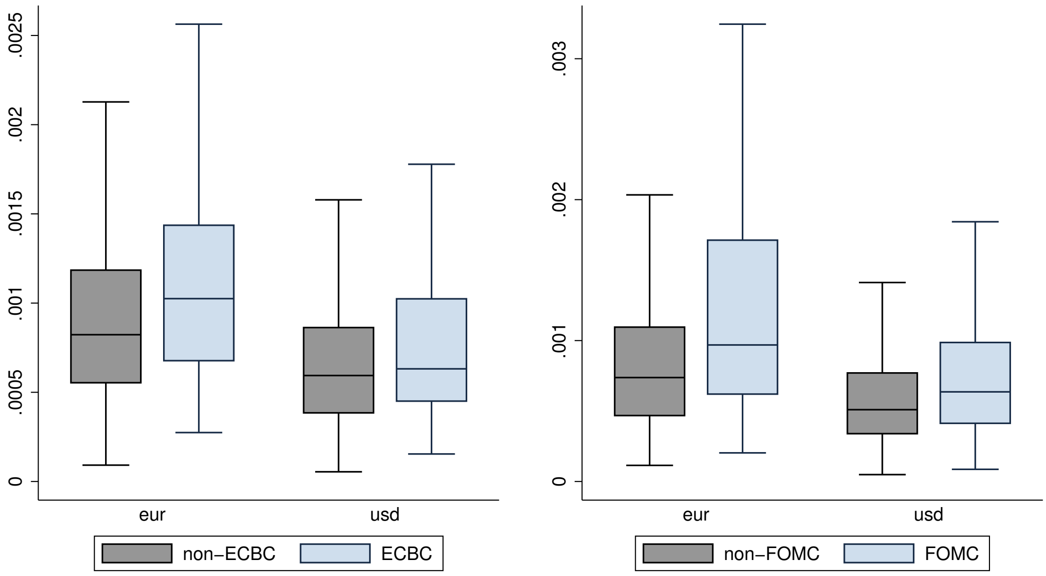
[7] The raw data is gathered from the public website `bitcoincharts.com` that contains tick data for dozens of Bitcoin exchanges. See Appendix A for details on the sources, data cleaning and computations. As there are various days that feature extreme movements in Bitcoin prices of several dozen percent, for the comparison I remove those days from the sample that are in the most volatile decile.

[8] The volatility of Bitcoin returns in EUR in the figure is somewhat higher than its counterparts in USD. This, however, is merely an artifact of the somewhat lower quality of the underlying raw data series in the early parts of the sample.

[9] It also holds for Bitcoin returns in CNY that are available in shorter time samples. Results for Bitcoin returns in EUR and USD also look similar in shorter time samples.

[10] Similar results are obtained when using trading volumes at major Bitcoin exchanges, which are also higher around monetary policy announcements.

Figure 1: BTC Price Volatility Around Monetary Policy Announcements by the FOMC and ECB Governing Council



Note. Box plot of volatility of Bitcoin returns (in EUR and USD) in narrow windows of ECB Governing Council meetings (left panel, 10 minutes prior to press statement until 75 minutes after the beginning of the press conference) and FOMC meetings (right panel, 10 minutes prior to 20 minutes after press statement / 60 minutes after the press conference (if there is one)), compared to days without monetary announcements in comparable time windows. Plots exclude outlier values as determined by `Stata`. Based on 5-minute spells. Days with 10 percent largest BTC price volatility removed. Time sample: January 2014 to June 2021. Source: author's calculations based on data from bitcoincharts.com.

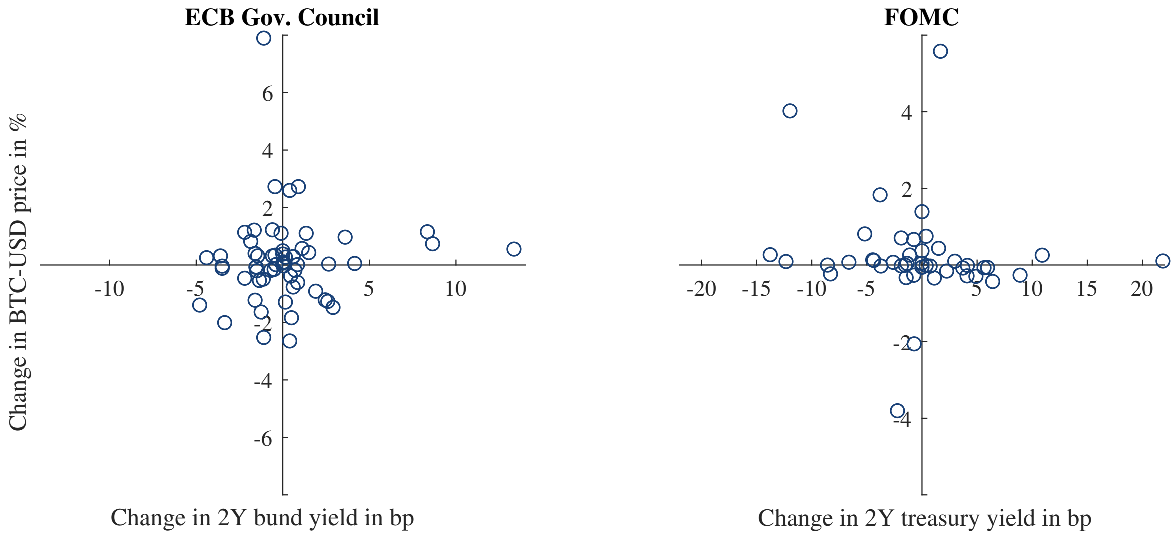
predict that an increase in interest rates should be associated with a decline in the value of non-interest bearing assets such as Bitcoin. Figure 2 reveals that things are not quite as simple. The figure shows scatter plots of changes in USD Bitcoin returns against changes in 2-year yields in German bunds (left) and US treasuries (right) for ECB Governing Council and FOMC announcements, respectively. It makes apparent that there is no clear relation between the two variables and indeed correlation coefficients are statistically insignificant and close to zero in both cases.[11]

While it turns out to also be difficult to discern a clear general pattern of how Bitcoin prices behave relative to other risky assets around monetary policy communication,[12] it might prove useful to observe the responses to those policy announcements that had a clear impact on the the prices of traditional financial assets. Figure 3 depicts two such occasions. Panel (a) shows returns of the Eurostoxx50, the USD-EUR exchange rate as well as Bitcoin prices in EUR and USD around the ECB Governing Council announcement on March 10, 2016. In it, the ECB communicated to the public a major set of policy

[11]For ECB Council announcements, the correlation is somewhat larger when computing Bitcoin returns in EUR. The correlation remains statistically insignificant, however, and mainly reflect an appreciation of the EUR against the USD that is generally associated with a rise in euro area interest rates.

[12]Figure C.1 reveals that there is a significant correlation of Bitcoin returns only with those of gold for ECB Governing Council meetings. The size of the correlation coefficients, however, is often fairly sensitive to the removal of outliers.

Figure 2: Bitcoin vs. Stock Price Responses to Monetary Announcements by the ECB Gov. Council and FOMC



Note. Scatter plots of responses of 2-year government bond yields and Bitcoin prices in narrow windows around ECB Governing Council (left) and FOMC announcements (right panel) between January 2014 and June 2021 (March 2021 for the left panel). Source: author's calculations based on data from `bitcoincharts.com`, Altavilla et al. (2019), Cieslak and Schrimpf (2019), Refinitiv.

changes meant to provide monetary stimulus.[13] As panel (a) shows, these measures led to an almost immediate increase in European stock valuations and an appreciation of the US dollar against the euro. Qualitatively in line with these responses, Bitcoin prices in EUR jumped after the press release and also Bitcoin prices in USD appreciated in the course of the announcement window.

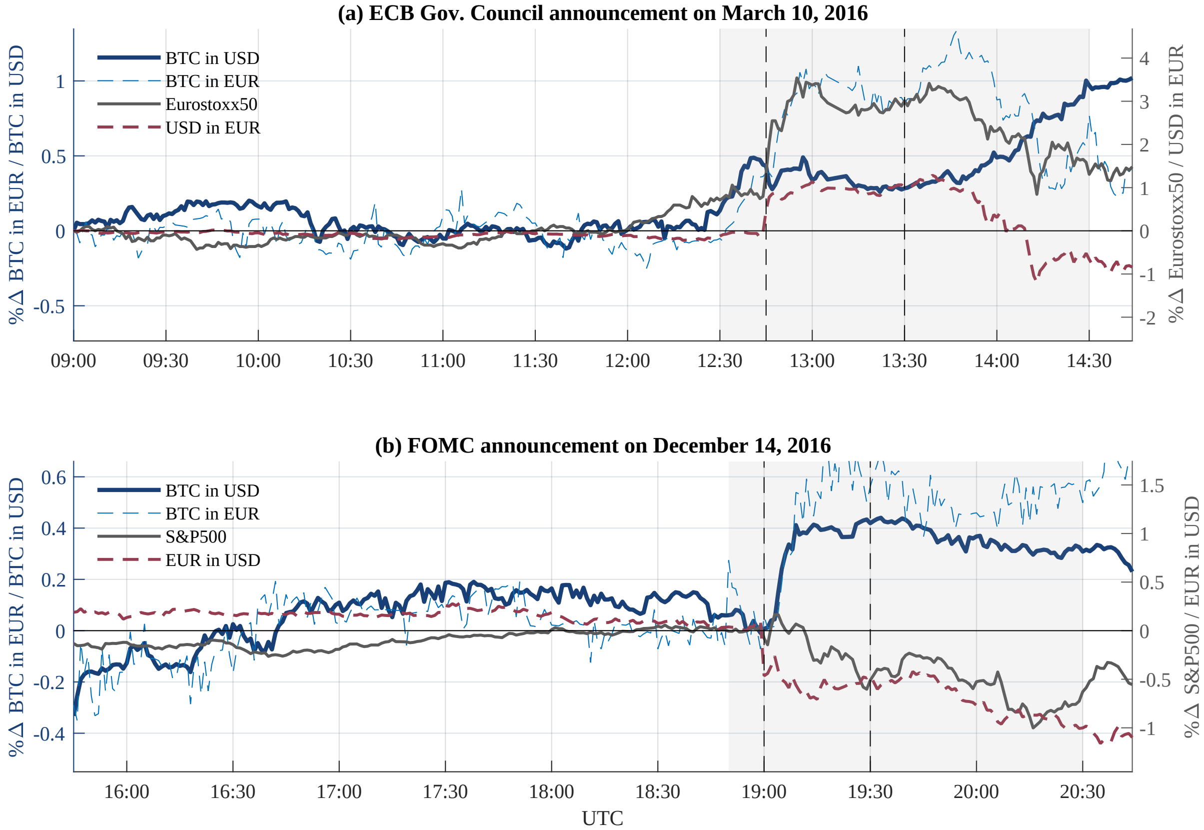
Contrast that with panel (b) in Figure 3 which shows responses to a monetary surprise from the Federal Reserve. On December 14, 2016, the FOMC announced that it would increase the target corridor for the effective federal funds rate by 25 basis points. This perceived monetary tightening was followed by a fall in both the S&P500 as well as the euro in terms of US dollars. However, in contrast to the responses to euro area monetary news, Bitcoin prices did not follow stocks and exchange rates, but *increased* on the news.

To be sure, while there are a few more occasions with similar patterns,[14] these curious responses might prove to be isolated cases that do not necessarily point to a general pattern. Indeed, the low levels of liquidity in Bitcoin compared to traditional financial assets and the large volatility of Bitcoin prices could make it difficult to ascertain clear patterns of responses

[13]Next to lowering the interest rates for its main refinancing operations as well as its marginal lending and deposit facilities, it announced in its press statement an expansion of monthly purchases of its asset purchase program from 60 to 80 billion EUR and the launch of a new series of targeted long-term refinancing operations (TLTROs).

[14]For instance, Bitcoin prices moved inversely to stocks and foreign exchange rates in response to FOMC announcements on July, 30 2014 as well as on March, 18 2015. More recently, the opposite could be observed: on March, 17 2021, stock prices rallied after an FOMC announcement, with Bitcoin prices also increasing on the news.

Figure 3: Examples of BTC Price Responses to Monetary News



Note. In both panels, the USD-EUR exchange rate is defined such that an increase refers to an appreciation of the respective foreign currency. Dashed vertical lines indicate the beginning of the press statements and press conferences, respectively. Shaded areas denote the time windows in which asset price responses to monetary news are commonly measured. Source: author's calculations based on data from `bitcoincharts.com`, `tickstory.com`.

in high-frequency analyses.[15] More fundamentally, it could be that it takes some time for effects to materialize, especially if Bitcoin interacted with economic and financial conditions in non-trivial ways. It would hence be of interest to assess to what extent any price effects are sizable and persist over longer horizons. Answering these questions requires a structural macroeconometric model that allows for feedback effects among a wide range of variables of interest, and for the proper identification of monetary policy shocks. Such a model is estimated in the main empirical analysis to follow and can also be used to study other parts of the Bitcoin ecosystem that could point to potential explanations of the observed price responses.

[15]What is more, Karau (2021a) shows evidence of anticipatory effects of monetary policy announcements in Bitcoin markets. Whereas there is an upward drift in Bitcoin valuations prior to ECB Governing Council announcements, for the FOMC the drift is downward. In that sense then, it could be that focusing attention solely on the announcement window itself underestimates the effect of monetary policy on Bitcoin prices.

3 Monetary Policy and the Bitcoin Market – Structural VAR Analysis

This part of the paper features the main empirical analysis based on various versions of a weekly structural VAR model. Section 3.1 describes the model setup with a focus on shock identification using an instrumental variable approach. Section 3.2 then provides an overview of the extensive dataset employed to study how monetary policy shocks affect cryptocurrency markets in the subsequent impulse response analysis. Section 3.3 features the main results for US and euro area monetary policy shocks. Subsequently, motivated by the response of Bitcoin prices to to Fed shocks, I focus on the effects of US policy that I explore in detail in Section 3.4 and discuss in Section 3.5.

3.1 Model Description and Shock Identification

Shock Identification. The analysis is based on a structural VAR model estimated in weekly frequency, detailed in Appendix B. Building on Stock and Watson (2018) and Mertens and Ravn (2013) and following Gertler and Karadi (2015), I use an external instrument in a proxy VAR to identify the structural monetary innovations, denoted as ϵ_t^p. For these instruments to be valid, the surprise series $\mathbf{Z}_t$ needs to be *relevant* and *exogenous* as follows:

$$\mathbb{E}[\mathbf{Z}_t \epsilon_t^{p\prime}] = \phi \neq 0, \tag{1}$$

$$\mathbb{E}[\mathbf{Z}_t \epsilon_t^{q\prime}] = \mathbf{0}, \tag{2}$$

where ϵ_t^q are structural shocks unrelated to monetary policy.

Often, researchers use high-frequency responses of short-term interest rates during narrow windows around monetary policy announcements as external instruments (Gertler and Karadi, 2015; Caldara and Herbst, 2019). Movements of rates within these short time intervals arguably represent new information that was not previously priced in and that can plausibly be attributed to the monetary policy news, satisfying condition (1). However, a number of recent papers noted that, in the presence of information asymmetries between the central bank and market participants, price responses during a narrow window around monetary policy announcements could contain "information effects" (Melosi, 2017; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021; Jarociński and Karadi, 2020; Kerssenfischer, 2019; Franz, 2020). This would be the case if, say, the central bank has an informational advantage concerning the state of the macroeconomy. If so, this additional information would be revealed, alongside any exogenous monetary policy shocks alone, during monetary policy announcements. For instance, an increase in expected future short-term interest rates following a monetary announcement might in some instances reflect the market's assessment that the central bank considers the economy to likely perform more favorably than anticipated. One sign of such an effect would be a contemporaneous increase

Table 1: Sign Restriction Identification for Proxy VAR Instrument

		Monetary	Information
High-frequency response	Interest rate	+	+
	Stock market index	−	+

Note. Sign restrictions for monetary and central bank information shocks. Restrictions are imposed only on impact. Instrument series $\mathbf{Z}_t$ is selected as the median-target series based on 1,000 draws.

in the price of risky assets like stocks. If the researcher then simply used the changes in expected interest rates as an instrument in a proxy VAR, the exogeneity assumption (2) is likely to be violated.[16]

Against this background, I do not simply use high-frequency responses of interest rates as instruments $\mathbf{Z}_t$, but adopt the following strategy, reminiscent of the one used in Jarociński and Karadi (2020). Next to the change in interest rates around monetary policy announcements, I additionally consider the response of stock market indices and feed both into a sign restriction procedure in order to produce $\mathbf{Z}_t$. As laid out in Table 1, I define those shocks as exogenous monetary innovations that lead to changes in interest rates and stock prices in opposite directions, in line with standard theory.[17]

Monetary Policy Surprise Data. To compute the instrument series $\mathbf{Z}_t$ I use two databases that contain information on the changes of asset prices in narrow time windows around monetary announcements. For FOMC meetings I rely on the database by Cieslak and Schrimpf (2019) that provides high-frequency responses of equity prices and interest rates at various maturities until December 2017,[18] which for robustness purposes I extend with self-computed data from Refinitiv. For ECB announcements, I rely on the monetary event study database by Altavilla et al. (2019),[19] which includes an even richer set of variables and is updated regularly.[20] In order to take into account not only responses to the announcement of policy statements but also to explanations provided to the public subsequently, I consider responses in time windows that include central bank press conferences. Details are provided in Appendix A.

[16]The researcher would then measure not the impulse response to an actual exogenous monetary policy shock, but instead that to some combination of fundamental shocks the central bank responds to. Some authors have recently argued against the prevalence of central bank informational advantages, see for instance Hoesch et al. (2020) and Bauer and Swanson (2020). However, for the purpose here, all is needed is to isolate pure monetary shocks from any other confounding factors revealed during the announcement.

[17]This identifying assumption is the same as in Jarociński and Karadi (2020) in order to isolate pure monetary policy shocks. Different to them, however, I use the resulting shock series as an instrument in the proxy VAR instead of directly as a first variable in a recursively identified model.

[18]Available at https://sites.google.com/site/ancieslak/.

[19]Available at https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx.

[20]In order to ensure that my results are comparable across monetary areas, I confirm that I get essentially the same responses when using the database by Cieslak and Schrimpf (2019) also for the euro area.

Table 2: VAR Model Specifications

Variable	Source	(1)	(2)	(3)	(4)
2-year interest rates	Bloomberg	•	•	•	•
VIX/Vstoxx	Bloomberg	•	•	•	•
S&P 500 / Eurostoxx50	S&P / Reuters	•	•	•	•
EUR-USD exchange rate	ECB	•	•	•	•
BTC in USD	bitcoinity.org	•	•	•	•
5-year inflation expectations	Bloomberg	•			
Blockchain transfer volume (total)	glassnode studio		•		
Blockchain transfer volume (median)	glassnode studio		•		
Bockchain tx fee (avg.)	blockchain.info		•		
Bockchain tx confirmation time	blockchain.info		•		
BTC-fiat spreads w.r.t. USD	bitcoinity.org, tickstory.com bitcoincharts.com, ECB, AC			•	
BTC holdings at EME exchanges	Bitcoin blockchain, AC				•
BTC holdings at AE exchanges	Bitcoin blockchain, AC				•
Inter-exchange flows (EME)	Bitcoin blockchain, AC				•
Figures		5, 6	7	8	9

Note. The table lists the variables included in each proxy VAR model (either US or euro area), alongside their sources. *AC* denotes author's calculations, *tx* stands for transaction.

Model Variants. I consider a multitude of variables to investigate the impact of monetary policy shocks on Bitcoin. Table 2 provides an overview of the model variants. Each model has a set of core financial variables, including the price of Bitcoin in USD. Additionally, I subsequently consider different sets of variables meant to investigate different aspects of the Bitcoin ecosystem as explained below.

3.2 Data

In the following I describe the construction and sources of the time series used in the VAR models. More details are provided in Appendix A and all computed time series are depicted in Figure A.4.

Financial Market Data. The main time series of interest in the VAR models is the price of Bitcoin, which is obtained in daily (and then transformed to weekly) frequency from bitcoinity.org in multiple currencies.[21] In addition, I include various other financial market variables. As interest rates I use 2-year government bond yields (German bunds and US treasuries, respectively). This is because the time sample under consideration includes periods in which central bank policy rates stayed near zero for extended periods of time. I hence follow the recent literature and consider somewhat long-term rates in order to also capture innovations in forward guidance.[22] I include stock market indices as well as the EUR-USD exchange rate and market-based measures of inflation expectations derived from inflation-linked swaps with a maturity of five years. Further, all VAR model variants

[21] In robustness exercises I use data from coinmarketcap.com and also compute weekly Bitcoin prices from scratch using the high-frequency tick data employed in Section 2. In both cases find my results to be essentially identical.

[22] I obtain very similar results when using 1-year rates or swap German bund yields with Eonia rates.

contain a measure of implied stock market volatility such as the VIX that is frequently used to control for perceived global uncertainty and investor risk appetite.[23] Finally, model (3) includes spreads of Bitcoin prices in several fiat currencies relative to its price in US dollars. I follow Makarov and Schoar (2020) and compute the BTC-USD spread of a currency i as $(P^{i/\text{B}}/P^{i/\$})/P^{\$/\text{B}}$, where $P^{j/i}$ is the price of currency i expressed in currency j. Details are provided in Appendix A.

Aggregate Blockchain Transaction Data. I use various time series measuring transfer activity of bitcoins at the aggregate level. First, average mining fees capture the demand for transaction space in blocks added by miners to the blockchain. Relatedly, I add a measure of the median time it takes for a transaction to be added that can equally be thought of as capturing congestion in the peer-to-peer payment system. Both of these series are obtained from `blockchain.info`. Second, I directly measure the amount of Bitcoin transfers as captured in the blockchain. To that end, I do not simply use aggregate measures as is sometimes done in applied work. As these series simply add up the reported transactions, and transfers between addresses of the same entities are frequent and large, using these data would tend to overstate or otherwise obfuscate the actual trading between different agents. Instead, I rely on entity-adjusted measures of total (and median) transactions that aim to filter out transfers that likely occur between the same entities by means of clustering addresses. These data are obtained from glassnode studio.[24]

Bitcoin Holdings and Flows from Blockchain Data. Next to aggregate blockchain transaction measures, I am interested in Bitcoin flows between, and Bitcoin holdings in, different geographical regions, as detailed below. As these are not readily available, I compute them myself from scratch using blockchain data containing hundreds of millions of transactions. In order to make this data useful for the analysis, there again needs to be an adjustment that filters out transfers between the same entities. I therefore make use of pre-clustered data (Kondor et al., 2014) by means of *input-address* or *common-sender heuristics*, the most common approach in the literature. These heuristics map input (sender) and output (receiver) addresses (*public keys*, equivalent to bank account numbers) in the form of 34-character strings into distinct users. Afterwards, I use external information to identify significant entities within the Bitcoin ecosystem among these entities. To that end, I use information from various websites that compile a large number of addresses, and employ algorithmic means in order to identify so-called *cold wallets*. Extensive details on these procedures are described in Appendix A.

[23] Results do not change when replacing the VIX with other measures of implied volatility (for instance those used in Dew-Becker and Giglio, 2020) and are if anything even stronger when replacing it with uncertainty indices that are available at a weekly frequency (for instance the Economic Policy Uncertainty Index and the Equity Market-related Uncertainty Index of Baker et al., 2016).

[24] Conclusions drawn from the VAR results do to not change when I use entity-adjusted aggregate data based on my own computations as outlined below.

As it is generally difficult to precisely assign addresses to users in certain geographical locations with accuracy,[25] I focus on the largest and most important entities in the ecosystem: the exchanges. This is useful for several reasons. First, through much of the time sample under consideration, exchanges can generally be classified according to which fiat currencies they offer. Hence, differences in Bitcoin valuations across currencies can directly be attributed to supply and demand conditions at particular exchanges. Second, exchanges are not mere trading platforms but store large amounts of customer funds. Tracking the holdings of large exchanges then allows to assign particular fiat currencies to large amounts of coins that these can be exchanged into. Third, and relatedly, a substantial share of transaction activity within the blockchain involves exchanges. To see that, consider FIGURE 4, which depicts aggregated blockchain trading relations among the most active entities in the Bitcoin ecosystem.[26] All edges in blue denote transactions with an exchange, edges in red denote transfers directly between exchanges. As the graph indicates, many of the large exchanges are central entities within the Bitcoin network and trading among exchanges is comparatively intensive.

For reasons that will become apparent below, I categorize all exchanges in two sets of groups. Namely, I classify them according to whether they allow trading of Bitcoin against one or more emerging market currencies or exclusively against currencies of advanced economies.[27] TABLE A.1 in Appendix A gives details on which (fiat) currencies can be traded at the exchanges covered and shows the resulting time series.

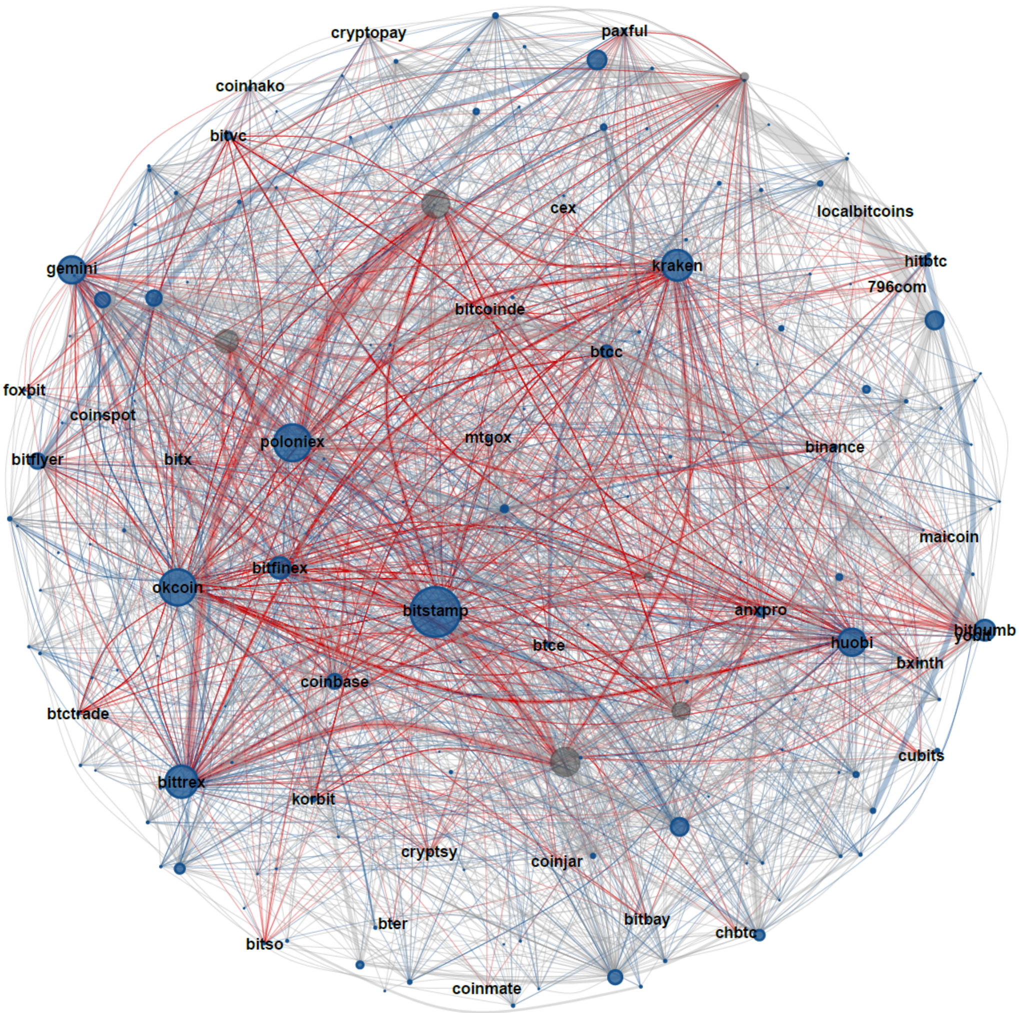
I then compute two sets of time series. First, *inter-exchange flows* (corresponding to the red edges in FIGURE 4), for which I track all Bitcoin flows that occur directly between exchanges of the two groups. This measure has the advantage that it can be thought of as a fairly direct metric of cross-border capital flows in Bitcoin, as for instance argued in Bitfury (2019). However, despite frequent transactions between exchanges it turns out

[25] There are some attempts to link cryptocurrency usage to geographical regions, e.g. via IP addresses (Lischke and Fabian, 2016) or probabilistic models (Athey et al., 2016). The most recent study is a report published in September 2020 by the analytical firm Chainalysis. While these attempts are sometimes comprehensive in scope, they cover only short time periods and generally do not aim to provide time series of cross-border Bitcoin flows and holdings.

[26] For the purpose of this graph, I filter out aggregate transactions with less than 1 million US dollars and entities involved in less than 20 trading relations. Labeled nodes in blue refer to exchanges, whereas grey nodes are not classified.

[27] A categorization according to the available currency pairs will not only turn out to be economically meaningful but also conceptually more useful than classifying them according their official country of residence, as is sometimes done. For instance, the analytical firm Bitfury Crystal classifies exchanges based where they are headquartered (Bitfury, 2019). As various important exchanges officially reside in tax havens or countries with different currencies than the ones offered by the exchanges, such a categorization will be of limited use for the purposes in this paper.

Figure 4: Blockchain Trade Linkages of Highly Active Entities



Note. Aggregated transaction relations of significant entities in the Bitcoin ecosystem between 2009:01 and 2017:12. Thickness of edges denotes size of trading relation in USD, size of nodes denotes *strength* of entity (number of relations in the graph weighted by their USD value). Nodes are in blue (denoting exchanges) or grey (unknown entities); edges are in red (transaction between two exchanges), blue (between an exchange and an unknown entity) or grey (between unknown entities). Graph contains only aggregated transaction relations of more than 1mn USD and *degree* (number of distinct trading relations) of 20. Source: Bitcoin blockchain, author's calculations.

that the value transferred across borders, as measured in US dollar terms, is fairly small.[28] I therefore complement inter-exchange transactions with a second metric. Specifically, I compute the *balances* of the largest exchanges, *i.e.* their cumulated in- and outflows. The resulting time series can be likened to a measure of Bitcoin holdings in different currency areas. While this second measure is less direct, it has the advantage that it is much more comprehensive.

[28]In fact, inter-exchange flows between broad geographic regions amount to only several millions of US dollars per week in some periods of the time sample under consideration. These flows grow in size only during and after the boom-bust period in Bitcoin prices in Winter 2017/18 but are still estimated in Bitfury (2019) to be in the range of only several billion US dollars per year. This at least in part reflects the fact that transactions are not captured if they do not occur directly between exchanges but involve any intermediate wallets. In other words, the measured flows likely cover only a fraction of all transaction that actually occur between different geographical locations.

3.3 The Impact of Monetary Policy Shocks on Bitcoin Prices

This section features the main results, which I report in the form of dynamic responses to an increase in 2-year interest rates of 10 basis points. All VAR model specifications are run in weekly frequency with 8 lags.[29] The main time sample starts in June 2013 which is chosen for reasons of data availability and aspects related to the maturity of the ecosystem.[30] Most time series are available for the entire sample until June 2021, a few for a shorter duration.[31]

Model (1): Monetary Policy Shocks and Bitcoin Prices. Figure 5 shows responses to contractionary euro area (upper) and US (lower row) monetary policy shocks in the baseline model. The VAR specification includes a number of financial market variables next to the price of Bitcoin in USD. As the figure makes clear, shock identification in the weekly setting works well in that it delivers plausible impulse responses that are in line with both standard theory and findings in the literature.[32] Following the monetary shock, risky asset prices in the form of the S&P500/Eurostoxx fall, as does the price of foreign currency,[33] whereas implied stock market volatility rises (not pictured). Also inflation expectations, as measured via inflation-linked swaps with a maturity of 5 years, fall significantly, confirming the disinflationary effects of the monetary policy shocks in both the US and the euro area.[34]

In notable contrast, the impact on the price of Bitcoin differs: whereas it persistently falls in response to contractionary euro area monetary policy shocks, it *increases* following a US monetary contraction. This finding adds weight to the observations made in Section 2 that Bitcoin prices even in short windows around FOMC announcements sometimes seem to move inversely to other risky asset prices whereas they move in tandem after ECB Governing Council decisions. Indeed, the VAR results show that this pattern is systematic and persist for multiple weeks. Quantitatively, the effects seem particularly large at first (with impact responses of around -20 and +7 percent, respectively), but are actually roughly in line with the other asset prices in the model when taking into account the substantially larger

[29] Changing the number of lags does not noticibly change the results provided some reasonable minimum.

[30] Tasca et al. (2016) find that there is almost no commercial activity before 2013 and most blockchain transactions are related to either mining or gambling. Further, the Bitcoin ecosystem was dominated by one single exchange, Mt.Gox, prior to mid-2013 after which there was a massive outflow of coins and the market became less centralized (Karau, 2021b). Finally, Urquhart (2016) finds that Bitcoin prices fail tests of market efficiency before mid-2013 but not afterwards.

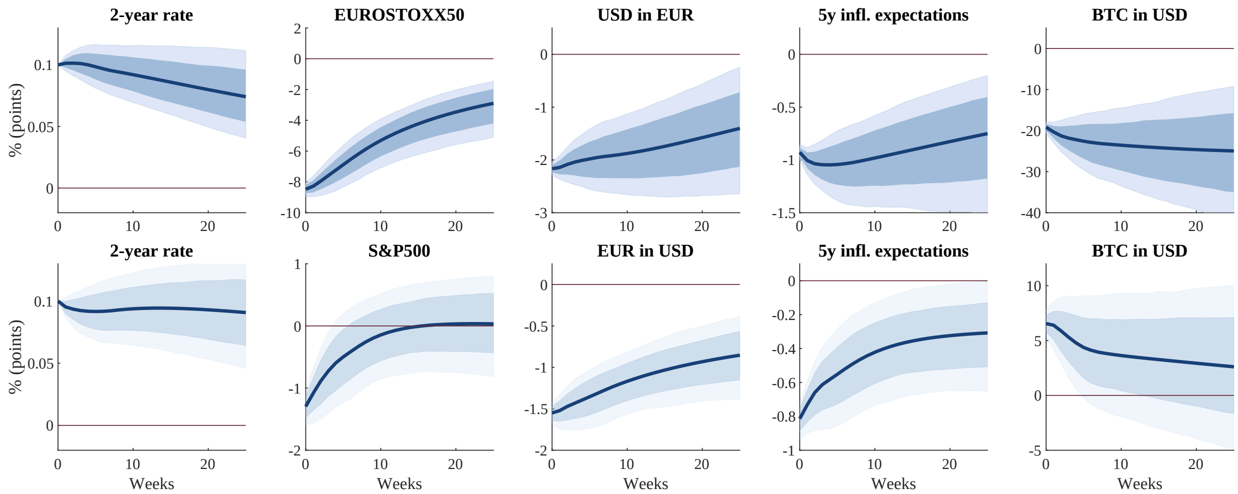
[31] This mostly concerns time series related to Chinese trading activity which fell and then stopped after regulatory crackdowns by Chinese authorities in February and September 2017. It also applies to the computed Bitcoin flows between and holdings of exchanges based on pre-clustered blockchain data, which is available until the end of 2017.

[32] F statistics for instrument relevance lie around 12 for the US and 30 for the euro area model, indicating sufficient instrument strength (>10).

[33] This result is not limited to the EUR-USD exchange rate but also applied to other foreign currencies, among them those are often associated with benefiting from uncertainty such as the Japanese yen.

[34] The quantitative effects are generally larger in the euro area model, which however mostly reflects the lower levels and higher persistence of interest rates in the euro area. Indeed, with the zero lower bound on short-term interest rates more acute, 2-year interest rates in the euro area stood between -0.5 and +0.3 percent in the time sample under consideration, whereas 2-year US rates moved between 0 and 3 percent. This then translates into larger effects of a given change in 2-year rates for the euro area model.

Figure 5: IRFs to Contractionary US and EA Monetary Policy Shocks: BTC and Other Asset Prices



Note. Impulse responses to a contractionary euro area (upper) and US (lower panel) monetary policy shock (model (1) in Table 2) identified as explained in Section 3.1. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to June 2021.

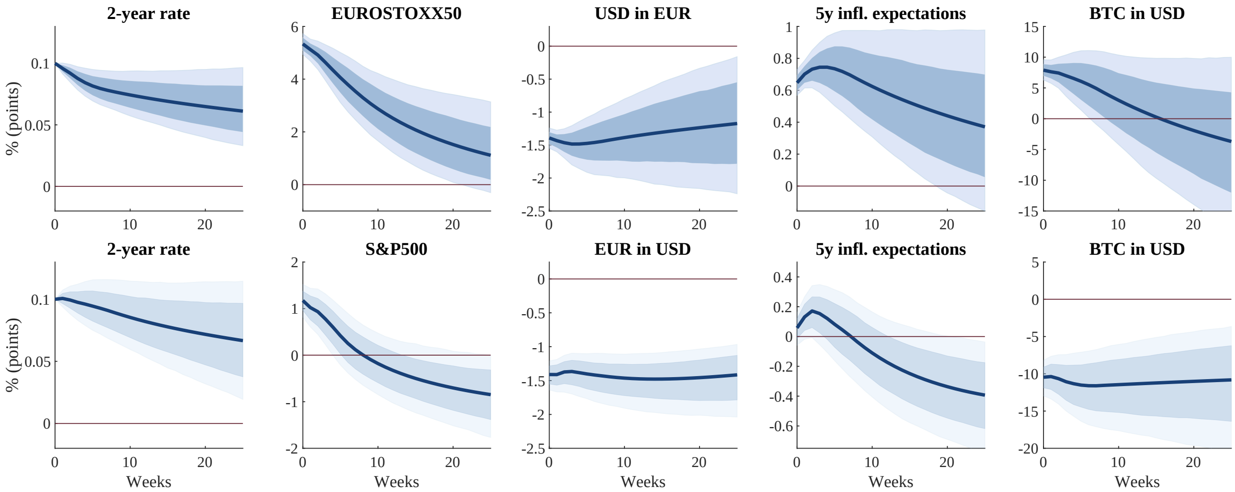
volatility of Bitcoin prices in general.

What might explain the strikingly different responses of Bitcoin prices? The contractionary impact of euro area monetary policy seems in line with a view that sees Bitcoin's design as a counter model to discretionary monetary policy based on fiat money creation. Indeed, Halaburda et al. (2020, p.53) write that "[e]nthusiastic supporters of cryptocurrencies often argue that Bitcoin will replace gold as the hedge against inflation". Accordingly, a disinflationary shock should reduce the propensity to invest in Bitcoin, just as observed in Figure 5. In contrast, the increase in Bitcoin prices in response to a US monetary contraction is more difficult to interpret and demands a different explanation. While it can by no means be excluded that the inflation hedge notion also plays a role with US monetary policy, at the very least there needs to be an additional channel at work that dominates the former and predicts an opposite effect.[35]

Central Bank Information Shocks and Bitcoin Prices. As outlined in Section 3.1, a recent literature noted that central bank rate hikes are often associated with increases in stock market valuations instead of declines. An explanation put forth by a number of authors is that central banks, by communicating their policy decisions, inform the public about their forecasts for economic activity. If a rate hike is communicated to be due to an

[35]One might conjecture that the qualitatively different results are driven by opposing trends in interest rates coupled with a generally increasing price of Bitcoin over time. Indeed, in much of the time sample under consideration, interest rates in the US have risen, while the opposite is true for euro area rates. Such a view, however, would be simplistic in that it is based on reduced-form trends rather than structural analysis. Indeed, Figure A.1 shows that the external instrument used to identify the structural shocks is fairly symmetrically distributed around zero for both the US and euro area with no discernible easing or tightening bias. The same is true for the identified structural shocks themselves.

Figure 6: IRFs to US and EA Central Bank Information Shocks: BTC and Other Asset Prices



Note. Impulse responses to an expansionary euro area (upper) and US (lower panel) central bank information shock (model (1) in Table 2) identified as explained in Section 3.1. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to June 2021.

improved economic outlook, market participants might adjust their own forecasts upward, leading to a rise in the price of risky assets such as stocks despite the increase in interest rates.

Estimating responses of Bitcoin valuations to these central bank information shocks might therefore serve to gain a better understanding of the results found for monetary policy shocks. In addition, identifying these shocks can also be used to test one potential explanation for the positive response of Bitcoin prices to a US monetary tightening: that Bitcoin is a bubble asset. For instance, in Blanchard and Watson (1982) a rational bubble is characterized by the asset value growing in expectations with the risk-free interest rate. To the extent that US short-term rates constitute the empirical counterpart, according to this view, an exogenous rise in US rates might serve to increase, rather than lower, the price of Bitcoin. Hence, if Bitcoin indeed is a rational bubble and unrelated to economic activity, the rate hike associated with a central bank information shock should cause its price to increase in the US model, just as in response to a monetary contraction.

Figure 6 shows impulse responses to the main variables in model (1) to a central bank information shock, identified as explained in Table 1.[36] In both models, stock prices increase following the rate hike. Inflation expectations increase as well, especially strongly and persistently so in the euro area model. This finding mirrors the result in Jarociński and Karadi (2020)and Miranda-Agrippino and Ricco (2021) that central bank information shocks are generally associated with rising prices, making them akin to demand shocks that are revealed by the central bank. In contrast, the response of the EUR-USD exchange rate seems almost entirely driven by the mechanical increase in the interest differential rather

[36] F statistics are lower in both the euro area and US VAR compared to the monetary policy shock and drop somewhat below 10 in the US model. Results there should hence be interpreted with more caution.

than the economic forces of the underlying shock.[37]

Strikingly, the responses of Bitcoin prices are different and again yield a mirror imagine: whereas the euro area information shock increases Bitcoin valuations, the US shock has the opposite effect and leads to a persistent decline. Therefore, it does not seem to be the case that Bitcoin prices in the US model are merely driven by changes in interest rates, as the rational bubble view would have it. Instead, the analysis points to a different pattern: In the US model, Bitcoin valuations benefit from conditions that lower risky asset prices, irrespective if these are caused by rising interest rates (following a monetary policy shock) or associated with falling rates (following a central bank information shock). In contrast, in the euro area model, Bitcoin valuations move in tandem with risky asset prices and benefit from shocks that are inflationary, again irrespective of the direction of interest rates. Whereas Figure 6 therefore adds weight to the view of Bitcoin as an inflation hedge following euro area shocks, the findings for the US models still appear puzzling. In the following I therefore analyze the response of different aspects of the Bitcoin ecosystem in order to explore potential explanations for the peculiar US result. Before I do so, however, I briefly outline some robustness checks for, and extensions of, the main results.

Robustness and Extensions. I make sure that my main results in the VAR analysis are robust along a number of dimensions, as detailed in Appendix C. In particular, they hold when changing the time sample (Figure C.2), when extending the instrument series in the US model (Figure C.4) or when the logged price of Bitcoin enters in first differences (Figure C.3). Notably, results also hold when computing impulse responses by means of local projections as suggested by Jorda (2005) (Figure C.6).

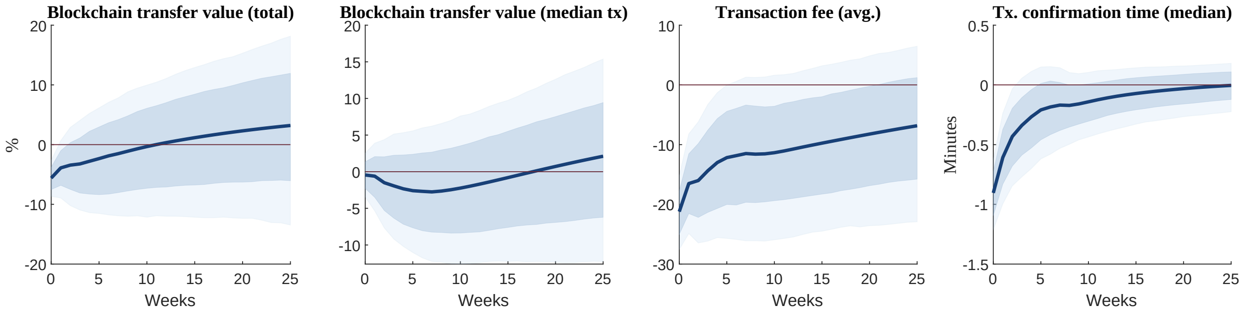
In addition to robustness considerations, Appendix C.2 also provides some further interesting results. First, I use the local projection framework to show that the effects of euro area shocks are fairly symmetric, whereas the effects of US shocks seem to be driven primarily by monetary contractions, in line with the view developed below. Second, I find positive Bitcoin price responses to contractionary risk-shift shocks as well that have recently been proposed by Kroencke et al. (2021) as a main driver of stock price movements following FOMC announcements. Lastly, I verify that other cryptocurrencies with sufficiently long time series available mostly respond qualitatively similarly to Bitcoin (Figure C.5).

3.4 Exploring the Impact of US Monetary Policy Shocks

In the following, I consider various aspects of the Bitcoin ecosystem, as laid out in Table 2. In model (2) I study the response of aggregate blockchain activity. Models (3) and (4) then explore international aspects based on price spreads in different currencies as well as Bitcoin holdings and flows measured via blockchain data.

[37] See Franz (2020) for an in-depth analysis of central bank information shocks on exchange rates.

Figure 7: IRFs to Contractionary US Monetary Policy Shock: Aggregate Blockchain Activity



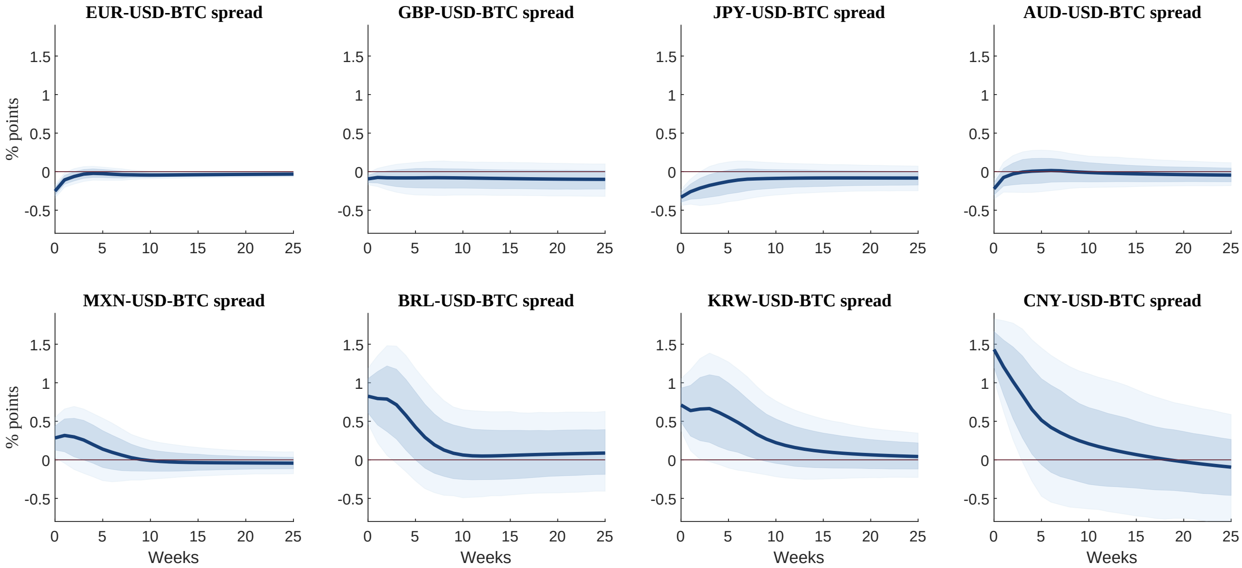
Note. Impulse responses to a contractionary US monetary policy shock (model (2) in Table 2) identified as explained in Section 3.1. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to June 2021 (January 2020 for the entity-adjusted blockchain data in panels 1 and 2).

Model (2): Aggregate Blockchain Activity. One peculiar feature of Bitcoin lies in its role as the medium of exchange in its own decentralized payment system. In particular, Bitcoin is often described as serving as a exchange medium not so much for ordinary goods and services but for illicit transactions. For instance, the Economist magazine cites data from Morgan Stanley according to which only three of the largest 500 online retailers accepted Bitcoin for payments in 2017. In contrast, Foley et al. (2019) estimate that 26 percent of Bitcoin users and 46 percent of Bitcoin transactions in the blockchain are associated with illegal behavior from 2009 to 2017. They conclude (p.1844) that the illegal use of Bitcoin "is likely to be a meaningful contributor to [its] fundamental value." Accordingly, Bitcoin's value as a medium of exchange could increase following a monetary policy shock if demand shifted towards these types of activities. More concretely, to the extent that a US monetary contraction depresses trade and employment in the formal economy, it might shift activity towards the underground economy.[38] There, tax evasion or paying for illicit employment or goods and services could be facilitated using Bitcoin's decentralized and pseudonymous payment system.

Figure 7 investigates if Bitcoin's role as a medium of exchange could serve as an explanation for the expansionary effects of a US monetary tightening. The first two panels depict impulse responses of entity-adjusted measures of total and median blockchain transfer volumes (in USD) to a US monetary tightening. If anything, the total value of transactions goes down while the median transaction size does not respond significantly. In addition, panels 3 and 4 show that metrics of blockchain congestion, which measure demand for space in transaction blocks, even decline. Average mining fees, which users add to their transactions in order to make it more likely that they are quickly added to the blockchain, fall by 20 percent on impact. And also the median time it takes for a transaction to be confirmed

[38] For instance, Schneider et al. (2010) find a negative correlation between estimates of the underground economy, for instance based on cash usage and labor force participation, and formal economic activity in a sample of more than 100 countries.

Figure 8: IRFs to Contractionary US Monetary Policy Shock: "Arbitrage Spreads"



Note. Impulse responses to a contractionary US monetary policy shock (model (3) in Table 2) identified as explained in Section 3.1. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to June 2021 (September 2017 for CNY, January 2020 for BRL spread).

falls by roughly one minute.[39] Taking these responses together, the US monetary shock seems to cause a fall in the demand for scarce transaction space, rather than an increase. On balance then, these findings run counter to the notion that Bitcoin's being used in more day-to-day transactions generally, or as a medium of exchange for illicit activity specifically, can account for the price increase following the US monetary policy shock.[40]

Model (3): Bitcoin Valuations in Different Currencies. Bitcoin is not native to any one country and can be held by users, and transferred across borders, irrespective of country of origin. Yet, cryptocurrency markets priced in different fiat currencies are not free from apparent arbitrage opportunities. Makarov and Schoar (2020) for instance document persistent spreads between the USD price of Bitcoin and the implicit USD price when buying Bitcoin in other currencies and converting it using market exchange rates. They link the existence of sizable spreads to the presence of capital controls, Kroeger and Sarkar (2016)

[39]This response is to some, but only limited, extent driven by a effects on mining profitability. I verify this by adding the logged hash rate – the total computational effort devoted by all miners – and the time it takes for blocks to get mined to the model. As mining rewards are denominated in bitcoins, an increase in the price of Bitcoin raises incentives of miners to invest in computational power (Ma et al., 2018). Accordingly, there is an increase in the hash rate and a corresponding fall in block creation times. The latter, however, is comparatively small relative to the decline in median transaction confirmation times. This implies that the reduced time it takes for transactions to get added to the blockchain is mainly driven by a fall in demand rather than increased mining effort.

[40]This view is corroborated by including a direct measure of illicit transactions in the model, as for instance computed by Foley et al. (2019). These authors estimate the share of transactions that can directly be linked to illegal activity or indirectly suggest an illicit use due to the employment of techniques meant to obfuscate transaction chains. Depending on the model specification, this measure either does not respond significantly or even falls after the US monetary policy shock.

point to transaction costs and price risk. As repatriating arbitrage profits requires capital flows through the established and regulated financial system, capital controls, time delays as well as withdrawal and deposit fees can prevent arbitrage trades from being readily realized, if at all. As the spreads vary over time as well as in size and persistence across currencies, it is instructive to see if they respond to monetary policy shocks. Such an analysis would give an indication of whether the increased demand for Bitcoin following the shock is uniform across currency areas.

Figure 8 reports impulse responses to the spreads computed for eight different fiat currencies that show a clear pattern: the upper row reveals that spreads with respect to advanced economy fiat currencies either do not respond (British pound) or even slightly fall (euro, Japanese yen, Australian dollar). Contrast that with the second row which considers emerging market fiat currencies. The first two panels show spreads with respect to currencies of two Latin American economies with histories of instability (Mexican peso, Brazilian real), the other two panels those of two Asian economies that feature various forms of restrictive capital controls (Korean won, Chinese yuan).[41] All four spreads increase, and especially the response of the Chinese yuan spread is large and persists for several weeks.

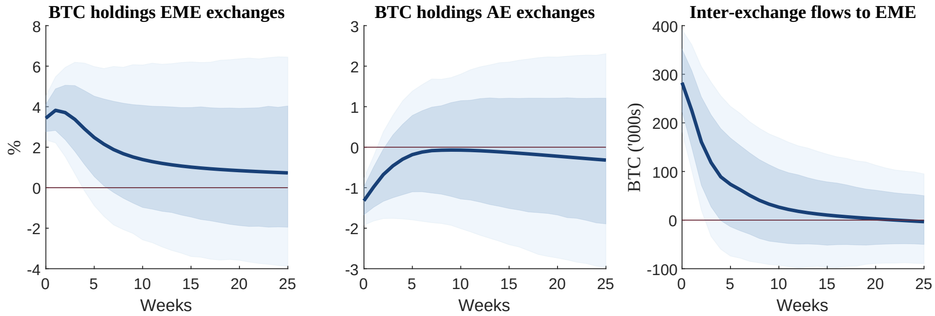
In other words, while Bitcoin prices in US dollars increase following a US monetary tightening, they increase especially strongly in emerging market economies. In contrast, the rise in value is equally pronounced or even weaker when measured in fiat currencies of advanced economies.[42] Importantly, the increase in spreads in emerging market currencies does not merely reflect increased frictions in international capital markets that might make it more difficult to capitalize on price differences via arbitrage trades. This is because the spreads are generally above unity, i.e. Bitcoin tends to be more expensive in the respective emerging market currency than in US dollars, and significant deviations from unity are almost exclusively positive.[43] Accordingly, if arbitrage forces indeed were to become weaker after a US monetary tightening – and increased demand for Bitcoin primarily stemmed from advanced instead of emerging economies –, one would expect the spreads to mechanically narrow instead of widen after the shock. In that sense then, the observed opening up of spreads is evidence that the increased demand for Bitcoin must be stronger in emerging markets than in the US or other advanced economies.

[41]Korea tightened capital controls in 2010 and limits the amount of money send abroad to 3,000 USD per transaction and 50,000 USD per year per person, which is often argued to contribute to the large deviations of Bitcoin prices in Korean Won, infamously known as the *Kimchi premium* (Choi et al., 2020). Similarly, China tightened controls, allowing Chinese residents to exchange not more 100,000 USD per year into foreign currency before 2017, which was then reduced to 50,000 USD. Further, Chinese banks have to report sizable transactions to authorities and scrutiny is reported to have increased during the time sample under consideration.

[42]Notably, this finding is despite the fact that the spreads across countries tend to move in tandem quite a bit. For instance, the KRW and JPY spreads are highly correlated across time (Makarov and Schoar, 2020) but still respond very differently to US monetary shocks.

[43]See Makarov and Schoar (2020) or Figure A.4. One exception is the spread with respect to the Chinese yuan, which dropped below unity for some time in mid 2017. However, the result of an increase in the CNY spread after the US shock continues to hold when excluding this episode.

Figure 9: IRFs to Contractionary US Monetary Policy Shock: International BTC Flows and Holdings at Exchanges



Note. Impulse responses to a contractionary US monetary policy shock (model (4) in Table 2) identified as explained in Section 3.1. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to December 2017.

Model (4): International Bitcoin Capital Flows and Holdings. Finally, in order to corroborate the notion that there is increased demand for Bitcoin in emerging markets, I again make use of blockchain data. However, rather than looking at aggregate transfer activity as in Figure 7, I study the response of Bitcoin holdings and flows more directly. For that purpose, as outlined in Section 3.2, I identify addresses of dozens of large Bitcoin exchanges from hundreds of millions of transaction contained in blockchain data. These exchanges are then categorized according to whether they allow to trade Bitcoin against an emerging market (EME) or only advanced economy fiat currency (AE). I then compute net flows of Bitcoin between the two groups of exchanges as well as Bitcoin holdings, and include them in my VAR framework. As indicated above, the series on the holdings have the advantage that a much larger share of coins is captured, while the series on net flows measure value transfers across borders more directly.

Figure 9 reports impulse responses. The first panel shows that holdings of coins at emerging market exchanges tend to increase by roughly four percent following the US monetary shock. In contrast, Bitcoin holdings fall in those exchanges that exclusively allow trading against fiat currencies of highly-developed countries, implying a redistribution of Bitcoin holdings across currency areas. Finally, the third panel shows that there is an immediate increase in the direct net flows of coins from advanced to emerging market exchanges after the shock. Taken together, these findings again provide an indication that the increased demand for Bitcoin following the US monetary shock is not uniform across geographic regions or income levels, but stems primarily from emerging market economies.

3.5 Discussion

The different responses of Bitcoin valuations to structural shocks have implications for the debate on how to best think of cryptocurrencies in general and on what drives the demand for Bitcoin in particular. To begin with, as laid out in Section 3.3, it is noteworthy that Bitcoin prices do not simply react to changes in interest rates *per se*: they respond very differently to monetary policy shocks on the one hand and central bank information shocks on the other, although both feature a surprise increase in rates. In that sense then, the underlying economics of the shock seems to primarily matter, pointing to a connection of Bitcoin to the traditional financial system despite its apparent disconnect – e.g. the lack of its use as a medium of exchange in the wider economy.

However, as regards the nature of such connection, the analysis reveals two distinct roles that Bitcoin seems to play. Following shocks from the euro area, Bitcoin price responses are in line with those of inflation expectations, a finding that is at least consistent with the view that sees Bitcoin as a form of *digital gold* that by virtue of its mechanically increasing and ultimately fixed supply offers investors protection from supposedly inflationary monetary policy. In contrast, in response to US shocks, a counteracting channel seems to be at work that leads to an increase in Bitcoin prices following a monetary contraction.

As explored in Section 3.4, the increased demand for Bitcoin seems to primarily stem from market participants in emerging economies. This finding echoes the notion that US monetary policy does not only have domestic but also substantial international ramifications. A growing literature finds that US monetary policy drives a large part of global capital flows and asset prices (Miranda-Agrippino and Rey, 2020). Rey (2015) argues that exchange rate flexibility does not suffice to shield less developed countries from policy spillovers. Degasperi et al. (2020) confirm this notion and find that detrimental effects of a US monetary contraction are roughly twice as large for the median emerging market economy compared to advanced economies.

Often-cited reasons for the importance of US policy lie in the role of the US dollar in global trade invoicing,[44] and the denomination of assets in the international financial system.[45] Bruno and Shin (2015) point to the role of globally active banks that provide USD-denominated loans internationally but curtail lending following a US monetary tightening.[46] Hofmann and Park (2020) show that a USD appreciation is associated with lower growth prospects in emerging markets, with growth-at-risk being affected even more strongly.[47] Kalemli-Özcan (2019) argues that emerging markets are most vulnerable to changes in global investors' risk perceptions that are driven by US monetary policy.

With emerging markets susceptible to US monetary policy shocks then, why would

[44] For instance, according to Iancu et al. (2020), more than 50 percent of all im- and exports are invoiced in US dollars although the US accounts for only 10 percent of global trade. Gopinath et al. (2020) show theoretically that the denomination of traded goods in a dominant currency can substantially increase international spillovers of shocks originating from the dominant currency area.

[45] Iancu et al. (2020) report that roughly half of cross-border bank claims and outstanding global debt securities as well as 75 percent of public debt economies are denominated in US dollars.

[46] Barajas et al. (2020) corroborate this notion and find that US dollar funding shortages negatively affect lending of global banks in emerging markets.

[47] Also here, however, the reason for changes in interest rates seems to matter. Ahmed et al. (2021) show theoretically that increases in US interest rates are not neccesarily contractionary and indeed can even have a stimulative effect on emerging markets, reiterating the empirical analysis in Hoek et al. (2020). Camara (2021) shows that central bank information shocks, although they increase interest rates in the US relative to emerging markets, can strengthen rather than weaken emerging market currencies. Consistently with the view developed here, Bitcoin prices fall after such an expansionary shock.

Bitcoin experience increased demand? One reason may be found in the well-documented low correlation of cryptocurrencies with traditional financial assets and business cycles that might – despite their volatile prices – grant it features akin to a *safe haven* in times of market stress (Bouri et al., 2017b; Corbet et al., 2020a).

Another reason, however, may lie in the institutional and technological particularities of Bitcoin and other cryptocurrencies. Payments can be made globally with the help of just an internet connection and users are not differentiated according to geographic location. Further, for much of the time sample under consideration, cryptocurrency markets were largely unregulated in many countries. These features may help users avoid the vetting of transactions by authorities or circumvent limits to cross-border value transfers altogether, both of which are present in many emerging markets as measures to control capital flows (Lee and Low, 2018).[48] In other words, particularly in times of stress, for market participants subject to these restrictions, Bitcoin may well be one of the few assets a flight into, or trading with internationally, is possible at all. Relatedly, Bitcoin's infrastructure can in principle provide access to other traditional currencies. More specifically, it is generally possible to buy Bitcoin on a local exchange and then transfer it via its payment system to an exchange where it can be traded for foreign currency. In other words, Bitcoin might not be sought as an investment in itself, but rather as a vehicle currency.[49]

More generally then, for market participants subject to capital controls and/or unstable domestic currencies, Bitcoin's value proposition might not so much lie in the feature often stressed when it comes to its value, namely its scarcity due to its finite supply. Instead, it seems to lie in the second defining feature of Bitcoin: its peer-to-peer decentralized payment infrastructure that is in principle separate from the traditional, regulated financial system. In other words, rather than constituting a form of *digital gold* in the sense of inflation hedge against too easy US monetary policy, Bitcoin seems to have served primarily as a global *digital cash* that is accessible internationally and is sought after following a contractionary US monetary tightening.

To be sure, the role of Bitcoin and other cryptocurrencies has evolved in the past and will continue to do so. Especially the recently observed demand from institutional investors

[48] Cifuentes (2018) offers an account of how cryptocurrencies are used to circumvent capital controls in Latin American economies such as Argentina, see also Financial Times (2015). There is anecdotical evidence of Brazilian and Nigerian entrepreneurs using Bitcoin to trade with foreign firms (Bitcoin.com, 2020; Coindesk.com, 2020) and of Chinese savers using Bitcoin to transfer wealth overseas (Cointelegraph, 2016). It is often alleged that fears of capital flight using Bitcoin was one of the main drivers of the regulatory crackdown by Chinese authorities in 2017 (New York Times, 2017).

[49] Bitcoin's decentralized system might be used to acquire USD-denominated assets indirectly, thereby increasing the demand for, and value of, the vehicle currency in the process. A model that features such effects can be found in Lyons and Viswanath-Natraj (2020). There, the authors want to explain why the USD-backed stablecoin Tether sometimes has a value larger than one USD. Their rationale is that there are two ways to invest in unbacked cryptocurrencies: via fiat currency and via Tether. If transaction costs for the route via fiat currency increase, this boosts the value of the alternative, *i.e.* Tether. Hence, in Lyons and Viswanath-Natraj (2020), Tether is used as a vehicle currency to invest in Bitcoin. Similarly, Bitcoin could be used as a vehicle currency to invest in US dollar assets for international investors, such that its value increases if it becomes more costly to acquire US dollars via the conventional financial system following a US monetary contraction.

in advanced economies and increasing regulatory scrutiny worldwide might fundamentally change what cryptocurrencies are primarily used for. The analysis here however reveals that already in the past Bitcoin seems to have had connections to the traditional financial system that are not obvious or easily ascertained from reduced-form analysis, and that had important implications for its market value.

4 Conclusion

This paper documents that monetary policy innovations by both the Fed and the ECB have a sizable impact on Bitcoin prices. Motivated by some stylized facts based on a high-frequency analysis, I study the impact of structural monetary policy shocks in a weekly proxy VAR setting on Bitcoin valuations as well as a broader set of variables related to the cryptocurrency ecosystem. I first show that disinflationary euro area monetary policy shocks lead to a persistent fall in Bitcoin valuations, whereas inflationary central bank information shocks lead to a price increase. Conversely, I find a mirror image for US shocks: Bitcoin prices increase after the monetary contraction but fall following the expansionary central bank information shock.

While the response to euro area shocks is consistent with notions of Bitcoin as a *digital gold* in the sense of an inflation hedge, I argue that for US shocks such an effect must be overcompensated by an additional channel. In exploring potential explanations for the atypical responses to US monetary policy shocks, I find that Bitcoin prices in several emerging market currencies increase particularly strongly after US monetary contractions – above all the Chinese yuan. Further, based on blockchain transaction data, the paper documents that coins systematically flow to exchanges that support trading of Bitcoin against emerging market currencies in response to the shock. Similarly, Bitcoin holdings at these exchanges increase. I conjecture that the technological and institutional particularities of Bitcoin make it akin to a global *digital cash* that enables cross-border transactions and capital flight in the face of deteriorating economic and financial conditions that contractionary US monetary shocks have globally.

The findings in this paper have implications along multiple dimensions. From the perspective of policy makers it is important to understand the use cases of Bitcoin, which was initially designed to challenge the existing monetary and financial system – both the discretionary decision-making by central banks and the intermediating role of commercial banks. Regulators are not only interested in the role of cryptocurrencies as speculative investments and the corresponding potential threats to financial stability. It is also important to understand to what extent cryptocurrencies facilitate cross-border value transfers and potential capital flight, and how they interact with the monetary transmission mechanism more generally. Not least, this could provide insights into the use cases of global stablecoin projects that currently occupy the minds of central bankers and regulators worldwide.

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A Data Appendix

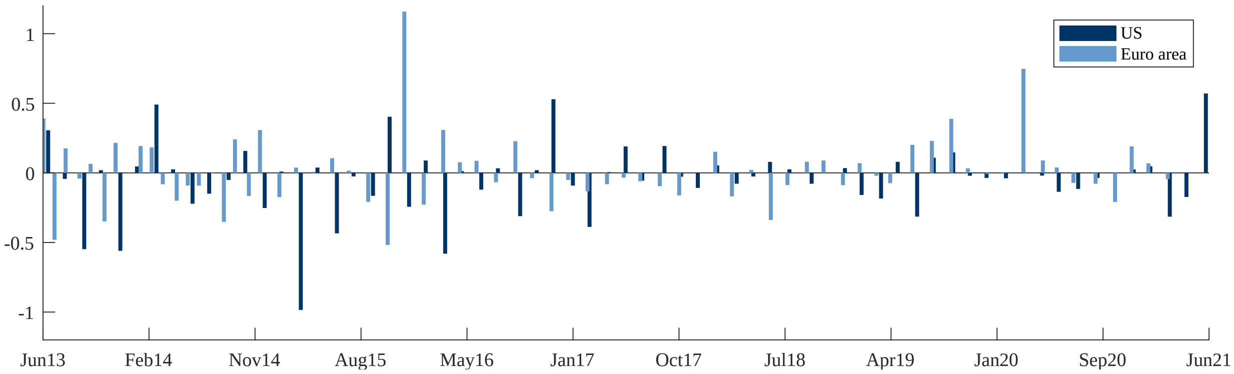
High-Frequency Bitcoin Price Data. The high-frequency price data featured in Section 2 is gathered from the website bitcoincharts.com/charts that contains tick data for dozens of Bitcoin exchanges. I download price and volume data in USD and EUR for various exchanges with large trading volumes and many observations over as long time periods as possible. For Bitcoin prices in USD I choose data from Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken and Mt.Gox. For Bitcoin prices in EUR I use data from Bitcoin.de, Bitstamp, Coinbase, Kraken, Mt.Gox and TheRockTrading.

In a next step I drop very small trades of below one unit of the respective currency. As there is a substantial number of outliers in the raw data series, I then apply an hourly price median filter. Specifically, for each hour I compute the median value of each exchange's price series and then drop all tick observations with values that depart more than ten percent in either direction from the median quote. In addition, I comb through each time series and manually remove a few more clear outliers not captured by the median price filter.

I then boil down the tick data to 1-minute and 5-minute observations and average the price data across the currency-specific groups of exchanges. I do so by weighting the price series according to trade volumes at the exchanges over the previous day. This process results in high-frequency time series of USD and EUR Bitcoin prices spanning the period from 2013 to 2021. It should be noted, however, that in the earlier parts of the sample, trading even at large exchanges was less frequent. As a consequence, there are some unavoidable gaps especially in the EUR series. In the analysis in Section 2 I therefore generally focus on the data with 5-minute spells and make sure that these data limitations do not unduly influence my results.

Proxy VAR Instrument Based on High-Frequency Data. As mentioned in the main text, the instrument series $\mathbf{Z}_t$ are derived from two databases that contain information on the changes of asset prices in narrow time windows around monetary announcements. For the euro area, I rely on the monetary event study database by Altavilla et al. (2019) and consider their *monetary event window* which spans the time window of roughly 15 minutes prior to the ECB press statement to more than one hour after the beginning of the press conference. For the US model, I use the database by Cieslak and Schrimpf (2019). Two complications arise. First, not every FOMC meeting in the time sample under consideration features a press conference after the chair's press statement. I deal with this issue by making use of the different time windows provided in the database by Cieslak and Schrimpf (2019). The chosen window starts 15 minutes prior and ends 60 minutes after the meeting if there is a press conference. If not, I consider a shorter time window of 10 minutes prior to 20 minutes after the press statement, as is common in the literature for the time period prior to 2011, before the Fed started holding regular press conferences (Gürkaynak et al., 2005). A second problem is related to the fact that the Cieslak and Schrimpf (2019) database

Figure A.1: Instrument Z_t Used in the Proxy VAR Models



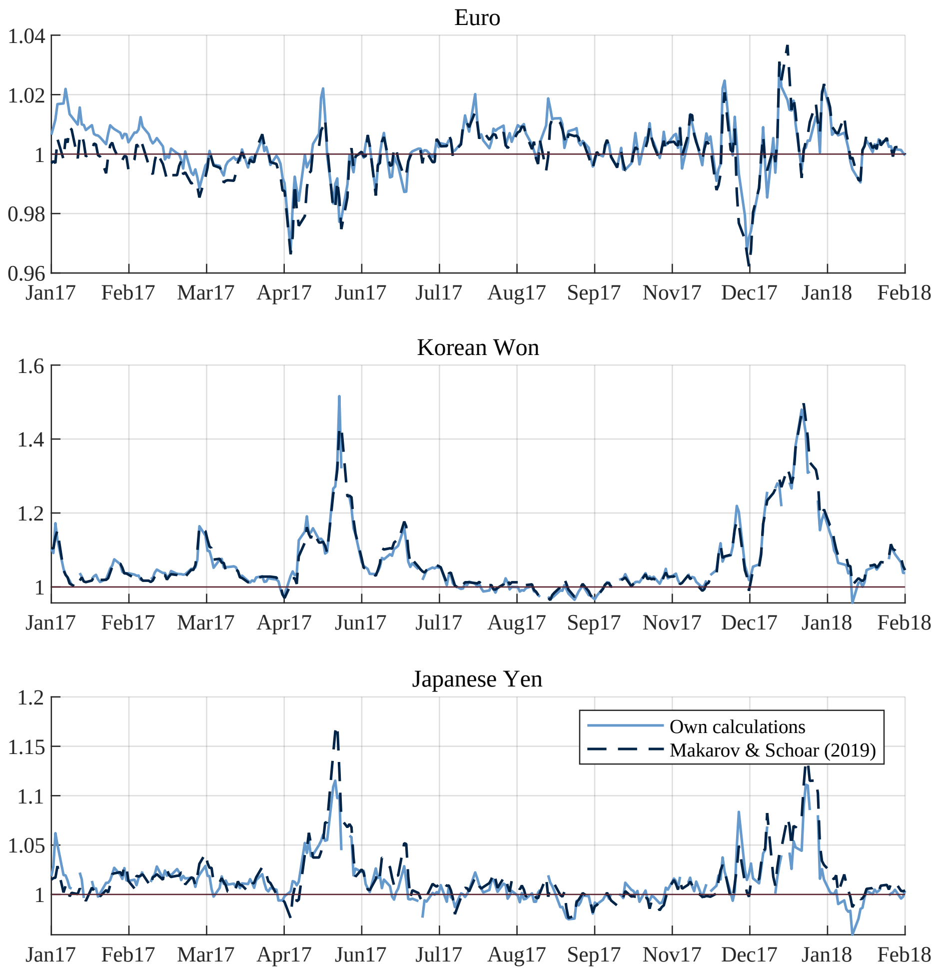
Note. Instrument series Z_t computed as described in Table 1 based on data by Altavilla et al. (2019) (euro area) and Cieslak and Schrimpf (2019). The depicted series for the US includes the sample period after December 2017, which is based on self-computed changes interest rates and stock prices based on data by the ECB, Refinitiv and `tickstory.com`.

ends in December 2017. Fortunately, the proxy VAR model employed throughout does not necessitate that the time samples for the VAR estimation and that of the instrument series are identical. I can therefore estimate the model in a more extensive sample ranging until June 2021, although the information used for the identification of exogenous shocks will stem from the earlier parts of the sample.

In order to gauge if my results would substantially change if the instrument series were longer, I extend it for the later parts of the sample. For that purpose I use self-computed changes in 2-year interest rates and the S&P500 in the same narrow time windows around FOMC announcements. As this data is only available to me starting from mid-2019, there is a substantial gap of around one and a half years (January 2018 until June 2019) that would dilute the informational content of the instrument. I therefore fill this gap in two ways. For stock prices, I use minute-by-minute data from `tickstory.com`. As for the interest rates such data is not available, I use daily changes around the missing FOMC meetings. The extended instrument series is employed in a robustness exercise in Figure C.4, producing very similar results to those in Figure 5. It generally yields somewhat lower F statistics for instrument strength, which remain slightly above 10, though.

Arbitrage Spreads. As described in Section 3.2, I follow Makarov and Schoar (2020) and compute the BTC-USD arbitrage spread of a currency i as $(P^{i/₿}/P^{i/\$})/P^{\$/₿}$, where $P^{j/i}$ is the price of currency i expressed in currency j. For the spread with respect to the euro, I employ the high-frequency Bitcoin price data described above, in addition to minute-by-minute data for the EUR-USD exchange rate from `tickstory.com`, to construct the spreads. For the other fiat currencies, for which no continuous long-term high-frequency Bitcoin price (or exchange rate) data are available, I rely on volume-weighted daily Bitcoin price data stemming from `bitcoinity.org`, in combination with daily exchange rate data from the ECB. In principle, using daily data with different fixings might introduce measurement error in the computed spreads. However, reassuringly, FIGURE A.2 shows that the computed series are very similar to the ones in Makarov and Schoar (2020) – based on high-frequency data – for the time period and currencies for which the samples overlap. What is more, any inaccuracies stemming from using daily data should be more problematic in the computation of Bitcoin spreads with respect to advanced economy fiat currencies as spreads here are generally smaller and less persistent. The larger and more persistent deviations observed for emerging market fiat currencies should therefore be more much robust to using lower-frequency data.

FIGURE A.2: BTC ARBITRAGE SPREADS, OWN CALUCLATIONS IN COMPARISON TO MAKAROV AND SCHOAR (2020)



Note. Bitcoin spreads for three fiat currencies relative to the price in US dollars, plotted as daily averages. In the absence of sizable frictions to arbitrage, the computed series would be close to unity at all times. Values above one indicate that Bitcoin is more expensive in the respective currency than in US dollar, and *vice versa*. Spreads in Makarov and Schoar (2020) based on maximum differences between exchanges from minute-by-minute data. Own computations for the euro spread based on volume-weighted minute-by-minute data, for the Korean Won and Japanese yen based on daily data.

Blockchain Data. I obtain the entire Bitcoin blockchain containing the universe of transactions from its inception to in January 2009 to February 2018 in pre-processed form as an updated version of the dataset used in Kondor et al. (2014). As a first step, I drop so-called *change transactions* that account for the difference between the total number of Bitcoin sent by the input addresses and the amount received by the output addresses. Such change is returned to the sender and therefore does not represent a meaningful transfer of value. In addition, I drop all transactions related to Satoshi Dice, a gambling site that is associated with a large share of trading activity in the early years of the Bitcoin network.[50]

Clustering. The Bitcoin blockchain contains input (sender) and output (receiver) addresses (*public keys*, equivalent to bank account numbers) in the form of 34-character strings. In order to map these into distinct entities or users, Kondor et al. (2014) apply the most common approach in the literature in the form of an *input-address* or *common-sender heuristic*.[51] This approach in essence assumes that all input addresses in a particular transaction stem from the same user. Additionally, if one of the input addresses is used in two or more separate transactions, then all input addresses contained in these transactions are assumed to stem from the same user. This assumption reflects the fact that initiating a transaction necessitates to have it signed with the passwords (*private keys*, equivalent to PIN numbers) of *all* input addresses, making it likely that the senders are actually the same entity. This approach has the advantage that it is simple and generally avoids producing false positives, *i.e.* clustering together addresses that do not in fact belong to the same user.[52] It should be noted, however, that false negatives cannot be ruled out, *i.e.* the heuristic will for instance fail to cluster together two sets of addresses that one single entity uses entirely separately from one another.[53] Following the clustering procedure, the dataset contains a bit more than 655 million transactions between roughly 350 million distinct entities. Finally, I drop within-user transactions from the dataset as they again do not reflect the transfer of Bitcoin between two actually distinct entities.

Labeling. As a next step, I use external information to identify significant entities within the Bitcoin ecosystem. This is achieved with the help of external information from a

[50]Users can play on the site by making Bitcoin transactions. These do not represent actual trades but, according to Kondor et al. (2014), produced over half of all Bitcoin activity in 2012. Following these authors, I therefore drop all Satoshi-Dice-related addresses, which characteristically start with `"1dice"`. The entity Satoshi Dice itself remains in the dataset.

[51]See also e.g. Ron and Shamir (2013), Ober et al. (2013), Athey et al. (2016), Tasca et al. (2016), Griffin and Shams (2020).

[52]Other heuristics employed in the literature, like change-address heuristics (see e.g. Meiklejohn et al., 2013 and Garcia et al., 2014) can in principle improve upon input-address heuristics, but are prone to producing false positives that would have to be eliminated in a very time-consuming manner. See Tasca et al., (2016, pp.4-7) for a discussion.

[53]In addition, the emergence of so-called *coinjoin* practices in principle pose challenges to input-address heuristics. In coinjoin transactions, multiple users agree to pool together transaction inputs, see http://www.coinjoinsudoku.com/advisory. This is in contrast to *mixers* or *tumblers*, which are third-party services meant to obfuscate the link between sending and receiving addresses. These charge fees for these services and involve their own sets of addresses in the process and are generally among the identified entities discussed below.

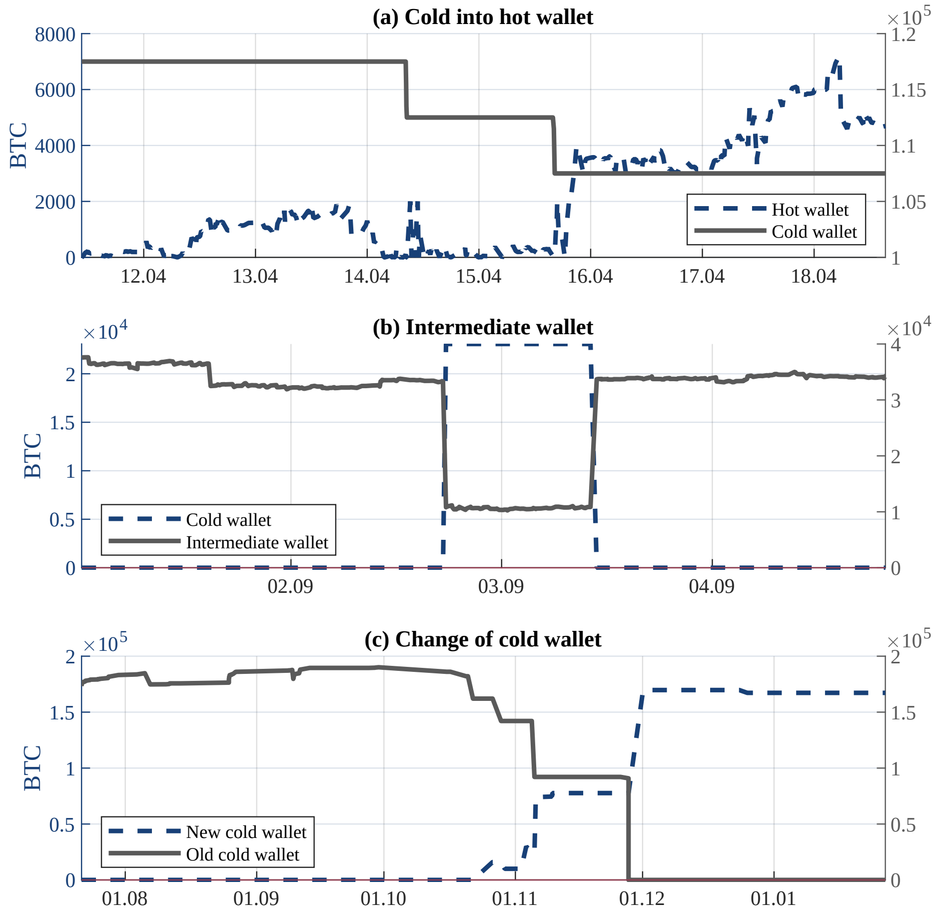
variety of different sources. The majority of addresses are based on information from walletexplorer.com, a website that collects millions of addresses of publicly known entities such as exchanges, mining pools, gambling sites, market places and others. The information contained on the site is mostly based on manual interactions with the entities, followed by the employment of input-address heuristics.[54] Second, I use information on individual large exchanges from the Bitfury Crystal database (crystalblockchain.com), which contains comprehensive coverage of exchange addresses as well as analytical tools to track Bitcoin flows. Third, I track the 10 thousand richest addresses on chain.info/richlist and include all wallets involved in transactions up to February 2018 of known exchanges.

Finally, I identify so-called *cold wallets* of exchanges in the dataset. In contrast to *hot wallets* the private keys to which are stored online, cold wallets allow for more secure storage offline. Following many incidents of hacks and thefts of Bitcoin hot wallets, it is common practice to keep only a fraction of coins in hot storage that are needed for day-to-day trading activity. In order to accurately measure Bitcoin holdings of exchanges, it is therefore essential to identify cold wallets, yet most publicly known addresses of large exchanges naturally refer to hot wallets. Next to screening through so-called *rich lists* on websites that track and label the largest individual wallets in the Bitcoin blockchain, I follow Griffin and Shams (2020) and employ algorithmic means to find cold storage addresses. Specifically, I define candidate cold wallets as those that at some point receive inflows on at least four days in a month of at least 100 Bitcoins. In addition, I require that at least 90 percent of these inflows stem from the same known hot wallet of an exchange. I then compute the balances of the candidate wallets and define all as cold wallets that at some point had an aggregate balance of at least 1000 Bitcoins.

I confirm that this algorithm-based scheme identifies various cold wallets that are known to belong to certain, often large, exchanges. However, I also verify that these algorithmic means do not suffice to reliably identify all wallets that are plausibly used as cold storage based on the manual tracking of Bitcoin flows. Consequently, I enrich the list of identified cold wallet addresses substantially by manually investigating individual transactions of already known hot and cold wallets. This turns out to be important as for some exchanges it seems to be common practice to move coins between hot and cold wallets not directly but in multiple intermediate steps and detours that often involve the splitting up of large sums into smaller transactions. On the other hand, very large cold wallets occasionally change addresses in a few very large transactions from one address to the next without involving the exchange's hot wallets at all. Any algorithm based merely on regular flows from hot into candidate cold wallets will fail to account for large cold wallets transitions.

[54]For Mt.Gox, the largest exchange in the early Bitcoin ecosystem, I instead mainly rely on information from an in-depth analysis of Mt.Gox conducted by the Bitcoin security blog https://blog.wizsec.jp, which contains detailed estimates of the balance of Bitcoin holdings at the exchange. A presentation of the analysis is available at https://breaking-bitcoin.com/slides/CrackingMtGox.pdf.

Figure A.3: Examples of Hot and Cold Wallet Interactions



Note. Examples of Bitcoin flows between hot and cold storage meant to illustrate patterns that guide the manual tracking of exchange wallets. Source: author's calculations based on blockchain data.

For the reasons outlined, I manually track sizable transactions of large exchanges' addresses to identify additional cold (and also hot) wallets. Naturally, this process involves some discretion as to whether a certain address can plausibly be linked to an exchange. In order to design this process as objectively as possible, I generally look for the following patterns. First, hot wallets accumulating a certain amount of Bitcoin balances over time that are then emptied in one large transactions that often brings the balance of the hot wallet address to or close to zero. I follow many of these transactions as they suggest a shifting of funds to a cold wallet for safer storage. Second, and conversely, hot wallets being charged from cold wallets in a number of relatively small transactions to provide enough coins for day-to-day trading activity or to finance outflows. An example of this is shown in panel (a) in Figure A.3 where the hot wallet of the Chinese exchange OKCoin receives two large transactions from cold storage. Third, cold wallets being emptied into intermediate wallets that are newly formed and exist for a limited number of time only, before being emptied again into the same cold wallet or one of the exchange's hot wallet. An example of this is shown in panel (b) in Figure A.3 for the case of Bitfinex. Fourth, as indicated above, occasionally large amounts of funds are shifted from one to another cold wallet directly in one or a few large transactions. As an example, consider panel (c) in FIGURE A.3 that shows the balances of address 3A1KUd5H4hBEHk4bZB4C3hGgvuXuVX7p7t being emptied abruptly in one large transaction of almost 100,000 coins, with the funds flowing to a well-known cold wallet of Bitstamp with address 3Nxwenay9Z8Lc9JBiywExpnEFiLp6Afp8v.[55]

Taken together, I identify more than 10,000 addresses that can be linked to individual exchanges and other entities. In conjunction with the clustering procedure, I am able to label 223 of the entities in my dataset, making up more than 42 million addresses. Based on these adjustments, I compute time series of aggregate blockchain transaction activity, as well as flows between and the holdings of exchanges, as discussed in the main text. As the series are sometimes volatile, I apply a 7-day moving average filter to all series computed from blockchain data. The efforts in tracking exchanges accurately notwithstanding, realistically it is unlikely that the list of identified addresses is entirely exhaustive. Given this uncertainty, all estimates of flows between and holdings of exchanges should be regarded as approximately lower bounds of actual activity. In general, due to the inherent limitations with the described heuristics, all results based on blockchain data in the empirical analysis should be interpreted as somewhat noisy estimates of the truth.

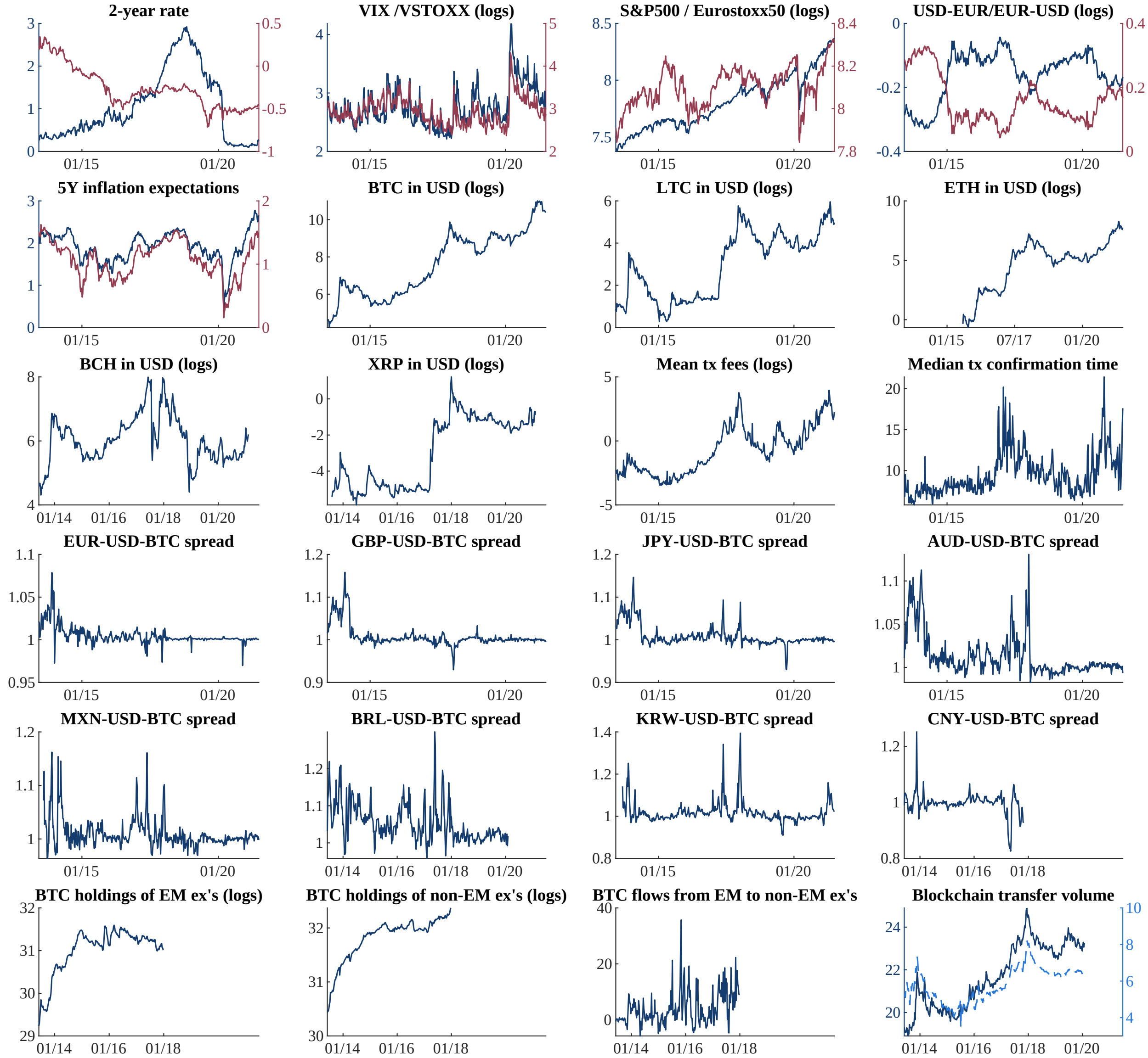
[55] For instance, Griffin and Shams (2020) identify 3Nxwenay9Z8Lc9JBiywExpnEFiLp6Afp8v as an address of Bitstamp's cold wallet.

Table A.1: Exchanges Tracked in Blockchain Dataset

Exchange	Supported currencies	Emerging market	Residence (if known)
AnxPro	*various*		Hong-Kong
Binance	EUR, GBP, USDT		Singapore / EU (Malta)
Bitbargain	GBP		
BitBay	PLN		EU (Malta)
Bitcoin24	EUR, GBP, PLN, USD		UK
Bitcoin.de	EUR		EU (Germany)
Bitcoinica	USD		New Zealand
Bitfloor	USD		
Bithumb	KRW	•	Korea
Bitso	MXN	•	Mexico
Bitstamp	EUR, USD		UK
Bittrex	USDT		US
Bitvc	CNY	•	Hong-Kong
Bit-x	EUR, GBP, USD		
Bleutrade	USDT		EU (Malta)
BTC38	CNY	•	China
BTC China	CNY	•	China
BTC-e	EUR, RUB, USD	•	EU (Cyprus)
BTCTrade	CNY	•	
Bter	CNY, USD	•	China
Bxinth	THB	•	Thailand
Cavirtex	CAD		Canada
C-cex	RUB	•	Russia
Cex.io	EUR, USD		UK
Coinbase	USD		US
Coinhako	SGD		
Coinspot	AUD		Australia
Cryptsy	USD		US
Exmo	EUR, RUB, USD	•	UK
Foxbit	BRL	•	BR
Gatecoin	EUR, HKD, USD		Hong-Kong
Gemini	USD		US
Hitbtc	EUR, USD		
Huobi	CNY	•	Seychelles
Korbit	KRW	•	Korea
Kraken	EUR, USD		US
LakeBTC	CNY, USD	•	UK
Localbitcoins	*various*	•	EU (Finland)
Maicoin	CNY	•	Samoa
Matbea	RUB	•	UK
Mercado	BRL	•	BR
Mt.Gox	*various*		Japan
OKCoin	CNY, USD	•	US
Paxful	*various*		US
Poloniex	USDT		US
Quadrigacx	CAD		Canada
TheRockTrading	EUR		EU (Italy)
Vircurex	EUR, USD		Belize
Virwox	EUR, GBP, USD		EU (Austria)
Yobit	RUB	•	

Note. List of exchanges for which a set of addresses is available and which are therefore included in the blockchain dataset used in Section 3. Exchanges classified according to whether they allow trading against emerging market currencies. Source: Bitfury (2019), Makarov and Schoar (2020), bitcoinity.org and various other websites and online fora.

Figure A.4: Time Series Employed in the Weekly Proxy VARs



Note. Time series used in weekly proxy VARs in Section 3. Series in red replace the ones in blue in the euro area VAR models. Light (dark) blue line in last panel refers to the median (total) transfer volume.

B VAR Estimation

Proxy VAR Model Description. The analysis is based on a structural VAR model represented by

$$\mathbf{A}_0\mathbf{y}_t = \mathbf{k} + \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}),$$

where $\mathbf{y}_t$ is an $(n \times 1)$ vector of endogenous variables, and $\mathbf{k}$ is a vector of constants. The corresponding reduced-form VAR is:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}),$$

with $\mathbf{c} = \mathbf{A}_0^{-1}\mathbf{k}$ and $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$ and $\mathbf{u}_t = \mathbf{A}_0^{-1}\epsilon_t$.

I partition the shock vectors into those of monetary policy, ϵ_t^p, and other shocks, $\epsilon_t^{q\prime}$, with corresponding residual vectors $\mathbf{u}_t = [u_t^p, \mathbf{u}_t^{q\prime}]'$. Denoting the impact matrix $\mathbf{A}_0^{-1}$ as $\mathbf{S}$, the interest lies in that set of coefficients, column $\mathbf{s}$, that measures the initial impact to a structural monetary policy shock. In what follows, I denote as $\mathbf{s}^q$ the initial impact of ϵ_t^p on $\mathbf{u}_t^q$, while s^p is the corresponding impact on the reduced-form monetary policy residual u_t^p.

Building on Stock and Watson (2018) and Mertens and Ravn (2013) and following Gertler and Karadi (2015), I use high-frequency market responses as an external instrument in the proxy VAR to identify the structural innovations ϵ_t^p. For these instruments to be valid, the surprise series $\mathbf{Z}_t$ needs to be *relevant* and *exogenous* as follows:

$$\mathbb{E}[\mathbf{Z}_t\epsilon_t^{p\prime}] = \phi \neq 0, \tag{A.1}$$

$$\mathbb{E}[\mathbf{Z}_t\epsilon_t^{q\prime}] = \mathbf{0}. \tag{A.2}$$

To estimate impulse responses to a structural monetary policy shock, I obtain estimates of $\mathbf{s}$ as follows. I extract the residuals $\mathbf{u}_t$ from the reduced-form VAR and use them in a two-stage least squares regression which include $\mathbf{Z}_t$ as instruments. In the first stage, u_t^p is linearly projected on $\mathbf{Z}_t$, delivering the fitted values $\hat{u}_t^p$. The latter, which are by assumption orthogonal to the remaining shocks ϵ_t^q, can be used in the second-stage regression:

$$\mathbf{u}_t^q = \frac{\mathbf{s}^q}{s^p}\hat{u}_t^p + \xi_t. \tag{A.3}$$

This procedure ensures that $\frac{\mathbf{s}^q}{s^p}$ is consistently estimated and can be used to obtain $\mathbf{s}$. I then normalize s^p so that the initial interest rate response is equal to 10 basis points. Given the modest number of observations and in order to avoid overfitting, I estimate the proxy VAR via Bayesian methods using standard macroeconometric priors as described next.

Bayesian Estimation. As is common in the structural VAR literature, I employ Bayesian techniques in order to impose more structure on the estimation and avoid overfitting given the relatively modest size of observations. I use standard Minnesota priors (as in Litterman, 1986) that are cast in the form of a Normal-Inverse-Wishart prior, which conveniently is the conjugate prior for the likelihood of a VAR with Gaussian innovations (see Miranda-Agrippino and Ricco, 2018).

Consider the setup for the proxy VAR:

$$\mathbf{A}_0\mathbf{y}_t = \mathbf{k} + \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{A.4}$$

where $\mathbf{y}_t$ is an $(n \times 1)$ vector of endogenous variables, and $\mathbf{k}$ is a vector of constants. The corresponding reduced-form VAR is:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}), \tag{A.5}$$

with $\mathbf{c} = \mathbf{A}_0^{-1}\mathbf{k}$, $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$ and $\mathbf{u}_t = \mathbf{A}_0^{-1}\epsilon_t$.

For Bayesian estimation, I specify a multivariate normal distribution for the regression coefficients, and an inverse Wishart distribution for the covariance matrix of the error term:

$$\mathbf{\Sigma} \sim \mathcal{IW}(\underline{\mathbf{S}}, \underline{\nu}), \tag{A.6}$$

$$\beta|\Sigma \sim \mathcal{N}(\underline{\beta}, \Sigma \otimes \underline{\mathbf{\Omega}}). \tag{A.7}$$

$\beta = vec([\mathbf{c}, \mathbf{B}_1, ..., \mathbf{B}_p]')$ are the stacked coefficient matrices and $\underline{\mathbf{S}}$, $\underline{\nu}$, $\underline{\beta}$ and $\underline{\mathbf{\Omega}}$ are hyperparameters. Specifically, $\underline{\mathbf{S}}$ and $\underline{\nu}$ are, respectively, the scale matrix and the degrees of freedom of the prior inverse Wishart distribution. As is standard, I specify $\underline{\mathbf{S}}$ as a diagonal matrix with entries σ_i^2 equal to the residual variance of the regression of each variable onto its own first lag. The degrees of freedom are set to $\underline{\nu} = n+2$ so as to ensure that the prior variances of the coefficient matrices exist and $\mathbb{E}(\beta) = \underline{\beta}$ and $\mathbb{V}ar(\beta) = \underline{\mathbf{S}} \otimes \underline{\mathbf{\Omega}}$.

I use a standard "Minnesota"-type prior in the spirit of Litterman (1986), which assumes the coefficient matrices to be independently normally distributed. Specifically, their first two moments are:

$$\mathbb{E}[(\mathbf{B_l})_{\mathbf{i,j}}|\mathbf{\Sigma}] = \begin{cases} \delta_i & i = j, l = 1 \\ 0 & \text{otherwise} \end{cases} \tag{A.8}$$

$$\mathbb{V}ar[(\mathbf{B_l})_{\mathbf{i,j}}|\mathbf{\Sigma}] = \begin{cases} \frac{\lambda^2}{l^2} & i = j, \forall l \\ \frac{\lambda^2}{l^2}\frac{\Sigma_{i,i}}{\sigma_j^2} & i \neq j, \forall l \end{cases} \tag{A.9}$$

where $(B_l)_{i,j}$ is the response of variable i to variable j at lag l. As the VAR is estimated in levels, generally I set $\delta_i = 1$, implying random-walk behavior of the underlying time series.[56] As is common, I formalize the idea that more recent lags of a variable tend to be more informative by specifying l^2 in the variance entries. Hence, equation (A.9) ensures a decaying variance of parameters for more distant lags and is, together with the assumptions above, achieved by specifying

$$\underline{\mathbf{\Omega}} = \begin{bmatrix} \phi & \mathbf{0} \\ \mathbf{0} & diag([1^2, 2^2, ..., p^2])^{-1} \otimes diag([\sigma_1^2, \sigma_2^2, ..., \sigma_p^2])^{-1} \end{bmatrix}, \tag{A.10}$$

where ϕ is a large number, implying a flat prior on the constant terms.

The hyperparameter λ controls the overall tightness of the Minnesota prior, which is determined optimally in the spirit of hierarchical modelling as in Giannone et al. (2015).

Combining the prior specification with the likelihood function, the posteriors can be shown to correspond to (see Miranda-Agrippino and Ricco, 2018):

$$\mathbf{\Sigma}|\mathbf{y} \sim \mathcal{IW}(\bar{\mathbf{S}}, \bar{\nu}) \tag{A.11}$$

$$\beta|\Sigma, \mathbf{y} \sim \mathcal{N}(\bar{\beta}, \mathbf{\Sigma} \otimes \bar{\mathbf{\Omega}}), \tag{A.12}$$

with

$$\bar{\mathbf{\Omega}} = (\underline{\mathbf{\Omega}} + \mathbf{x}'\mathbf{x})^{-\mathbf{1}}, \tag{A.13}$$

$$\bar{\beta} = vec(\bar{\mathbf{B}}) = vec\Big(\bar{\mathbf{\Omega}}\Big(\underline{\mathbf{\Omega}}^{-1}\underline{\mathbf{B}} + \mathbf{x}'\mathbf{x}\hat{\mathbf{B}}\Big)\Big), \tag{A.14}$$

$$\bar{\mathbf{S}} = \hat{\mathbf{B}}'\mathbf{x}'\mathbf{x}\hat{\mathbf{B}} + \underline{\mathbf{B}}'\underline{\mathbf{\Omega}}^{-\mathbf{1}}\underline{\mathbf{B}} + \underline{\mathbf{S}} + \Big(\mathbf{y} - \mathbf{x}\hat{\mathbf{B}}\Big)'\Big(\mathbf{y} - \mathbf{x}\hat{\mathbf{B}}\Big) - \bar{\mathbf{B}}'\Big(\underline{\mathbf{\Omega}}^{-\mathbf{1}} + \mathbf{x}'\mathbf{x}\Big)\bar{\mathbf{B}}, \tag{A.15}$$

where $\mathbf{x}_t = [\mathbf{1}, \mathbf{y}_{t-1}, ..., \mathbf{y}_{t-p}]$ is the projection set of lagged endogenous variables. The credible sets are then constructed by drawing from the posteriors and for each draw making use of the external instruments approach outlined in the main text.

[56] As some of the variables could be considered to be a priori stationary – e.g. those that are first-differenced in a robustness check –, I experiment with setting $\delta_i = 0$, as in Banbura et al. (2010), but generally find my results to be hardly affected.

C Additional Results

C.1 High-frequency Analysis

Figure C.1 depicts correlations of the USD Bitcoin price with that of other risky assets that cryptocurrencies are frequently compared to.[57] Again, it is well established that the correlation of Bitcoin prices to traditional financial assets in general is low. For instance, daily Bitcoin returns in USD between January 2014 and January 2020 (before the beginning of the COVID-19 pandemic) yield statistically insignificant correlation coefficients of below 0.05 with those of the S&P500, the USD-EUR exchange rate and the price of gold in USD. Figure C.1 shows that the correlation coefficients are higher within narrow windows of monetary policy announcements but remain mostly statistically insignificant. Only the relation of Bitcoin returns to gold around ECB Governing Council announcements is significantly elevated. This finding gives a first indication that Bitcoin could play a role as a digital alternative to gold in hedging inflationary concerns, as is often argued by its committed supporters.

C.2 Structural VAR

Robustness of VAR Results. I make sure that my main results in the VAR analysis are robust along a number of dimensions. In particular, they hold when ending the time sample in late 2017 before a major regulatory crackdown by Chinese authorities – which effectively ended Bitcoin trading in Chinese yuan on exchanges and resulted in a structural shift towards the US dollar – and the meteoric Bitcoin price increase in Winter 2017/18, (Figure C.2), when starting the sample later (e.g. in 2015) or when excluding the COVID-19 market crash in early 2020.

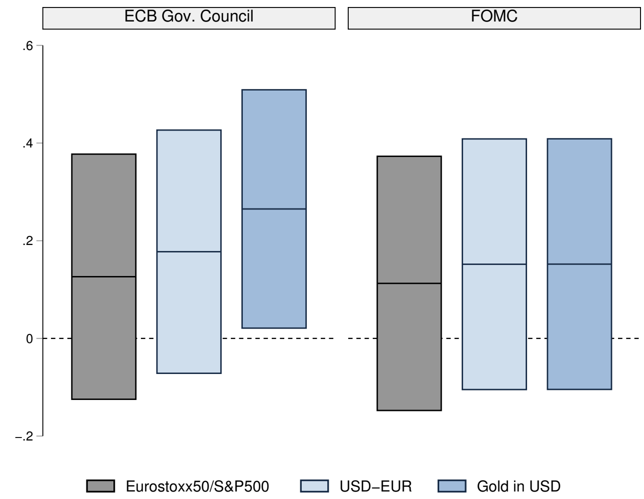
In addition, there might be concerns regarding the only partial overlap of the time samples of the US VAR model on the one hand and the instrument series on the other. As descibed in Appendix A, with the high-frequency price responses in the Cieslak and Schrimpf (2019) database only available until the end of 2017, shock identification in the baseline US model primarily stems from the earlier parts of the sample. Therefore, I verify that the Bitcoin price response to a US monetary contraction looks similar when I extend the instrument series, albeit imperfectly, in the later parts of the sample (Figure C.4).

Another concern could be related to stationarity given the enormous increase in the price of Bitcoin over the sample period. Here I make sure that my results also hold when adding the logged Bitcoin price in first (and even second) differences (Figure C.3) or when also first-differencing the other non-stationary variables in the model.

Finally, I verify robustness with respect to the econometric approach, as discussed in the following.

[57] For this comparison, I download one-minute data of the S&P500, Eurostoxx50, the USD-EUR exchange rate and the price of Gold in USD from tickstory.com.

Figure C.1: Correlation of BTC With Other Assets Around Monetary Policy Announcements



Note. Correlation of Bitcoin returns in USD with the prices of conventional assets in narrow windows of ECB Governing Council meetings (left) and FOMC meetings (right panel). Time sample: January 2014 to June 2021. Shaded areas denote 95% confidence bands. Source: author's calculations based on data from `bitcoincharts.com`, `tickstory.com`.

Local Projections. As a an additional robustness exercise I construct impulse responses following Jorda (2005) by relating the exogenous shocks to Bitcoin valuations in a dynamic regression framework. Indeed, whereas local projections and VARs estimate the same impulse responses in population, in finite samples the estimates might differ (Plagborg-Møller and Wolf, 2021). It will hence instructive to assess if the responses of Bitcoin prices to monetary policy shocks differ from the ones obtained in the VAR.

Formally, the regression framework reads

$$y_{t+h} = \alpha_h + \beta_h \epsilon_{s,t} + \sum_{j=1}^{6} (\gamma_h^y y_{t-j} + \gamma_h^\epsilon \epsilon_{s,t-j} + \mathbf{X}_{t-j} \Gamma_h^X) + t + e_t, \quad h = 0, 1, ...H \tag{C.1}$$

where $\epsilon_{s,t}$, is either the external instrument used to identify the respective structural shock in the proxy VAR, or the identified shock itself,[58] y_t indicates the logged price of Bitcoin in USD, $\mathbf{X}_t$ is a set of controls, and t is a time trend. The coefficients β_h will then measure the impulse response that are hence constructed without imposing a recursive VAR model structure.

The first four panels in the first row of Figure C.6 reports results.[59] As in the VAR model, an exogenous monetary contraction in the euro area leads to a fall in the price of Bitcoin, irrespective of whether it is measured by the instrument (first) or identified

[58] Piffer (2016) provides a guide on how to extract the shocks in a proxy VAR setting.

[59] Confidence bands are constructed using heteroskedasticity- and autocorrelation-robust Newey West standard errors. When using only heteroskedasticity-robust White standard errors, as recently suggested by Montiel Olea and Plagborg-Møller (2021) in a model with lag augmentation, results are almost identical.

structural shock (second panel). Similarly, an otherwise equal contraction by the Fed has the opposite effect, and increases Bitcoin valuations as in the VAR.[60]

Easing vs. Tightening. Next to being useful as a robustness check, local projections naturally lend themselves to the study of nonlinearities. In particular, it is straightforward to assess the differing impact of expansionary and contractionary shocks by simply splitting up the shock measure into positive and negative values and use them separately in the regressions. The first four panels in the second row of Figure C.6 report results for such an exercise, whereby the impulse response to an easing is multiplied by minus one in order to aid comparison. The figure reveals that an easing (solid lines, light bands) and a tightening (dashed lines, dark bands) have fairly similar (absolute) effects in the euro area model. In contrast, it seems to be primarily monetary contractions instead of expansions that drive the Bitcoin price response in the US model. Notably, this finding further supports the view developed in Section 3.4. In there, the focus lies on a tightening of Fed policy and its detrimental effects on the value of emerging market currencies and global economic and financial conditions. Hence, it is the negative impact of the tightening that makes Bitcoin attractive as a safe haven asset, for capital flight or as a vehicle currency, and an easing of monetary conditions arguably would not have same quantitative impact in reverse.

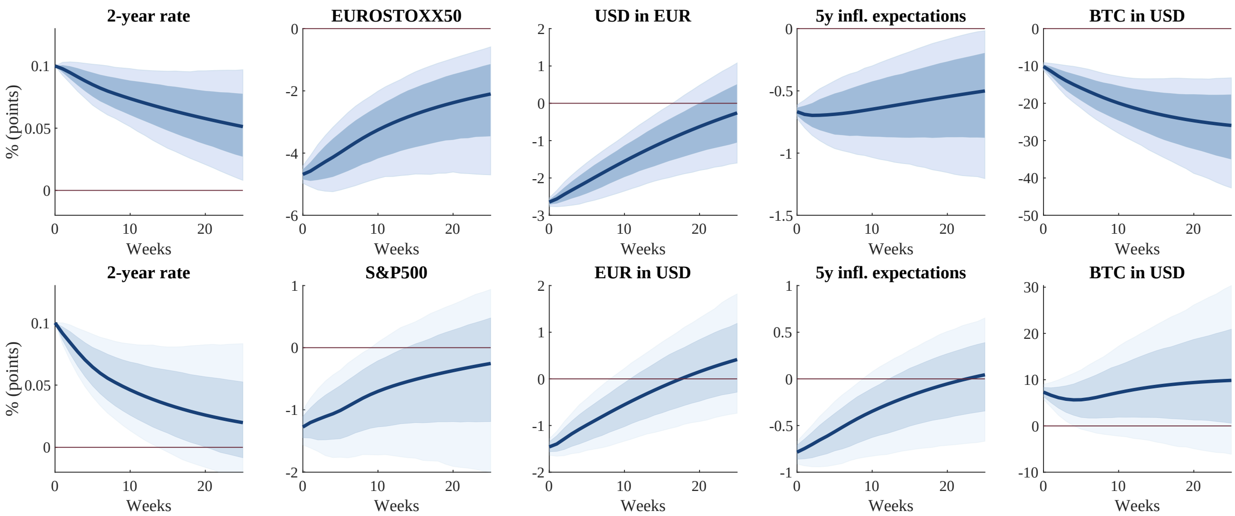
Monetary Policy and Risk-Shift Shocks. A recent paper by Kroencke et al. (2021) argues that monetary policy announcements by the FOMC also contain "extended information shocks" that are not associated with current and future risk-free interest rates, but can instead be captured by price changes of risky assets. Using data on surprise responses of CDS spreads, the VIX and the USD exchange rate, they construct a measure of *risk shifts* employing factor analysis. They go on to show that these risk shifts drive a large portion of the response of equity excess returns unexplained by changes in risk-free rates. Similar to the case of central bank information shocks, it will be instructive to asses how Bitcoin valuations respond to risk shifts. Whereas the former capture changes in economic outlook that might be relevant for the decision to hold Bitcoin, the latter capture orthogonal shifts in the willingness to take risky asset positions, which are arguably important as well.

The rightmost column in Figure C.6 depicts impulse responses to contractionary risk-shift shocks. In the upper panel, again in corroboration of the results so far, the shock, associated with a lower willingness to hold other risky assets, leads to an increase in Bitcoin prices. In the lower panel, I again test whether the response is asymmetric. Similarly to the case of the US monetary tightening, it is the contractionary shocks that drive the results, whereas here an expansionary shock even leads to the opposite effect. Arguably, this further corroborates the notion that Bitcoin valuations benefit from conditions that have the opposite effect on risky asset prices.

[60] I obtain equally similar results to the VAR model when doing the same exercise with central bank information shocks.

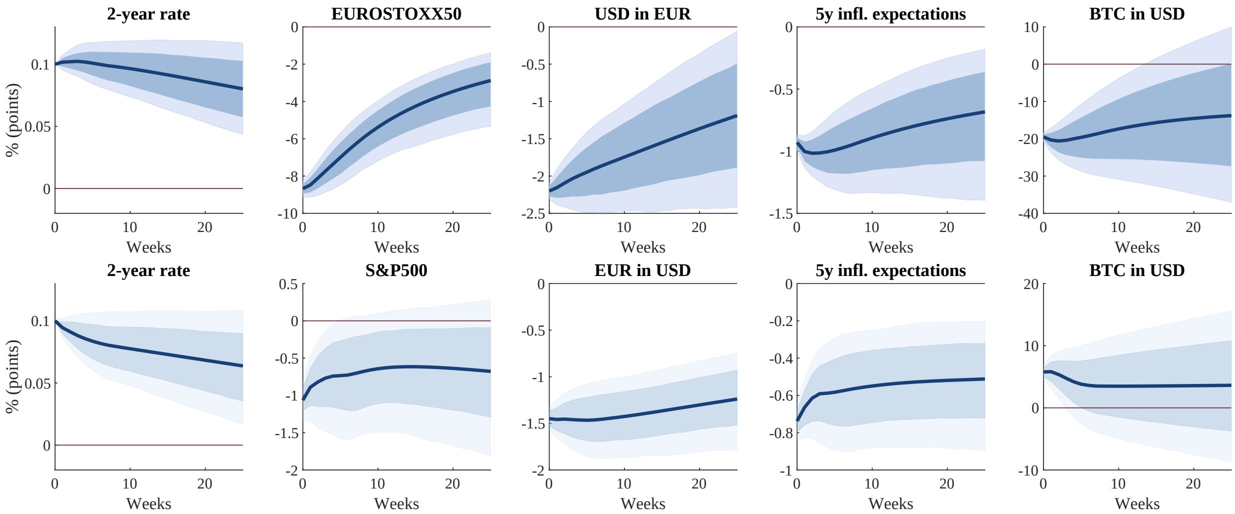
Other Cryptocurrencies. I test whether I obtain similar responses to monetary policy shocks for similar cryptocurrencies for which there is sufficiently long time series data available and which have similar characteristics in terms of decentralized transactions and mechanical supply schemes. Figure C.5 shows that Litecoin (LTC), Ether (ETH) and Bitcoin Cash (BCH) all respond similarly to Bitcoin to both euro area and US monetary policy shocks, while the response of Ripple (XRP) is insignificant in the US model.

Figure C.2: Robustness: IRFs to US and EA Monetary Policy Shocks: Shorter Time Sample



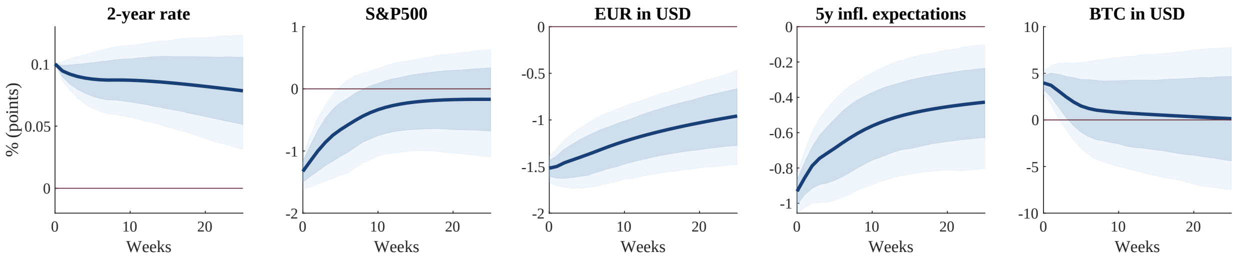
Note. Impulse responses to a contractionary euro area (upper) and US (lower panel) monetary policy shock in shorter time sample (June 2013 to September 2017). Remaining details as in Figure 5.

Figure C.3: Robustness: IRFs to US and EA Monetary Policy Shocks: BTC in first differences



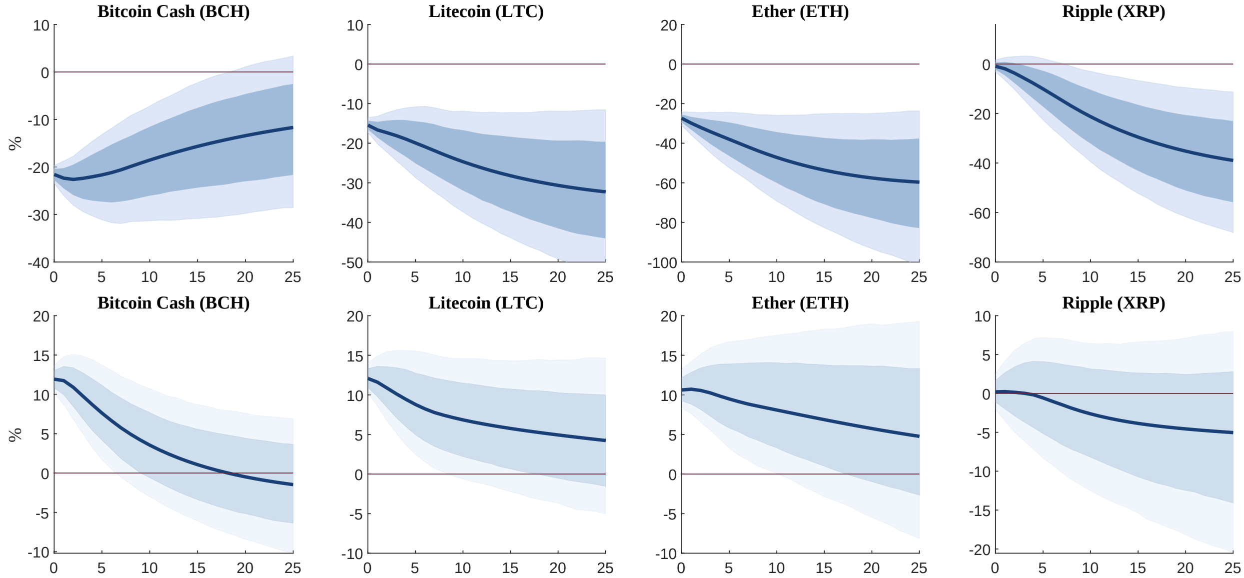
Note. Impulse responses to a contractionary euro area (upper) and US (lower panel) monetary policy shock where Bitcoin prices enter in (logged) first differences. Remaining details as in Figure 5.

Figure C.4: Robustness: IRFs to US Monetary Policy Shocks: Extended Instrument



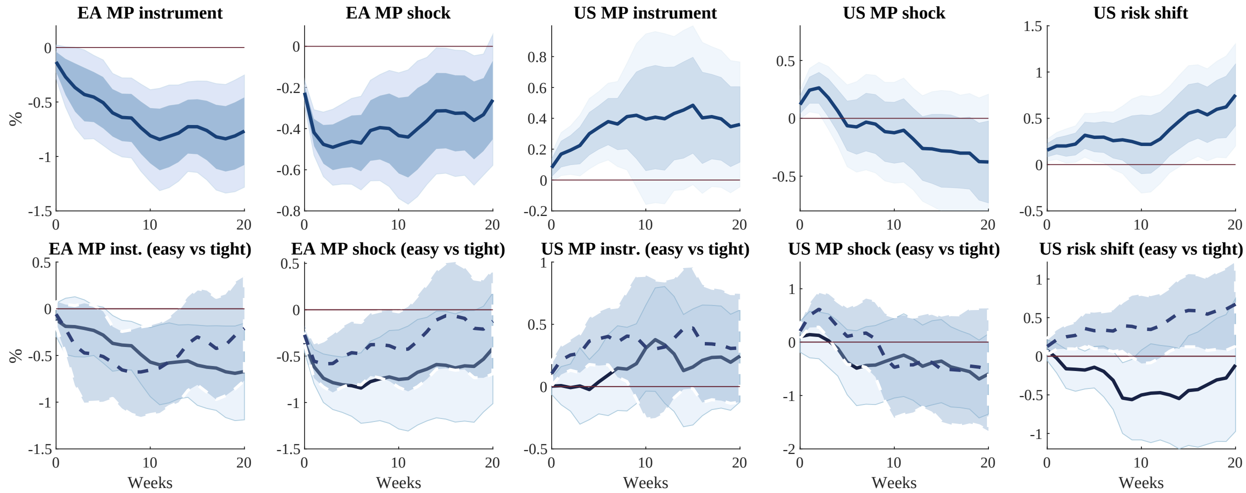
Note. Impulse responses to a contractionary and US monetary policy shock with an extended instrument series. Remaining details as in Figure 5.

Figure C.5: IRFs to Contractionary US Monetary Policy Shocks: Other Cryptocurrencies



Note. Impulse responses of other cryptocurrency prices to a contractionary euro area (upper) and US (lower panel) monetary policy shock. Remaining details as in Figure 5.

Figure C.6: IRFs of BTC Price to Monetary Policy-Related Shocks: Local Projections



Note. Impulse responses of Bitcoin prices in USD to US shocks in local projection analysis in equation (C.1). First row shows local projection responses to instrument series and identified structural shocks (panels 1-4) and risk-shift shocks as in Kroencke et al. (2021), which are defined as "contractionary" in that they lead to declines in stock market prices. Shaded areas denote 68% and 90% confidence bands. Second row compares easing (solid lines, light area, multiplied by minus one) with tightening (dashed lines, dark areas).